Water Supply

Water Supply Vol 22 No 2, 1388 doi: 10.2166/ws.2021.344

Performance-based multi-objective design and expansion of water distribution networks considering life cycle costs and future demands

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ABSTRACT

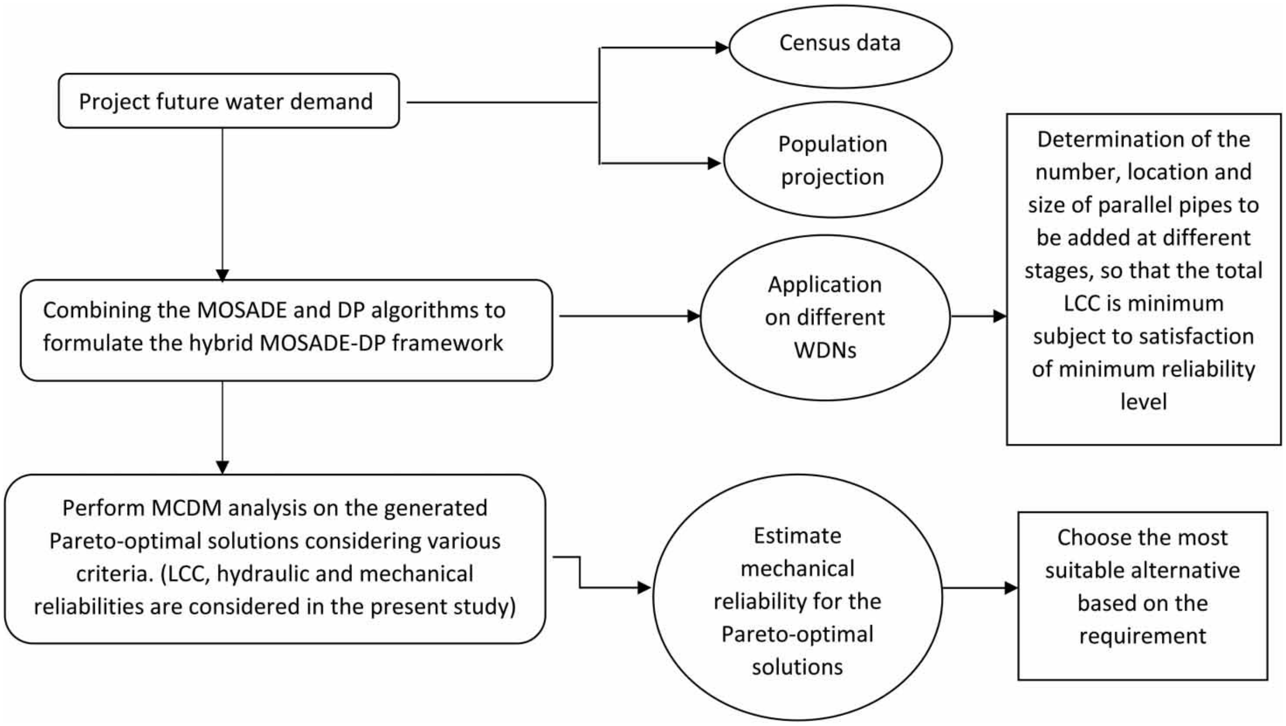
Designing the Water Distribution Networks (WDNs) consists of finding out pipe sizes such that the demands are satisfied and the desired performance levels are achieved at minimum cost. However, WDNs are subject to many future changes such as an increase (or decrease) in demand due to population change and migration, changes in water availability due to seasonal and climatic change, etc. Thus, the capacity expansion of WDNs needs to be performed such that the cost of interventions made is minimum while satisfying the demand and performance requirements at various time periods. Therefore, the current study proposed a Dynamic Programming (DP) framework for capacity expansion of WDNs and solved using Multi-Objective Self Adaptive Differential Evolution (MOSADE). The methodology is tested on three benchmark WDNs, namely Two-loop (TL), GoYang, and Blacksburg (BLA) WDNs, and applied to a real case study of the Badlapur region, Maharashtra, India. The results show that the proposed methodology leads to effective Pareto optimal fronts, making it an efficient method for solving WDN expansion problems. Subsequently, an Analytical Hierarchy Process (AHP) based multi-criteria decision-making (MCDM) analysis was performed on the obtained Pareto-optimal solutions to determine the most suitable solution based on three criteria: Life Cycle Cost (LCC) of expansions, hydraulic reliability, and mechanical reliability. The main advantage of the proposed methodology is its capability to consider hydraulic performance as well as structural integrity and demand satisfaction in the face of hydraulic and mechanical failures.

Key words: future demands, MCDM analysis, MOSADE-DP, phased expansions, water distribution network expansion

HIGHLIGHTS

- A novel MOSADE-DP framework for solving WDN expansion problems.
- Takes into consideration LCC and future water demands.
- Pareto-optimal fronts generated between LCC and hydraulic reliability.
- Multi-objective multi-criteria decision-making analysis to find out the most suitable option based on LCC, and hydraulic and mechanical reliabilities.
- Takes into account hydraulic performance as well as structural integrity.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Water demand is one of the most crucial input variables that may change in the future and alter the performance of the Water Distribution Networks (WDNs). Water demand depends on factors such as population and per capita water consumption. Thus, the future water demand of any area increases (or decreases) based on the changes in these factors. Similarly, water availability may also get affected due to factors such as a change in climatic and seasonal conditions. Thus, it is necessary to consider these future uncertainties for designing the WDNs. Hence, considering the various future uncertainties, the design of WDNs is an inquisitive task. Thus, expansions need to be planned so that satisfactory performance is achieved at all stages, and the cost of these interventions is minimal.

For incorporating the future changes in water demand, several past studies presented different methodologies. Schneiter *et al.* (1996) presented an optimal rehabilitation strategy for WDNs, which depends on the deterioration of pipes. Kleiner *et al.* (1998) proposed a framework for optimal rehabilitation scheduling of WDNs by integrating it into a decision support system. The method uses Dynamic Programming (DP) amalgamated with partial enumeration schemes to determine the rehabilitation options and when it is to be executed. Agrawal *et al.* (2007) presented an iterative method for strengthening and expanding the WDNs, based on the ratio of marginal capacity factor to the marginal increase in cost. Naik & Gupta (2009) presented a WDN expansion methodology based on a Genetic Algorithm under the fund's constraint conditions, such that sufficient funds are available at the current stage, while insufficient funds are available for the ultimate stage. Huang *et al.* (2010) presented a flexible design approach by developing a scenario tree for representing the uncertain nodal water demands and then optimizing the solutions for phased construction considering the likelihood of different demand scenarios. Creaco *et al.* (2013) proposed a framework for the expansion of WDNs considering the growing demands. The results showed that appending parallel pipes at different time intervals leads to better solutions than single-step design (all the construction is implemented at the start of the planning horizon, considering a peak value of the water demand). Basupi & Kapelan (2015) proposed a flexible WDN design approach for WDN expansion, considering future changes in water demand, and compared with the results of precautionary and staged deterministic methods. The results showed that flexible design methodology leads to the best design solutions compared to the other two methods. Saldarriaga & Vega (2018) presented a rehabilitation methodology for a real WDN to plan the topological changes considering the pipe replacement considering various demand conditions to readjust the network to achieve minimum pressure requirement and enhance the hydraulic performance of the network. Dell'Aira *et al.* (2021) presented a comprehensive method for designing and expanding WDNs based on NSGA-II considering the evolution of the urban areas. Thus, it was noticed that there exist few past studies on designing WDN expansions, considering the future changes in water demand. However, most of these approaches try to find the most optimal solution considering only the forecasted demand for a given future state without considering the overall design period and thus may not explore all the possible solutions. Thus, it is necessary to develop an efficient methodology to consider the possible changes throughout the design period.

Also, most of these past studies did not consider the Life Cycle Cost (LCC) associated with the various components. Some past studies emphasized the importance of taking into account the LCC in the design formulation. Jayaram & Srinivasan (2008) performed the multi-objective design of WDNs considering minimizing LCC and maximizing network performance. The study noticed that considering the life cycle components in the design framework leads to better design solutions rather than overdesigning the WDN at the start of the design period. Piratla & Ariaratnam (2012) presented a reliability-based design of WDNs considering life cycle components. It was found that considering the minimization of LCC and life cycle CO_2 emissions while taking reliability as a constraint leads to the most promising solutions. Liu *et al.* (2020) presented a framework for assessing the lifecycle operational resilience of WDNs taking into account pipe deterioration and accidents. Thus, considering LCC for the entire planning horizon is essential rather than considering only the cost of pipes, leading to better solutions and overall lower-cost solutions. The lifecycle analysis of the networks also helps to account for different failures and their associated costs.

In addition to LCC, consideration of the desired performance of WDNs in terms of reliability forms an essential component, which implies the need for the multi-objective formulation of the WDN expansion problem. Reliability is defined as the level of demand satisfaction considering working as well as failure conditions, classified as hydraulic and mechanical (Bao & Mays 1990). While hydraulic reliability ensures satisfactory performance considering uncertain parameters, mechanical reliability ensures satisfactory performance considering the failure of the components such as pipes, pumps, valves, and so on. Uncertainty modeling is required for hydraulic reliability estimation, considering the extent of probable estimates of the uncertain input parameter instead of a single deterministic value. Several previous studies presented various methods for uncertainty analysis, which consists of representing the uncertain parameters as either fuzzy or random variables. Vamvakeridou-Lyroudia *et al.* (2005), Farmani *et al.* (2005), and Shibu & Reddy (2014) applied fuzzy set theory to represent the uncertainty in nodal demands. Different researchers also applied various probabilistic approaches for modeling the uncertainty in nodal demands, such as the Monte Carlo Simulation (MCS) method (Gupta & Bhave 1996; Tolson *et al.* 2004; Fu & Kapelan 2011), and First Order Second Moment (FOSM) method (Sumer & Lansey 2009). Jensen & Jerez (2018) presented a stochastic framework for the reliability and sensitivity analysis of large-scale WDNs. They pointed out that the major drawback of the Monte Carlo simulation approach is that it is very time-consuming and inefficient, especially considering the large-sized WDN problems.

Nonetheless, nearly all reliability estimation methods have the drawback of enormous computing needs because of the extensive number of hydraulic simulations required. Hydraulic simulations can be more efficient if it is performed based on the loop equation approach (Ivetić *et al.* 2015; Vasilić *et al.* 2018). Different studies proposed reliability surrogate measures (RSMs) such as entropy (Awumah *et al.* 1990), resiliency (Todini 2000), network resilience (Prasad & Park 2004), etc., to overcome the issue of substantial computational drawbacks. The use of these RSMs is more effective for reduction in computational demands. RSMs have the privilege that these are simple to carry out and need just a single hydraulic simulation to estimate one index value. Many past studies adopted resiliency as a surrogate for reliability (Farmani *et al.* 2006; Reca *et al.* 2008) and noted it as an appropriate alternative for hydraulic reliability (Raad *et al.* 2010; Banos *et al.* 2011; Atkinson *et al.* 2014). Some studies also found that there exists a certain amount of association between the two, which means ensuring resiliency can ensure reliability to a certain extent (Sirsant & Reddy 2020). The current study thus employs resiliency as a substitute for reliability. The primary purpose of resiliency is to generate Pareto-optimal solutions considering minimization of LCC and maximization of resiliency, which is used as initial solutions for further optimization runs considering reliability. Consideration of reliability in the optimization model is vital because maximization of reliability is the ultimate objective since it represents the accurate picture of the system's performance. In contrast, consideration of resiliency for initial runs leads to a considerable reduction in computational time.

The existing WDN expansion methods have the shortcoming of inadequate investigation of the search space by optimizing the solutions at every stage rather than the entire design period. The problem must be ideally solved as a staged expansion problem exploiting every potential solution considering the entire planning horizon, making it an ideal problem for solution by DP. However, DP possesses the drawback of huge computational time, which increases as the size of the problem increases. This issue can be addressed by implementing Evolutionary Algorithms (EAs) to solve such problems, giving optimal or near-optimal solutions in an equitable proportion of computational time (Zheng *et al.* 2015; Reddy & Kumar 2020). Several such algorithms prevail in the literature, such as Genetic Algorithm (GA; Gupta *et al.* 1999), Particle Swarm Optimization (PSO; Montalvo *et al.* 2008), Ant Colony Optimization (ACO; Ostfeld & Tubaltzev, 2008), Differential Evolution (DE; Dong *et al.*, 2012), Self-Adaptive DE (SADE; Zheng *et al.* 2013), etc., as well as multi-objective variants of these algorithms such as multi-objective GA (MOGA; Prasad *et al.* 2003), Non-dominated sorting GA-II (NSGA-II; Zhang *et al.* 2019), etc. However, these EAs may converge to sub-optimal solutions due to the wrong choice of factors such as mutation and crossover rates. Among the various algorithms, self-adaptive EAs are effective (Zhang & Sanderson 2009; Wang *et al.* 2010; Sirsant & Reddy 2018). Also, in the past, WDN expansions have been framed mostly as single-objective optimization problems considering cost minimization subject to reliability as a constraint. Therefore, in the present study, a Multi-Objective Self-Adaptive Differential Evolution (MOSADE) is illustrated to find the solutions for the WDN design problem in a DP framework accounting for future water demands and phased expansion. The procedure utilizes the strengths of DP methodology for multi-stage decision-making while alleviating the enormous computational burden associated with DP by engaging MOSADE for effective exploration of the search space.

For finding out the most suitable design solution considering the multiple criteria that may affect the selection of the solution, Multi-Criteria Decision Making (MCDM) analysis is performed using the Analytical Hierarchy Process (AHP). Few past studies presented MCDM analysis for choosing the best alternative (Vamvakeridou-Lyroudia *et al.* 2006; Tanyimboh & Kalungi 2009; Aghaarabi *et al.* 2014) considering various criteria such as total expenditure, public evaluation, political repercussions, water quality, health effects, flexibility, water demand management, time of water insufficiency, population effects, communal danger, etc. Three criteria are considered in the present study; that is, minimum LCC of expansion, maximum hydraulic reliability, and maximum mechanical reliability. The main advantage of considering these three criteria is that it considers the total cost of expansions and repair and replacement cost while searching for solutions with maximum demand satisfaction considering uncertainties such as fluctuations in nodal demands while minimizing the deficits that may take place because of mechanical failures.

The specific objectives of the present study are: (1) to formulate a hybrid MOSADE-DP methodology for tackling the staged expansion problem of WDNs taking into account LCC and future demand scenarios; (2) to assess the efficacy of developed framework by application to a few benchmark WDNs as well as for an actual case study; (3) to apply an AHP-based MCDM approach for selecting the best solution considering LCC, and hydraulic and mechanical reliability.

2. MATERIALS AND METHODS

The expansion problem of WDNs is framed as an optimization problem for finding out the number, size, and location of the parallel pipes to be added at various stages, such that the LCC of the parallel pipes being added is the least and the required reliabilities are attained.

The overall formulation for planning WDN expansions comprises the following basic steps:

1. Determine the initial pipe sizes assigned to the WDN, considering the predicted demand for the next ten years.
2. In subsequent periods of the planning horizon, at each stage, the location, number, and size of the parallel pipes to be appended are determined such that the LCC of pipes is minimum for different reliability levels (expressed in terms of resiliency).

It should be noted that real-life expansions comprise many complexities such as multiple future demand projections, deterioration of existing and new pipes, addition of new sources or tanks, availability of funds at different stages etc. The present study, however, considers a generic model with the following assumptions.

1. Only a single future demand projection is considered for each WDN problem.
2. For real case study applications, even if some wards are showing a decrease in population, future projections are made considering increasing trends, so as to depict the most adverse conditions.
3. Expansions are planned only to add parallel pipes adjacent to the existing pipes, while other components such as the addition of new pumps or tanks are not considered.

4. The pipes are assumed to deteriorate with an exponential increase in the break rate of pipes.
5. It is assumed that sufficient funds are available at each stage so there are no restrictions placed on the cost of expansion.

In order to perform each of the steps mentioned above, the methodologies and techniques adopted in the study are presented, followed by the traditional WDN expansion methods and the proposed DP and MOSADE-DP frameworks.

2.1. Mathematical formulation for design of WDNs

The design of WDNs is framed as an optimization problem for cost minimization and resiliency (or reliability) maximization, subject to fulfillment of the least head requirements and conservation of mass and energy. Mathematically, the problem can be stated as

$$\text{Minimize LCC} \tag{1}$$

$$\text{Maximize R} \tag{2}$$

Subject to:

$$H_i \geq H_{\min} \qquad \text{(for all nodes)} \tag{3}$$

$$\sum HL_i - \sum E_p = 0 \qquad \text{(for all loops)} \tag{4}$$

$$\sum Q_{in} - \sum Q_{out} = 0 \qquad \text{(for all nodes)} \tag{5}$$

with

$$HL_i = \frac{10.68\, Q_i^{1.85}\, L_i}{C_{HW}^{1.85}\, D_i^{4.87}} \tag{6}$$

and

$$Q_i = \frac{\pi}{4} D_i^2 V_i \tag{7}$$

where LCC is life cycle cost, R is reliability, D_i is the diameter and L_i is the length of pipe i, H stands for pressure head, H_{min} is the least desired head at a junction, HL is the loss of head for a link, E_p is the energy added by the pump, Q_{in} and Q_{out} are the inflowing and outflowing discharges from a junction respectively, C_{HW} is the Hazen-William's roughness coefficient, and V is the velocity of flow in a particular pipe. The values in Hazen-William's equation stated above for head loss calculation should be substituted be in SI units; that is, diameter, length and head in meters, and discharge in cumecs. R and R_{min} are the actual and least desired reliability, respectively. However, the present study uses resiliency for generating initial solutions, and then further optimization runs are carried out using reliability for designing the expansions.

In order to understand the concept of estimation of LCC, the concept of break rate and service life of pipes needs to be understood, which is included in the supplementary materials Text S1.

2.2. Evaluating life cycle costs

The present study assesses the LCC as the sum of initial installation cost (IC) and the break cost (BC, which includes repair and replacement costs)

$$LCC = IC + BC \tag{8}$$

The IC can be calculated as a function of the length and diameter of pipes using

$$IC = \sum_{i=1}^{n_p} f(D_i) L_i \tag{9}$$

The break cost can be calculated as

$$BC = \sum_{i=1}^{n_p} BR(i) + RC(i) + AR(i) \tag{10}$$

The first component, BR, is the break repair cost, RC is the replacement cost, and AR is the repair cost for any repairs after all the replacements of the i^{th} pipe are made within the planning horizon, which can be estimated as follows

$$BR(i) = \begin{cases} \sum_{m=1}^{k(i)} \sum_{r=1}^{s(i)} \left[\frac{1}{(1+I)^{((m-1).s(i))+r}} .N_{D_i}.e^{A((m-1).s(i))+r}.B_{D_i}.L_i \right], & \text{if } k(i) \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

$$RC(i) = \begin{cases} \sum_{m=1}^{k(i)} \frac{1}{(1+I)^{m.s(i)}} .R_{D_i}.L_i, & \text{if } k(i) \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

$$AR(i) = \sum_{r=k(i).s(i)+1}^{y} \left[\frac{1}{(1+I)^r} .N_{D_i}.e^{A(r-k(i).s(i))}.B_{D_i}.L_i \right] \tag{13}$$

In the above equations, $s(i)$ stands for the service life of pipe i, I is the discount rate per year, N_{Di} is the number of breaks per year per unit length for links having diameter D_i, B_{Di} is the repair cost per break for links having diameter D_i, A is the break growth rate coefficient per year, R_{Di} is the replacement cost per unit length for links having diameter D_i, y is the design period, and $k(i)$ is the number of times link i needs to be replaced during the entire planning horizon and is given by

$$k(i) = \text{int}\left(\frac{y}{s(i)}\right) \tag{14}$$

where *int* stands for the integer value.

2.3. Resiliency of WDNs

In order to ensure the satisfactory performance of the WDNs, the concept of reliability should be taken into account in the design formulation. The uncertainty in input parameters such as nodal demands, pipe roughness coefficients, and so on, needs to be considered for estimating hydraulic reliability. To model the uncertainties of nodal demands, the present study assumes the uncertain parameters to follow a normal distribution with a coefficient of variation (CV) of 0.1. More details about the estimation of hydraulic reliability can be found in Sirsant & Reddy (2018). However, estimating reliability is a hugely tedious task, and therefore to lower the computing requirements, resiliency is employed as a substitute for reliability. The concept of resiliency was proposed by Todini (2000). It is an estimate of the power accessible for internal consumption in case of abrupt failure and is estimated using the following equation

$$I_r = \frac{\sum_{i=1}^{n} q_i^*(h_i - h_i^*)}{\sum_{k=1}^{n_R} q_{R,k} h_{R,k} - \sum_{i=1}^{n} q_i^* h_i^*} \tag{15}$$

where q_i* and h_i* are the minimum required flow and head values for any node i, $q_{R,k}$ and $h_{R,k}$ are the flow and head available from the reservoir, h_i is the actual head at node i, n and n_R are the numbers of demand nodes and supply sources respectively.

2.4. DP based framework for WDN expansion problem

The solution of WDN expansion problem using DP requires determining the size, location, and the number of parallel pipes to be added at each stage, where the stage is considered the time (in years) at which the expansions are designed. Thus, the state variables are the size, location, and the number of parallel pipes, and the stage is the time period in years at which these pipes are being added. For solving a multi-objective DP, the following functional equation is used (Klötzler 1978)

$$F(S) = opt(\cup_{d \in D(S)}\{R(S, d) + e, e \in F(T(S, d))\}) \tag{16}$$

Here, *F(S)* is the Pareto-front of the optimization sub-problem for the state (time period) *S*, *D(S)* is the set of decisions (choice of parallel pipes to be added) that can be made for a given state *S*, *T(S, d)* is the transformation function, which gives the possible choices for the next stage when decision *d* is taken at state *S*, *R(S, d)* is the function which gives the cost for each objective function if the decision *d* is taken from state *S*; in the present study it comprises a vector of LCC and negative value of resiliency/reliability (as resiliency/reliability needs to be maximized, the negative of it will comprise minimization of the same). Lastly, *opt* stands for the set of non-dominated vectors for a given set of vectors.

However, the method becomes computationally very extensive, as finding out all possible combinations of parallel pipes even for a small problem would lead to many alternatives. For example, considering a problem consisting of 16 available pipe diameters, and for $(N\text{-}n) = 9$, would lead to 16^9 (≈68,719,476,736) possible cases. Thus, finding out the solution using DP becomes computationally intractable for standard configuration PC systems. The enormous computational burden of DP is taken care of by presenting a hybrid MOSADE-DP framework in the current study.

2.5. MOSADE-based methodology in DP framework for WDN design accounting phased expansion

The presented methodology generates and exploits all probable combinations of parallel pipes using the MOSADE methodology within the DP framework. Before going into the details of the proposed framework, the basic steps involved in MOSADE can be found in Huang *et al.* (2009).

The notation used in the methodology: let *N* be the total number of pipes added till the current stage (including all previous stages) and *n* be the number of parallel pipes to be added till the previous stage, and *N_poss* is the maximum possible number of parallel pipes that can be added to the WDN.

The steps involved in the MOSADE-DP framework are as follows:

1. Determine and assign the initial pipe diameters for the WDN considering the projected demand (say for the next ten years).
2. Allocate the predicted demand for the considered stage.
3. Set $N = 1$, and $n = 1$ (for 2nd stage onwards, else $n = 0$).
4. For *N* ranging from 1 to *N_poss* and *n* ranging from 1 to *N* (for 2nd time period onwards), perform the following steps:
   a. For stage 2 onwards, select the solutions that have *n* parallel pipes being added till the last stage, else proceed to the next step.
   b. Initialize parameters for MOSADE: $iter = 0$; set I_{max} (maximum number of iterations), *NP* (population size), mutation, and crossover parameters.
   c. Formulate a random sample of (*N-n*) pipes to be parallelized at the present stage, consisting of the initial population or target vector for the MOSADE algorithm.
   d. For every population member, perform hydraulic simulation using EPANET simulator and estimate flows and pressures in the pipe network. Then calculate the LCC, head, and reliability values.
   e. Perform mutation and crossover on the initial population to formulate the trial vector.
   f. Evaluate the member solutions (similar to step d); and calculate the LCC, head, and reliability values.
   g. Combine the target and trial vectors to form the combined vector. Sort the combined vector using non-dominated sorting and crowding distance calculations (Deb *et al.* 2002) and forward top NP solutions to the next iteration.
   h. After every ten iterations, update the mutation and crossover parameters based on the productive values of these parameters.
   i. Increase iteration count ($iter = iter + 1$), and reiterate steps (e) to (h) till a maximum number of iterations is reached.
   j. Set $N = N + 1$, and reiterate steps 4(a) to (i).
   k. If $N > N\_poss$, repeat steps (2) to (4) for the next stage.
5. Save the results as Final_1, Final_2……, etc., feasible solutions for the different number of *N* parallel pipes being added for stage 1, stage 2,…., etc., and corresponding time in years as Final_*t1*, Final_*t2*,…., etc.
6. Generate the final Pareto-optimal front considering the solutions obtained at the final stage.

Here, the LCC and minimum resiliency(or reliability) value (out of all stages) are the considered objective functions. The steps mentioned above are also shown in a flowchart form in Fig. S1.

Thus, the overall methodology followd in the study can be summarised as follows:

1. First, MOSADE-DP methodology is applied to generate Pareto-fronts to minimize the LCC and maximize resiliency.
2. Then, the solutions thus obtained are used for further optimization for minimizing the LCC and maximizing the reliability.
3. The MCDM analysis is then carried out considering three criteria, minimum LCC and maximum hydraulic and mechanical reliabilities.

2.6. Analytical hierarchy process for multi-criteria decision making

Analytical Hierarchy Process (AHP) (Saaty 2003) is a method for determining the most suitable alternative given a set of criteria and sub-criteria. AHP leads to breaking down the problem into an array of sub-problems, making it more comprehensive and easier for subjective evaluation. The subjective evaluations are transformed into numerical values and processed to assess each option on a numerical scale. The detailed steps involved in AHP are presented in supplementary resources Text S2 and summarised in Fig. S2.

3. CASE STUDIES OF WDNS

The proposed MOSADE-DP framework is first applied and evaluated on three benchmark WDNs; that is, Two loop (TL), GoYang (GOY), and Blacksburg (BLA) WDNs. After that, the framework is applied to a real WDN of Badlapur in Maharashtra, India. TL network comprises 8 pipes, 6 demand nodes, and a supply reservoir providing water by gravity, at a fixed head of 250 m (Alperovits & Shamir 1977). BLA is a WDN comprising 35 pipes, of which 12 pipes have a prespecified diameter, 30 demand nodes, and a reservoir with a constant head of 715.56 m (Sherali *et al.* 2001). GOY is a medium-sized WDN problem comprising 30 pipes, 22 demand nodes, a pump of constant power of 4.52 kW, and a supply source having a constant head of 71 m (Kim *et al.* 1994). Badlapur WDN comprises 1,041 pipes, 914 demand nodes, and two reservoirs at heights of 12.7 m and 9 m, providing water by pumping. The layout of the benchmark WDNs is shown in Figure 1, the layout of the Badlapur WDN is shown in Figure 2. These WDNs are described in more detail in the supplementary resources Text S3.

For forecasting the future water demands for benchmark WDNs, hypothetical scenarios of future water demand are considered. The analysis is performed for a design period of 50 years. The expansions are to be designed after every ten years. The water demand is assumed to increase exponentially with time as per the following equation

$$Dem_t = Dem * \left(1 + \frac{r}{100}\right)^t \tag{17}$$

where Dem_t represents the increased demand at time t, Dem represents the initial demand at the start of the design period, and r is the rate of demand increase. In the present study, r is taken as 3.

For applying the methodology on Badlapur WDN, future water demand is projected for 2021, 2031, 2041, 2051, 2061, and 2071 using the logistic curve method and ward-wise census data collected for years 2001 and 2011. The forecasted population for the year 2021 is taken as the base year, and interventions are designed for the years 2031, 2041, 2051, 2061, and 2071. Details of the logistic curve method are provided in the supplementary resources Text S3. The population data for 2001 and 2011 and the projected population for years 2031 to 2071 are presented in supplementary resources Table S1. It should be noted that some of the wards (such as Ward no. 10, 11, 12, 18, 19, 22, and 25) show a decrease in population from 2001 to 2011. In such cases, a positive trend in population is considered to depict the most adverse conditions.

4. APPLICATION AND RESULTS OF MOSADE-DP FRAMEWORK AND MCDM METHODS FOR WDN EXPANSION

In order to test the efficacy of the proposed methodology (Figure 3), first it is applied for a few benchmark WDNs. The MOSADE-DP framework was used for generation of Pareto optimal solution to the WDN expansion problems, and AHP based MCDM methodology was used for finding out the most suitable solution from the obtained Pareto optimal solutions considering three criteria (i) minimum LCC, (ii) maximum hydraulic reliability, and (iii) maximum mechanical reliability. The

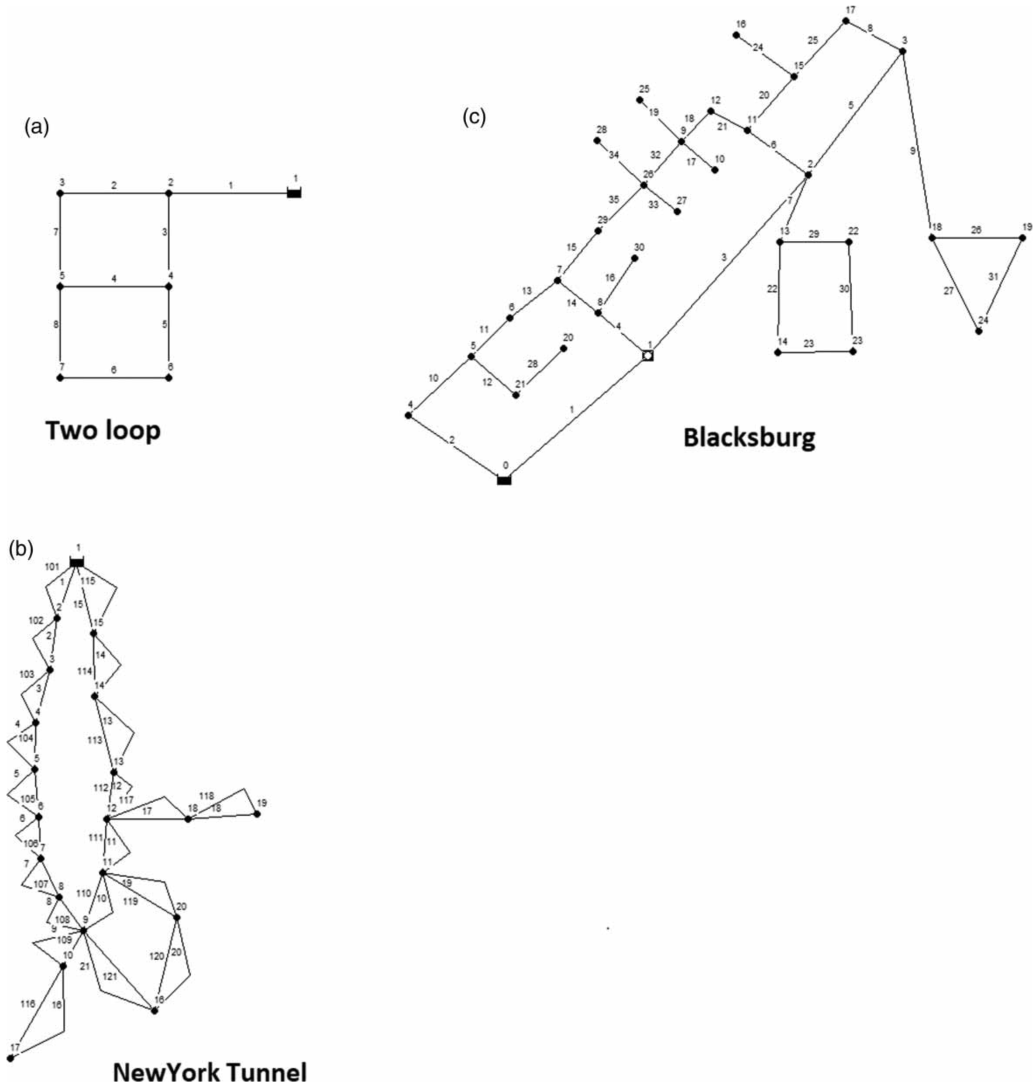


Figure 1 | Layout of benchmark WDN problems considered in the study.

overall framework for the proposed methodology for multi-objective multi-criteria decision-making analysis is shown in Figure 3.

For the MOSADE-DP approach, the population size and the maximum number of iterations at various stages differ based on the number of parallel pipes to be added. The population size is taken as ten times the number of parallel pipes and maximum iterations as ten times the population size considering the suggestions from past studies (Storn 1995; Liu & Lampinen 2005). In the present study, *N_poss* is set to two times the number of pipes in the initial stage, with a maximum of two parallel pipes being added for each pipe. So, *N_poss* is set to 16 for Two loop, 60 for GoYang, 70 for Blacksburg, and 2,082 for Badlapur WDN. Thus, in the case of Two loop WDN, the population size for determining 16 parallel pipes is kept as 160 for 1,600 iterations. Similarly, for GoYang, for 60 parallel pipes, population size is kept as 600 for 6,000 iterations, while for Fossolo WDN, for 70 parallel pipes, population size is kept as 700 for 7,000 iterations. Also, for Badlapur WDN, for 1,041 parallel pipes, a population size of 10,410 is taken for 50,000 iterations.

4.1. Generation of pareto-optimal solutions considering LCC and reliability

To solve the problem, interventions are designed after every 10 years over 50 years of the planning horizon, so every 10 years represents one stage. A planning horizon of 50 years with expansions being made at every 10 years is chosen as per the recommendation of past studies (Engelhardt *et al.* 2000; Basupi & Kapelan 2015), suggesting that consideration of a long

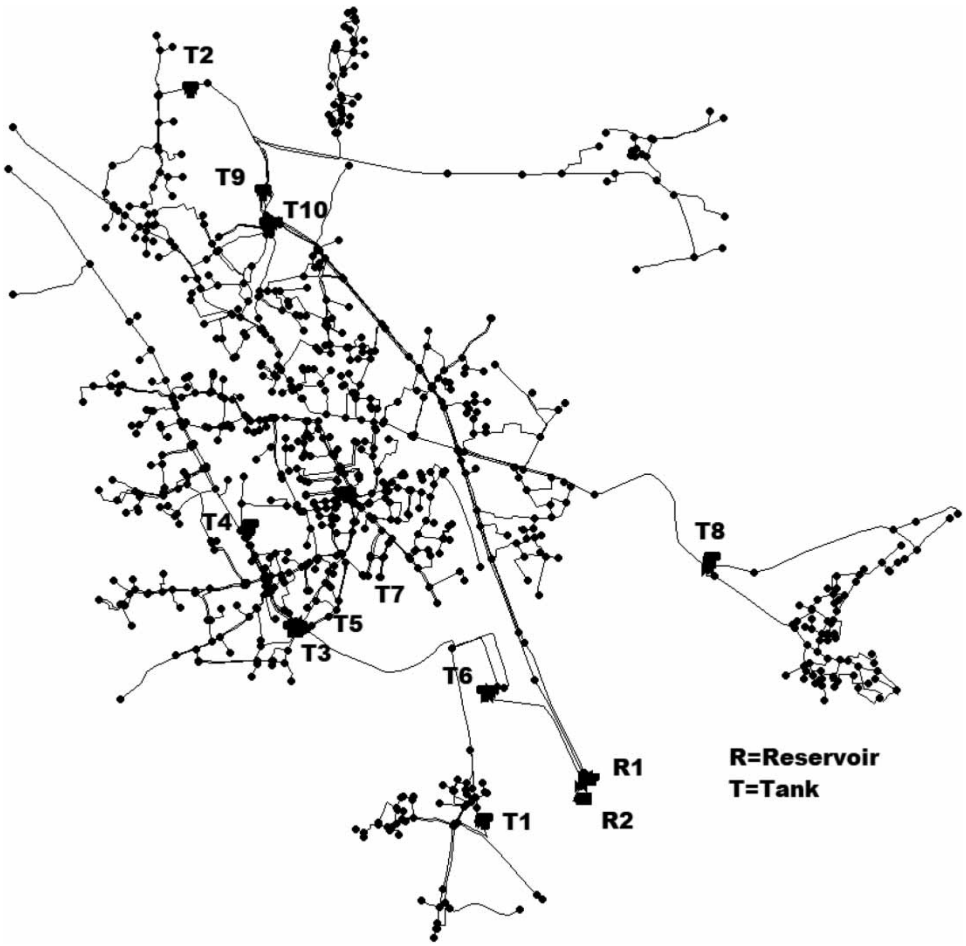


Figure 2 | Layout of Badlapur WDN.

planning horizon leads to extra savings in economy. The results for TL, GOY, BLA, and Badlapur WDNs are presented in Figure 4(a)–4(d), respectively. Figure 4 shows the trade-offs between the LCC and reliability. The results obtained for the maximization of the resiliency model lead to solutions scattered around the Pareto front, which act as sub-optimal solutions for further optimization. The subsequent multi-objective optimization with reliability maximization leads to a smooth Pareto front between LCC and reliability. The trade-off solutions obtained between the LCC and reliability (minimum out of four stages) are presented in Table 1 for Two Loop WDN. The details in terms of diameter and time (in years) of parallel pipes to be appended for these solutions are also provided in Table 1. The LCC and reliability results at four stages are presented in Table S3 for GoYang, and Table S4 for Blacksburg and Badlapur WDNs. The convergence of the MOSADE-DP algorithm in terms of IGD values is presented in Fig. S4 for all four WDN problems. It can be seen that the algorithm converges consistently for all four WDN problems. Also, small spacing metric values (presented in Fig. S4) are obtained, which implies uniformly distributed solutions. The spacing-metric values have a lower standard deviation, which ensures the algorithm's performance for different runs.

As mentioned earlier, to save the computational time and effort (while solving the model with reliability maximization), this study considered initial exploration (for some iterations) with resiliency (considered as a substitute for reliability) and then final exploration with reliability. To find out how many iterations are needed for initial exploration considering resiliency (and later additional iterations with reliability), sensitivity analysis is carried out at different IGD convergence levels such as 20, 40, 60, 80, and 100% of total iterations needed for optimization (considering resiliency). The total number of iterations and computational time are reported in Table S5. From the table, it can be seen that as the convergence level increases, the initial number of iterations considering resiliency increases, while further iterations considering reliability decreases. The minimum number of iterations is achieved at a 40% convergence level, leading to a considerable reduction in

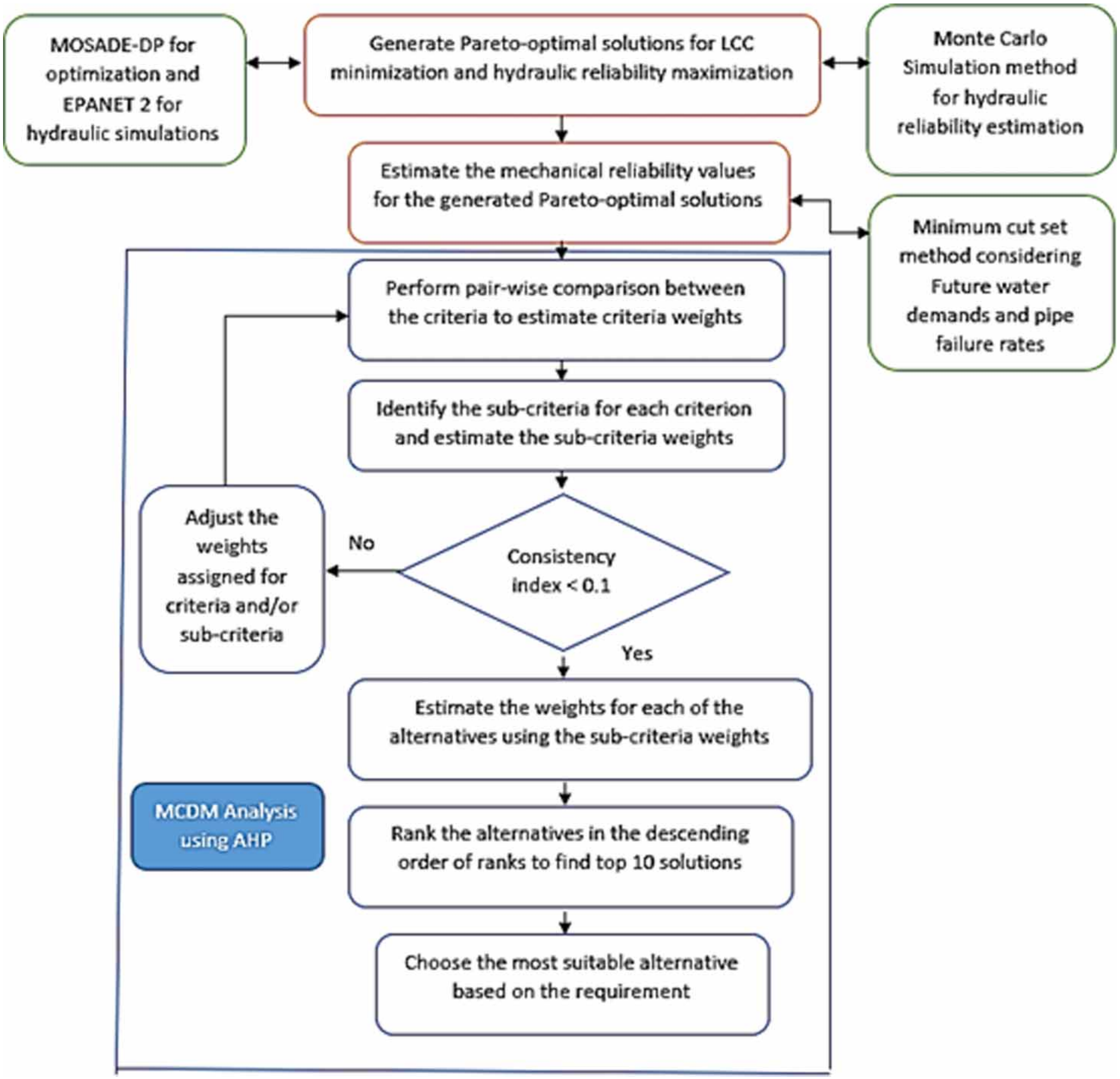


Figure 3 | Overall framework for performing the multi-objective multi-criteria decision-making analysis.

computational requirement (by almost half). Also, it can be noticed that the number of iterations needed is nearly ten times the number of decision variables for initial runs considering resiliency. The simulation-optimization procedure is carried out on an Intel i5-10210U computer with 8 cores and a processor speed of 2.11 GHz.

The results are also compared with those of MOSADE. To solve the problem using MOSADE, random initialization is performed for the diameter of parallel pipes and the corresponding time (in years) for scheduling the expansion. The steps of MOSADE are followed to evolve towards better Pareto-optimal fronts. On solving the four WDN problems using MOSADE, it is found that the results obtained are more or less the same as those obtained using MOSADE-DP. However, the success rate for MOSADE is much lower than that of MOSADE-DP. The success rate obtained using MOSADE-DP and MOSADE methods are 90 and 60% for Two-Loop; 80 and 50% for GoYang; 80 and 50% for Blacksburg; and 70 and 40% for Badlapur WDNs, respectively. Better convergence can be attributed to the fact that MOSADE-DP aims to explore more effectively by considering feasible solutions at every stage and then combining all the solutions to generate the final Pareto-optimal

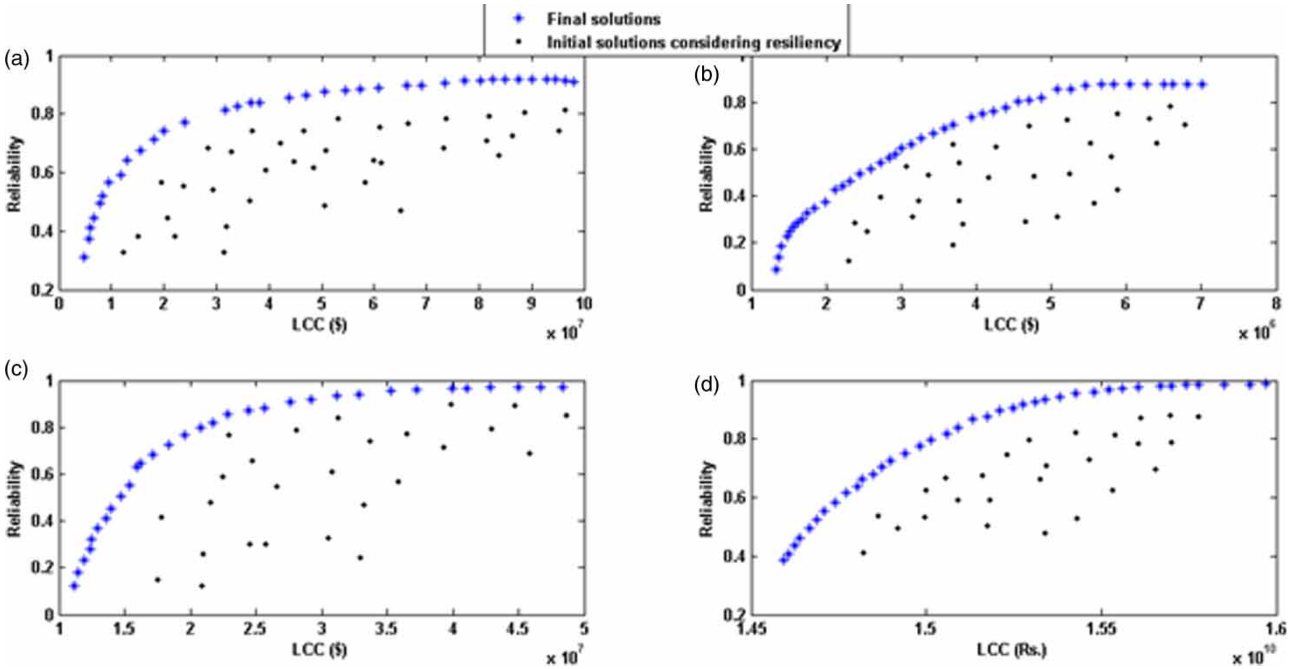


Figure 4 | Pareto optimal solutions obtained considering minimization of LCC and maximization of reliability and initial solutions used considering minimization of LCC and maximization of resiliency for (a) Two Loop (b) GoYang (c) Blacksburg and (d) Badlapur WDNs using MOSADE-DP method. ***Note:*** The black dotted points shows the initial solutions obtained for the multi-objective model considering minimization of LCC and maximization of resiliency as objectives.

front. MOSADE, on the other hand, explores the solutions considering all the stages together. However, the number of iterations needed by both algorithms is almost the same for all four WDNs. Thus, it can be said that the MOSADE-DP framework is more reliable and efficient than MOSADE alone for solving the WDN capacity expansion problems.

4.2. Decision making using AHP

The most appropriate solution is selected (from the generated Pareto-optimal solutions) for a given set of criteria using AHP based MCDM analysis. As mentioned previously, three criteria are used in the analysis (i) minimization of LCC, (ii) maximization of hydraulic reliability, and (iii) maximization of mechanical reliability. Since the Pareto-optimal solutions are generated considering the first two criteria, the third criteria; that is, the mechanical reliability, is calculated for the obtained Pareto-optimal solutions. Mechanical reliability is calculated using the minimum cut set method (Su *et al.* 1987), considering future pipe failure rates (as presented in Text S1).

Table 2 shows the criteria weights calculated and used in the study. Each of the criteria is further sub-divided into different classes. Here, the classes for LCC vary for each WDN problem, whereas those for hydraulic and mechanical reliabilities are the same for all the case studies. For Two Loop WDN, the LCC is sub-divided into three sub-classes as presented in Table 2. A similar procedure is adopted for each sub-criteria to estimate weights as those used for criteria weights calculation. The final weights for each sub-classes are then estimated as the product of criteria weight and the weight of each sub-class. The process is repeated for all the criteria. In the present study, the criteria weights, sub-classes, and their weights in the case of hydraulic and mechanical reliability are kept the same and are presented in Table 2. For GoYang, Blacksburg, and Badlapur WDNs, the sub-classes for LCC and estimation of their weights are presented in Table S6.

The criteria values, estimated weights, and ranks for all four WDN problems are presented in Tables S7-S9 for benchmark problems and Table 3 for Badlapur WDN. The tables show that the best solution for Two-Loop WDN has an LCC of 15.37 M$ with hydraulic and mechanical reliability values of 0.7074 and 0.8613, respectively. For GoYang WDN, the best solution has an LCC of 595.620 $\times$ 10^4 $ with hydraulic and mechanical reliability values of 0.8841 and 0.8424, respectively. For Blacksburg WDN, the best solution has an LCC of 16.891 M$ with hydraulic and mechanical reliability values of

Table 1 | LCC and reliability value (minimum out of four stages) for a representative sample of Pareto-optimal solutions obtained for expansion of Two Loop WDN

	Diameter of parallel pipes (in mm) to be added for pipe no. (and corresponding time in years)																LCC for adding parallel pipes (M$)	Reliability and min reliability out of the four stages
Sol. No.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**		
1	355.6 (40)	25.4 (20)	254 (40)	254 (40)	203.2 (50)	76.2 (30)	355.6 (50)	254 (40)	355.6 (50)	406.4 (50)	254 (50)	0 (50)	0 (50)	0 (40)	0 (50)	0 (50)	5.661	0.7881, 07645, **0.3241**, 0.8876
2	508 (20)	254 (40)	457.2 (30)	203.2 (30)	406.4 (40)	355.6 (30)	304.8 (50)	152.4 (40)	508 (40)	355.6 (50)	508 (50)	0 (50)	406.4 (50)	0 (40)	0 (50)	355.6 (50)	20.065	0.7927, 0.7651, 0.7562, **0.7432**
3	609.6 (20)	558.8 (30)	558.8 (20)	304.8 (20)	508 (30)	355.6 (20)	457.2 (40)	406.4 (50)	609.6 (40)	508 (50)	609.6 (50)	406.4 (50)	406.4 (50)	0 (30)	457.2 (50)	152.4 (50)	64.611	0.8972, 0.9016, **0.8786**, 0.8927
4	355.6 (40)	25.4 (30)	304.8 (40)	254 (40)	203.2 (50)	101.6 (30)	355.6 (50)	355.6 (40)	355.6 (50)	406.4 (50)	254 (50)	0 (40)	0 (50)	0 (40)	0 (50)	0 (50)	6.427	0.6576, **0.3748**, 0.5346, 0.5417
5	457.2 (40)	25.4 (30)	304.8 (40)	254 (40)	254 (50)	101.6 (30)	355.6 (50)	254 (40)	355.6 (50)	406.4 (50)	254 (50)	0 (40)	0 (50)	0 (40)	0 (50)	0 (50)	7.159	0.6576, **0.4210**, 0.5948, 0.5044
6	406.4 (30)	355.6 (30)	355.6 (40)	0 (20)	355.6 (40)	203.2 (30)	355.6 (40)	304.8 (40)	406.4 (50)	406.4 (50)	406.4 (50)	0 (40)	0 (50)	0 (30)	355.6 (50)	25.4 (50)	11.267	0.7849, 0.7843, 0.8305, **0.7714**
7	406.4 (40)	355.6 (40)	355.6 (30)	355.6 (30)	304.8 (50)	0 (20)	304.8 (50)	304.8 (40)	406.4 (50)	0 (40)	406.4 (50)	0 (50)	0 (50)	0 (50)	152.4 (50)	0 (50)	9.168	0.6576, 0.5391, 0.5252, **0.5207**
8	508 (30)	355.6 (20)	355.6 (30)	254 (40)	355.6 (40)	50.8 (20)	406.4 (40)	406.4 (40)	406.4 (50)	406.4 (50)	457.2 (50)	0 (50)	50.8 (50)	0 (40)	0 (50)	0 (50)	15.170	0.7144, **0.6658**, 0.6901, 0.68251
9	508 (20)	355.6 (20)	457.2 (30)	406.4 (30)	406.4 (40)	355.6 (30)	355.6 (40)	355.6 (40)	508 (50)	304.8 (50)	508 (40)	0 (50)	508 (50)	0 (40)	0 (40)	0 (50)	24.289	0.7844, 0.7981, 0.7800, **0.7701**
10	508 (20)	508 (30)	355.6 (20)	203.2 (20)	355.6 (30)	254 (20)	355.6 (30)	355.6 (20)	558.8 (40)	508 (40)	558.8 (50)	0 (40)	508 (50)	0 (50)	508 (40)	355.6 (50)	33.876	0.8578, **0.8267**, 0.8287, 0.8746
11	508 (30)	355.6 (20)	406.4 (30)	304.8 (40)	355.6 (40)	0 (30)	355.6 (40)	355.6 (40)	406.4 (50)	508 (50)	457.2 (50)	0 (50)	254 (50)	0 (40)	0 (50)	0 (50)	16.180	0.7629, 0.7148, **0.6843**, 0.7621
12	508 (30)	457.2 (20)	355.6 (30)	304.8 (40)	355.6 (40)	203.2 (30)	406.4 (40)	406.4 (40)	406.4 (50)	508 (50)	457.2 (50)	0 (40)	254 (50)	0 (40)	25.4 (50)	0 (50)	19.294	0.7576, 0.7247, 0.7127, **0.7071**
13	406.4 (40)	355.6 (40)	355.6 (30)	254 (30)	304.8 (50)	0 (20)	355.6 (50)	304.8 (40)	406.4 (50)	0 (40)	406.4 (50)	0 (50)	0 (50)	0 (50)	152.4 (50)	0 (50)	8.637	0.6810, 0.5235, **0.4987**, 0.4994
14	406.4 (40)	355.6 (30)	304.8 (30)	0 (30)	355.6 (50)	152.4 (20)	355.6 (40)	355.6 (40)	406.4 (50)	304.8 (50)	355.6 (50)	0 (50)	0 (50)	0 (40)	304.8 (50)	152.4 (50)	9.991	**0.5389**, 0.7081, 0.7716, 0.6983
15	406.4 (40)	355.6 (30)	304.8 (40)	0 (40)	203.2 (50)	0 (20)	355.6 (50)	355.6 (40)	406.4 (50)	304.8 (50)	355.6 (50)	0 (50)	0 (50)	0 (40)	0 (50)	152.4 (50)	7.827	0.6862, 0.6911, **0.4451**, 0.6599
16	457.2 (30)	355.6 (30)	355.6 (40)	101.6 (50)	355.6 (40)	101.6 (30)	406.4 (40)	355.6 (40)	406.4 (50)	406.4 (50)	406.4 (50)	0 (50)	0 (50)	0 (50)	203.2 (50)	101.6 (50)	12.334	0.6576, **0.6151**, 0.6452, 0.6853
17	406.4 (30)	355.6 (30)	304.8 (40)	203.2 (40)	355.6 (40)	0 (30)	355.6 (40)	355.6 (40)	406.4 (50)	406.4 (50)	406.4 (50)	0 (50)	0 (50)	0 (50)	76.2 (50)	152.4 (50)	10.689	0.7128, **0.5643**, 0.6724, 0.8408
18	609.6 (20)	609.6 (30)	609.6 (20)	406.4 (40)	508 (20)	406.4 (20)	558.8 (30)	508 (40)	609.6 (40)	558.8 (40)	609.6 (50)	0 (50)	558.8 (50)	0 (50)	609.6 (50)	355.6 (50)	95.954	**0.9059**, 0.9072, 0.9559, 0.9863
19	558.8 (20)	508 (30)	508 (20)	254 (30)	406.4 (20)	355.6 (20)	457.2 (30)	355.6 (40)	609.6 (40)	508 (50)	558.8 (50)	0 (50)	355.6 (50)	0 (40)	457.2 (50)	203.2 (50)	44.812	0.8576, 0.8925, 0.8809, **0.8522**
20	558.8 (20)	508 (30)	508 (20)	254 (30)	508 (20)	254 (20)	457.2 (30)	355.6 (40)	609.6 (40)	508 (50)	558.8 (50)	152.4 (50)	609.6 (50)	0 (40)	457.2 (50)	0 (50)	51.546	0.8637, 0.8781, 0.8814, 0.9065
21	609.6 (20)	609.6 (30)	558.8 (20)	406.4 (20)	508 (30)	304.8 (30)	457.2 (40)	508 (20)	609.6 (40)	457.2 (50)	609.6 (50)	0 (40)	609.6 (50)	0 (40)	508 (50)	0 (50)	78.907	0.8980, **0.8957**, 0.8959, 0.8898

Note: *B*old numbers indicate the minimum reliability out of the four stages.

Table 2 | Pairwise comparison matrix for criteria and sub-classes considered within each criterion for estimating relative preferences among identified criteria and sub-criteria for Two Loop WDN

Criteria weights matrix						**Normalized criteria matrix**							
	LCC		**Hyd. Rel.**		**Mech. Rel.**		**LCC**		**Hyd. Rel.**		**Mech. Rel.**		**Criteria weights**
LCC	1		2		2	LCC	0.5		0.5		0.5		**0.5**
Hyd. Rel.	0.5		1		1	Hyd. Rel.	0.25		0.25		0.25		**0.25**
Mech. Rel.	0.5		1		1	Mech. Rel.	0.25		0.25		0.25		**0.25**
Sum	2		4		4								
Sub- criteria weights for criteria 1 (LCC)						Normalized matrix							Final weights for each sub-criterion (criteria weight * sub-criteria weight)
Class/range (LCC in M$)	0–40		40–80		80–120	Class/range (LCC in M$)	0–20		20–40		40–60	Sub-criteria weights	
0–40	1		2		2	0–40	0.5		0.6006		0.3333	**0.4779**	**0.2389**
40–80	0.5		1		3	40–80	0.25		0.3003		0.5	**0.3501**	**0.1751**
80–120	0.5		0.33		1	80–120	0.25		0.0991		0.1667	**0.17192**	**0.0859**
Sum	2		3.33		6								Sum = 0.5 (=criteria weight)
Sub- criteria weights for criteria 2/3 (Hydraulic/Mechanical Rel.)						Normalised matrix							Final weights for each sub-criterion (criteria weight * sub-criteria weight)
Class/range (Hyd./Mech Rel.)	0–0.2	0.2–0.4	0.4–0.6	0.6–0.8	0.8–1.0	Class/range (Hyd./Mech Rel.)	0–0.2	0.2–0.4	0.4–0.6	0.6–0.8	0.8–1.0	Sub-criteria weights	
0–0.2	1	0.33	0.2	0.143	0.11	0–0.2	0.04	0.0202	0.0209	0.0306	0.0616	**0.0346**	**0.0086**
0.2–0.4	3	1	0.33	0.2	0.143	0.2–0.4	0.12	0.0612	0.0346	0.0428	0.0802	**0.0677**	**0.0169**
0.4–0.6	5	3	1	0.33	0.2	0.4–0.6	0.2	0.1837	0.1049	0.0706	0.1122	**0.1342**	**0.0335**
0.6–0.8	7	5	3	1	0.33	0.6–0.8	0.28	0.3062	0.3148	0.2139	0.1851	**0.2600**	**0.0650**
0.8–1.0	9	7	5	3	1	0.8–1.0	0.36	0.4286	0.5247	0.6419	0.5608	**0.5032**	**0.1258**
Sum	25	16.33	9.53	4.673	1.783								Sum = 0.25 (=criteria weight)

Table 3 | Alternatives, their attributes, weights and ranks estimated using AHP for Badlapur WDN

Solution number	LCC (10^9 Rs.)	Hyd. Rel.	Mech. Rel.	Weight	Rank
1	14.592	0.3875	0.8147	0.3817	12
2	**14.606**	**0.4065**	**0.9058**	**0.3983**	**10**
3	14.624	0.4370	0.7270	0.3375	24
4	14.638	0.4636	0.9134	0.3983	11
5	14.666	0.4940	0.6324	0.3375	25
6	14.689	0.5245	0.0975	0.2811	33
7	14.707	0.5549	0.2785	0.2894	32
8	14.739	0.5853	0.5469	0.3060	31
9	**14.771**	**0.6158**	**0.9575**	**0.4297**	**1**
10	**14.803**	**0.6386**	**0.9649**	**0.4297**	**2**
11	14.817	0.6614	0.1576	0.3126	28
12	**14.849**	**0.6804**	**0.9706**	**0.4297**	**3**
13	**14.872**	**0.7033**	**0.9572**	**0.4297**	**4**
14	14.899	0.7261	0.4854	0.3375	26
15	**14.940**	**0.7527**	**0.8003**	**0.4297**	**5**
16	14.982	0.7755	0.1419	0.3126	29
17	15.014	0.7984	0.4218	0.2737	35
18	**15.060**	**0.8174**	**0.9157**	**0.4267**	**6**
19	15.092	0.8402	0.7922	0.3659	13
20	**15.133**	**0.8668**	**0.9595**	**0.4267**	**7**
21	15.174	0.8783	0.6557	0.3659	14
22	15.211	0.8973	0.0357	0.3096	30
23	**15.247**	**0.9049**	**0.8491**	**0.4267**	**8**
24	**15.275**	**0.9201**	**0.9340**	**0.4267**	**9**
25	15.311	0.9277	0.6787	0.3659	15
26	15.339	0.9353	0.7577	0.3659	16
27	15.380	0.9429	0.7431	0.3659	17
28	15.426	0.9543	0.3922	0.3179	27
29	15.481	0.9582	0.6555	0.3659	18
30	15.522	0.9696	0.8147	0.3375	19
31	15.559	0.9734	0.9058	0.3375	20
32	15.605	0.9772	0.1270	0.2204	38
33	15.669	0.9810	0.9134	0.3375	21
34	15.701	0.9810	0.6324	0.2767	34
35	15.742	0.9848	0.0975	0.2204	39
36	15.779	0.9848	0.2785	0.2287	37
37	15.852	0.9848	0.5469	0.2453	36
38	15.925	0.9848	0.9575	0.3375	22
39	15.971	0.9886	0.9649	0.3375	23

The highlighted numbers indicate the top ten best alternatives.

0.9023 and 0.9575, respectively. For Badlapur WDN, the best solution has an LCC of 14.978×10^9 Rs with hydraulic and mechanical reliability values of 0.8241 and 0.9134, respectively. Thus, it can be seen that the best solutions obtained have intermediate LCC with high hydraulic and mechanical reliability values. Also, on observing the top ten best solutions, it can be seen that each solution is slightly weaker than the solution with just a higher rank for at least one criteria value. However, solutions beyond rank 10 have either high LCC and low-reliability values, or moderate cost and one low and one high-reliability value, leading to moderate overall weight values. On carefully observing the top ten solutions, the topmost solution has moderate LCC with high-reliability values. For lower ranked solutions, the reliability values are smaller for one or the other case.

Thus, depending on the need of the project, the decision maker can easily choose the most suited value from these top ten solutions. For example, for Two-Loop WDN, if the purpose is to maintain a minimum of 0.75 reliability, the solutions with both hydraulic and mechanical reliabilities above 0.75 with the least LCC can be selected (solution 53, rank 2, Table 1, Table S7). However, if one desires to have hydraulic reliability >0.8 and mechanical reliability >0.7, then solution 42 with rank 1 (Table 1, Table S7) can be selected. Similarly, in the case of Badlapur WDN, if the purpose is to maintain minimum reliability of 0.75, then solution 15 (rank 5, Table 3) can be selected. However, if a minimum reliability level of 0.8 is to be maintained, then solution 16 (rank 6, Table 3) can be selected. Therefore, it can be seen that the ranked solutions obtained using AHP make the decision-making process very convenient. Thus, AHP based MCDM facilitates a simple and easy process in the decision-making.

4.3. Effect of change in criteria weights

For studying the effect of change in criteria weights on the results, three different combinations of criteria weights are considered as (case 1: w1 = 0.5, w2 = 0.25, w3 = 0.25; case 2: w1 = 0.539, w2 = 0.297, w3 = 0.163; case 3: w1 = 0.2, w2 = 0.4, w3 = 0.4). Case 1 represents higher importance for LCC and equal relative importance for hydraulic and mechanical reliabilities. Case 2 represents the scenario with relatively higher importance for LCC and hydraulic reliability than mechanical reliability. Case 3 represents the scenario if the importance for LCC is decreased compared to reliability and keeping equal weightage for hydraulic and mechanical reliabilities. The analysis is performed on a representative sample of solutions from the obtained Pareto-optimal solutions. The results thus obtained are presented in Table 4 for Two-Loop WDN and Table S10–S12 for GoYang, Blacksburg, and Badlapur WDNs. The results are presented in terms of the individual weights for each attribute and the total weights for the top ten solutions for each combination of criteria weights. The results are also presented in Figures 5 and 6. The weights corresponding to three criteria (A1, A2, and A3) for the top ten solutions are presented in Figure 5; and the location of these solutions in the Pareto-optimal front depicting the rank for the top five solutions are presented in Figure 6. As shown in Figure 5, case 2 leads to higher A1 than case 1, while case 3 leads to the lowest A1 values. This is because these weight values are affected by the chosen criteria weights. For example, for case 2, w1 is higher compared to case 1, and so we are getting higher values of A1 for case 2. From Table 4, it is visible that case 2 leads to solutions with lower mechanical reliability and higher LCC. For case 3, solutions with higher LCC are obtained with high hydraulic and mechanical reliabilities. Similar observations are noticed for other WDNs as presented in Table S10–S12. This is evident because case 2 corresponds to the case when mechanical reliability has slightly lower weightage, thus leading to solutions with low mechanical reliability. Similarly, in case 3, higher weightage is given to hydraulic and mechanical reliabilities compared to LCC. Thus, solutions with high reliabilities having high LCC are assigned higher weightage. Thus, it can be seen that the results are affected by changing the criteria weights, and selecting the correct criteria weights is important to obtain the desired results. Thus, AHP is a useful tool that can be modified suitably but carefully to fulfill the project demands and get the desired output.

5. SUMMARY AND CONCLUSIONS

The study illustrated an efficacious framework for the phased expansion of WDNs accounting for LCCs and future water demands. The existing expansion methods have this drawback: they cannot consider the various possible options for minimizing the overall LCC of the expansions while assuring the minimum reliability values at all stages. Also, most of the past studies formulated it as a single-objective problem, but here a multi-objective formulation is needed to generate a set of alternative solutions considering multiple objectives. The current study proposed a DP-based model formulation for WDN expansion that can aid in investigating all possible options. However, solving the enormous size problems using DP leads to much computational time and is practically difficult. Therefore, a hybrid MOSADE-DP framework is presented. The methodology considers the global search proficiency of DP while lessening its computational needs by combining it with MOSADE. The MOSADE-DP framework is applied and tested on three benchmark WDNs, TL, GOY, and BLA networks, and a real case study of Badlapur WDN in India. Pareto-optimal solutions are first generated considering LCC

Table 4 | Effect of change in criteria weights on the obtained results for Two Loop WDN

Case 1: w1 = 0.5, w2 = 0.25, w3 = 0.25					Case 2: w1 = 0.539, w2 = 0.297, w3 = 0.163					Case 3: w1 = 0.648, w2 = 0.229, w3 = 0.122				
A1	A2	A3	Total weight	Sol^n (LCC, Hyd. Rel., Mech. Rel.)	A1	A2	A3	Total weight	Sol^n (LCC, Hyd. Rel., Mech. Rel.)	A1	A2	A3	Total weight	Sol^n (LCC, Hyd. Rel., Mech. Rel.)
0.239	0.065	0.126	0.430	(20.065, 0.743, 0.873)	0.258	0.982	0.260	1.499	(33.876, 0.827, 0.515)	0.070	1.433	0.585	2.089	(78.907, 0.896, 0.714)
0.239	0.065	0.126	0.430	(24.289, 0.770, 0.851)	0.189	1.064	0.239	1.491	(78.907, 0.896, 0.714)	0.070	1.406	0.585	2.061	(64.611, 0.878, 0.722)
0.239	0.034	0.126	0.398	(7.159, 0.421, 0.954)	0.189	1.044	0.239	1.471	(64.611, 0.879, 0.722)	0.096	1.323	0.637	2.056	(33.876, 0.827, 0.515)
0.239	0.126	0.034	0.398	(33.876, 0.827, 0.515)	0.258	0.915	0.280	1.453	(24.289, 0.770, 0.851)	0.034	1.449	0.540	2.024	(95.954, 0.906, 0.881)
0.239	0.017	0.126	0.382	(6.427, 0.375, 0.829)	0.189	1.026	0.218	1.433	(51.546, 0.864, 0.450)	0.096	1.232	0.688	2.015	(24.289, 0.770, 0.851)
0.239	0.065	0.065	0.369	(12.334, 0.615, 0.650)	0.258	0.883	0.280	1.421	(20.065, 0.743, 0.873)	0.070	1.382	0.535	1.987	(51.546, 0.864, 0.450)
0.175	0.126	0.065	0.366	(64.611, 0.878, 0.722)	0.189	1.012	0.202	1.403	(44.812, 0.852, 0.040)	0.096	1.189	0.688	1.972	(20.065, 0.743, 0.873)
0.175	0.126	0.065	0.366	(78.907, 0.896, 0.714)	0.093	1.076	0.220	1.389	(95.954, 0.906, 0.881)	0.070	1.364	0.495	1.929	(44.812, 0.852, 0.040)
0.086	0.126	0.126	0.338	(95.954, 0.906, 0.881)	0.258	0.840	0.204	1.302	(19.294, 0.707, 0.066)	0.096	1.095	0.540	1.731	(16.18, 0.684, 0.578)
0.239	0.065	0.034	0.338	(16.18, 0.684, 0.578)	0.258	0.813	0.220	1.291	(16.180, 0.684, 0.578)	0.096	1.131	0.500	1.727	(19.294, 0.707, 0.066)
0.175	0.126	0.034	0.334	(51.546, 0.864, 0.450)	0.258	0.791	0.204	1.252	(15.170, 0.666, 0.109)	0.096	0.984	0.590	1.670	(12.334, 0.615, 0.650)
0.239	0.065	0.009	0.313	(15.17, 0.666, 0.109)	0.258	0.731	0.241	1.229	(12.334, 0.615, 0.650)	0.096	1.065	0.500	1.661	(15.17, 0.666, 0.109)
0.239	0.065	0.009	0.313	(19.294, 0.707, 0.066)	0.258	0.670	0.200	1.128	(10.689, 0.564, 0.527)	0.096	0.903	0.490	1.488	(10.689, 0.564, 0.527)
0.175	0.126	0.009	0.310	(44.812, 0.852, 0.040)	0.258	0.640	0.200	1.097	(9.991, 0.539, 0.554)	0.096	0.862	0.490	1.448	(9.991, 0.538, 0.554)
0.239	0.034	0.034	0.306	(9.991, 0.538, 0.554)	0.258	0.619	0.189	1.065	(9.168, 0.521, 0.305)	0.096	0.674	0.637	1.407	(7.159, 0.421, 0.954)
0.239	0.034	0.034	0.306	(10.689, 0.564, 0.527)	0.258	0.592	0.189	1.039	(8.637, 0.499, 0.234)	0.096	0.833	0.463	1.392	(9.168, 0.521, 0.305)
0.239	0.034	0.017	0.290	(8.637, 0.498, 0.235)	0.258	0.500	0.260	1.018	(7.159, 0.421, 0.954)	0.096	0.798	0.463	1.357	(8.637, 0.498, 0.234)
0.239	0.034	0.017	0.290	(9.168, 0.521, 0.305)	0.258	0.529	0.183	0.970	(7.827, 0.445, 0.071)	0.096	0.600	0.611	1.306	(6.427, 0.375, 0.829)
0.239	0.034	0.009	0.281	(7.827, 0.445, 0.071)	0.258	0.445	0.249	0.952	(6.427, 0.375, 0.829)	0.096	0.712	0.450	1.258	(7.827, 0.445, 0.071)
0.239	0.017	0.009	0.265	(5.661, 0.324, 0.185)	0.258	0.385	0.173	0.815	(5.661, 0.324, 0.185)	0.096	0.519	0.423	1.038	(5.661, 0.324, 0.185)

Note: w1, w2 and w3 and the criteria weights and A1, A2, and A3 are the weights corresponding to each attribute.

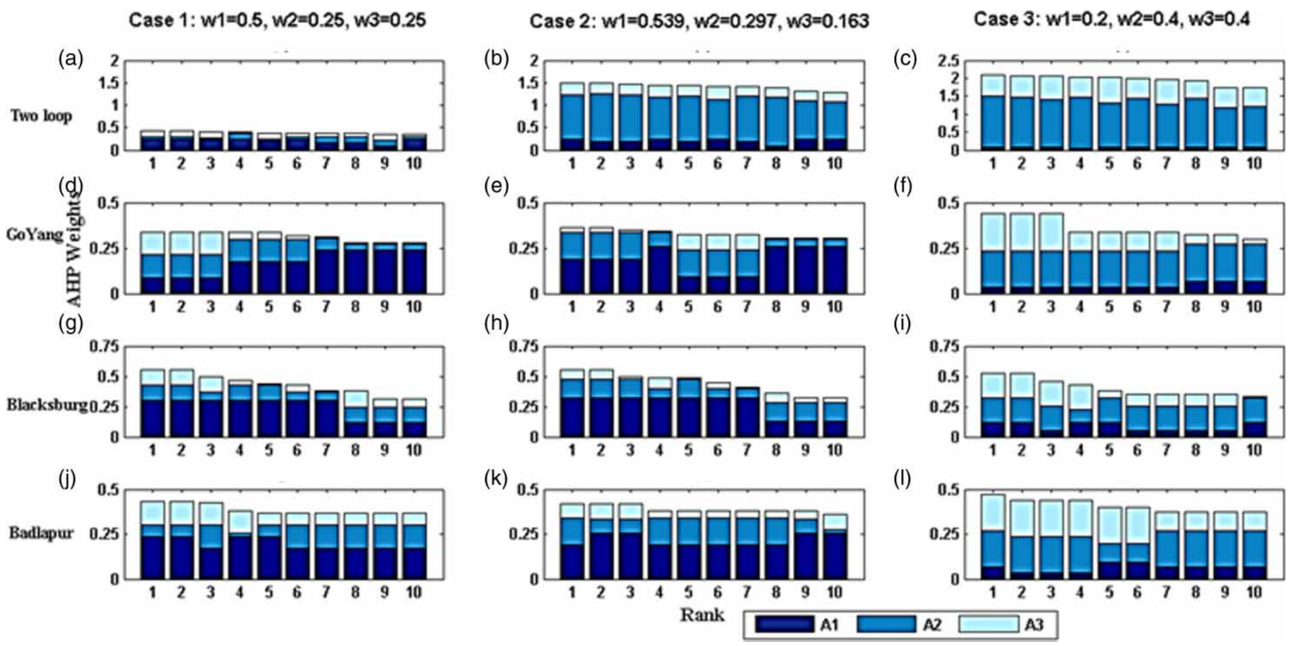


Figure 5 | Attribute weights obtained for three cases of criteria weights used for top ten solutions obtained for Two Loop (subplots a-c), GoYang (subplots d-f), Blacksburg (subplots g-i) and Badlapur (subplots j-l) WDNs. ***Note:*** w1, w2 and w3 are the criteria weights and A1, A2, and A3 are the weights corresponding to three attributes (i.e., LCC, hydraulic reliability and mechanical reliability).

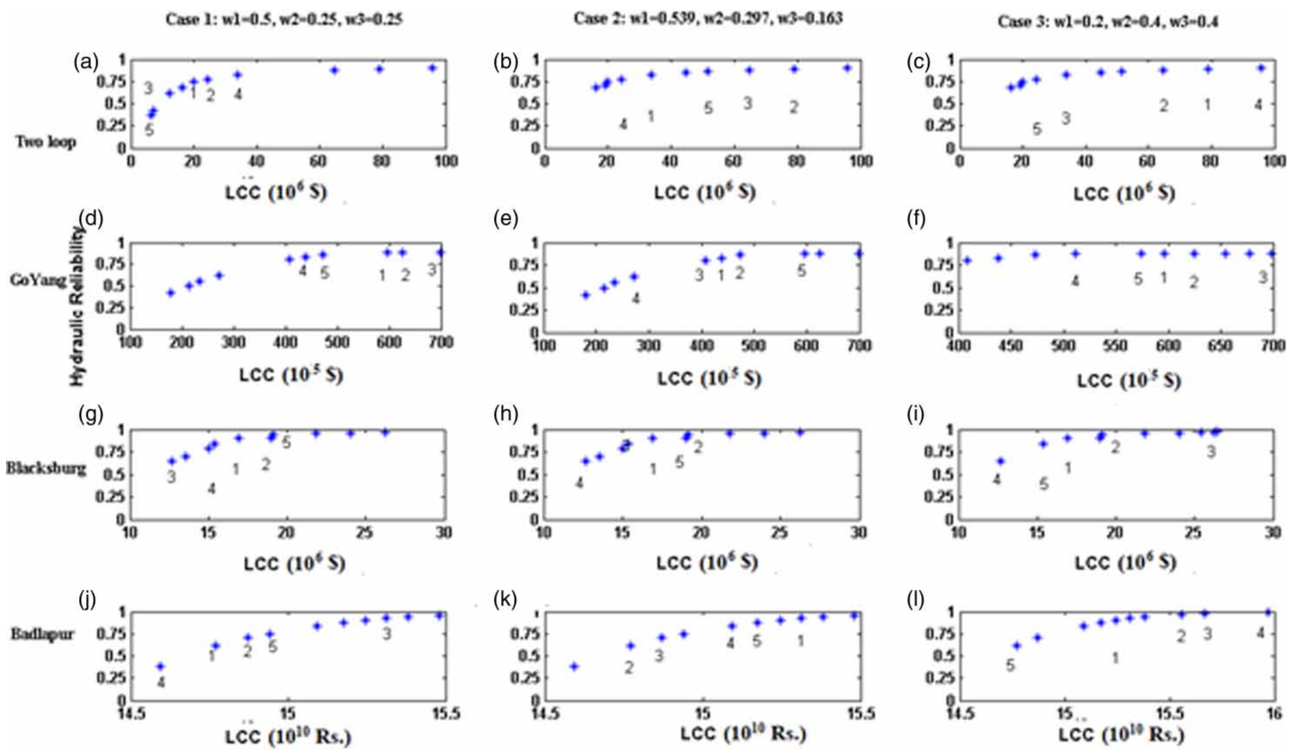


Figure 6 | Top ten solutions presented in the Pareto fronts along with the top five ranks for Two Loop (subplots a-c), GoYang (subplots d-f), Blacksburg (subplots g-i) and Badlapur (subplots j-l) WDNs.

minimization and resiliency maximization. These solutions are then used as initial solutions for further optimization, considering LCC minimization and reliability maximization. Sensitivity analysis is performed to determine the optimum number of iterations needed for initial iterations considering resiliency so that the total number of iterations required for the optimization is the least. Finally, an AHP-based MCDM analysis is applied considering three criteria: minimum LCC and maximum hydraulic and mechanical reliabilities. The mechanical reliability values are estimated for the obtained Pareto-optimal solutions considering future pipe break rates and water demands.

The major conclusions drawn from the obtained results are as follows:

1. The MOSADE-DP approach performs efficiently for the staged expansion of WDNs, leading to smooth Pareto-optimal fronts between LCC and reliability. The algorithm's convergence is also consistent for different runs for various WDN problems, showing its consistent performance.
2. Consideration of resiliency in the formulation for the generation of initial solutions for further optimization using reliability leads to a massive reduction in computational time. It is found that the least computational time is obtained at 40% convergence for initial iterations using resiliency. Also, the optimal number of iterations needed (for initial iterations) is nearly ten times the number of decision variables.
3. Comparing the results obtained using MOSADE-DP with that of MOSADE, it is found that similar solutions are obtained with a higher success rate in the case of MOSADE-DP, requiring almost the same number of function evaluations.
4. The presented AHP based MCDM analysis proves to be an efficient means of finding a solution with satisfactory hydraulic and mechanical reliability with the least LCC. The solutions obtained possess the advantage that both hydraulic and mechanical reliabilities are ensured with minimum LCC.
5. On analyzing the impact of change in criteria weights used for AHP methodology, it is found that the results were affected by change in the criteria weights, and choosing the most suitable weight combinations is essential to get the desired results. AHP performs efficiently by generating the desired output as per the requirement of the project.

Therefore, the present study recommends the MOSADE-DP approach for the WDN expansion problem, using resiliency for formulating the initial solution, which reduces the computational time by a considerable amount. Further, the use of AHP for performing MCDM analysis is found to be an effective tool that can aid the decision-makers in selecting the most suitable alternative based on the project requirement.

However, it should be noted that the model results will be affected due to many uncertainties involved. While considering a planning horizon of 50 years, the future predictions may change with time, affecting the expansions. Thus, considering uncertainty in future predictions and the uncertainties within a given prediction would make the model much more robust. The break rate of pipes affects both the LCC as well as the estimated mechanical reliability. Therefore, a proper record of the historical pipe failure data may help the practicing engineers to have a better prediction of future break rates. Similarly, maintaining proper demand uncertainty data will aid in modelling these uncertainties more accurately. If the model incorporates the addition of new water sources and/or pumps, it may lead to more realistic results, which will affect the cost and the addition of parallel pipes. Also, the availability of funds at various stages will affect the possible expansions. In such cases, an additional constraint of maximum possible expansion cost needs to be imposed in the model at each stage. Also, the present study has not compared the results to any real-life expansions made in the past due to the lack of data, and the relevant issues should be considered in future studies.

DATA AVAILABILITY STATEMENT

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

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First received 25 June 2021; accepted in revised form 27 September 2021. Available online 8 October 2021