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Fuzzy optimization-based Water Distribution Network design using Self-Adaptive Cuckoo Search Algorithm

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ABSTRACT

Water Distribution Network(s) (WDN) design is gaining prominence in the urban planning context. Several factors that play a significant role in design are uncertainty in data, non-linear relation of head loss & discharge, combinatorial nature of the problem, and high computational requirements. In addition, many conflicting objectives are possible and required for effective WDN design, such as cost, resilience, and leakage. Most of the research work published has used multiobjective evolutionary optimization in solving such complex WDN. However, the challenge of such population-based evolutionary approaches is that they provide multiple trade-off Pareto optimal solutions to the decision-maker who will have to choose another set of techniques to arrive at a single optimal solution. The present study employs a fuzzy optimization approach that would provide a single optimal WDN design for Hanoi and Pamapur, India. Maximization of network resilience (NR) and minimization of network cost (NC) are employed in a multiobjective context. Later, minimization of network leakages (NL) is also incorporated, leading to three objective problems. Hyperbolic membership function (HMF), exponential membership function (EMF), and non-linear membership function (NMF) are employed in Self-Adaptive Cuckoo Search Algorithm-based fuzzy optimization. HMF is found suitable to determine the best possible WDN design for chosen case studies based on the highest degree of satisfaction.

Key words: Cuckoo search, exponential, fuzzy optimization, hyperbolic, non-linear, WDN

HIGHLIGHT

- Most of the research conducted until now have used evolutionary multiobjective optimization in solving WDNs. But, the challenge of such evolutionary approaches is that they provide multiple trade-off Pareto optimal solutions to the decision-maker who will have to further choose another methodology to converge to a single optimal solution. The proposed methodology would simplify the decision-making process for an engineer.

1. INTRODUCTION

Water Distribution Network(s) (WDN) design is gaining prominence in the urban planning context. Several factors that play a significant role in design are uncertainty in data, non-linear relation of head loss & discharge, combinatorial nature of the problem, and high computational requirements. In addition, many conflicting objectives are possible and required for effective WDN design, such as cost, resilience, and leakage. Most of the research work published has used multiobjective evolutionary optimization in solving such complex WDN. However, the challenge of such population-based evolutionary approaches is that they provide multiple trade-off Pareto optimal solutions to the decision-maker. Later these points are expected to be reduced/filtered so that it will be convenient for engineer/manager to choose the suitable one from reduced/filtered solutions using ranking approaches. This process is computationally complex as it involves three phases: generation of Pareto front, clustering of data sets on the Pareto front, and ranking for arriving at a single solution that the design engineer/manager can use. Another challenge in multiobjective problems is the quantification of relative importance/weights of chosen objectives. Approximation of these weights may lead to different points on the Pareto front.

Interestingly, there are many parameters/techniques involved in each phase, making it difficult to achieve the satisfactorily single optimal solution.

In addition, randomness associated with various components of WDN in terms of the unit cost of pipe, available head at demand nodes, discharge at the reservoir, demand at nodes, leakages, and pipe roughness make the problem more complex. Fuzzy logic-based approaches are suitable for managing imprecision with ease compared to deterministic methods, which are not well equipped to model such difficult conditions (Raju & Duckstein 2003). They would simplify the decision-making process for an engineer/manager who would prefer a single optimal WDN design to a set of WDN designs in a multiobjective framework without generating an entire Pareto front. This background is the primary motivation of the research work proposed in this manuscript. A few essential advantages in this approach are (a) fuzziness of available resources is described by the membership functions (MF); and (b) a simple mathematical background that transforms the multiobjective problem into a single-objective problem to maximize the degree of satisfaction (λ). Here, the constraints are related to the MF of chosen objectives (in addition to case study-based constraints) and (c) extendable to any number of objectives without significant computational complexity. Lence *et al.* (2017) opined that the fuzzy programming approach would lead to improved WDN design.

Limited research works have reported on fuzzy logic in water resources, including WDN, which are as follows: Bhave & Gupta (2004) considered demands in a fuzzy scenario for benchmark WDN and solved them using fuzzy linear programming. They compared the results with previously published work and concluded that their approach provided a satisfactory solution. Vamvakeridou-Lyroudia *et al.* (2005) minimized costs and maximized a benefit/quality function using Genetic Algorithm (GA) for Anytown WDN. Fuzzy aggregation operators were used to combine individual MF of criteria. It was concluded that the developed model provided a better solution than previously studied. Christodoulou & Deligianni (2010) applied fuzzy logic, artificial neural networks, numerical and analytical methods to Limassol city and New York City to develop a knowledge base for water loss and water-main breaks. They also discussed in detail the sustainable management of WDN. Fu & Kapelan (2011) applied a fuzzy probabilistic approach to the Hanoi and New York tunnels WDN for optimal design/rehabilitation. Nodal head requirements and water consumption in the future are considered as fuzzy random variables. System performance in terms of fuzzy reliability and total design cost are objectives. Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is used. The proposed approach was found to handle uncertainties effectively. Amirabdollahian *et al.* (2011) used a fuzzy GA (FGA) with the objective of least-cost design for two WDN and found it provided better optimum solutions. Shibu & Reddy (2014) employed cross-entropy optimization under demand uncertainty represented as a triangular fuzzy number and applied to two WDN. Geem (2015) proposed minimization of cost and maximization of triangular MF-based velocity reliability index. Two-loop and Yeosu WDN were the case studies. A harmony search algorithm was used in multiobjective optimization, and an efficient Pareto set was generated. Creaco *et al.* (2015) considered gradual WDN growth and related uncertainty for northern Italy. The study suggested flexible conservative pipe sizes to adapt to various situations of temporal demand. Srivastava & Singh (2015) developed a fuzzy programming approach to Soraon canal command, India. They discussed different optimization techniques/MF in detail. Amirabdollahian & Mokhtari (2015) employed FGA to the Anytown WDN. The algorithm was effective in designing WDN under several uncertain hydraulic constraints. Gaur *et al.* (2015) employed fuzzy optimization in groundwater planning problems for a case study in France and Morankar *et al.* (2016) in irrigation planning for a case study in India. Sivakumar *et al.* (2016) discussed the uncertainties resulting due to various parameters in WDN. They employed GA and concluded that the study helped to analyze the pipe network under uncertainty. Lence *et al.* (2017) developed a fuzzy multiobjective programming model to the WDN of Farhadgerd, Iran. They considered two objectives with the goal of maximum λ. Yuan *et al.* (2017) proposed a random fuzzy optimization model for hydropower scheduling for Qing River in China. The model is competent to minimize frequent unit switches. Sabzkouhi & Haghighi (2018) coupled many-objective GA and fuzzy-based transient simulation models and applied them to the Baghmalek WDN, Iran. The model was found to be computationally efficient.

Moosavian (2018) studied the optimal design of WDN under uncertainty for three case studies and employed more than eight evolutionary algorithms. He considered multiobjective optimization in a fuzzy environment and employed MF to consider uncertainty. Lu & Qin (2019) coupled fuzzy simulation and GA with Low Impact Development design under uncertainties for the hypothetical urban catchment. Shruti & Deka (2020) reviewed fuzzy logic applications in hydrology and water resources. They discussed the merits and demerits of fuzzy logic, appreciated its role in data-scarce modeling situations and predictive capability. Pandey *et al.* (2020) reviewed fuzzy and probabilistic approaches in WDN extensively. Sreethu & Gupta (2020) applied Jaya optimization algorithm for fuzzy node flow analysis on a benchmark WDN using a pressure-dependent approach. The uncertain parameter is nodal demand, analyzed through the triangular MF and α cut approach. However, no study has been reported other than Lence *et al.* (2017) on the design of WDN in the fuzzy framework. Accordingly, the following objectives were formulated focusing on to (i) design of a Multiobjective Water Distribution Network (MOWDN) with three objectives related to resilience, cost, and leakages using Self-Adaptive Cuckoo Search Algorithm (SACSA), (ii) studying the applicability of Hyperbolic Membership Function (HMF), Exponential Membership Function (EMF), and Non-linear Membership Function (NMF) for MOWDN design problem, and (iii) studying the influence of various parameters employed in MF. Proposed objectives were applied to two case studies, Hanoi & Pamapur WDN. Details about SACSA and MF are presented in the next section, followed by two case studies and description of objectives, results and discussion, and summary and conclusions.

2. METHODOLOGY AND DESCRIPTION OF TECHNIQUES

The present study considers three objectives, minimization of cost (NC), maximization of resilience (NR), and minimization of leakages (NL) for WDN design. Two situations are proposed. In the first situation, the fuzzy optimization problem with only two objectives, NR and NC, and termed as O_2 scenario is analyzed. Here O represents objectives, and suffix 2 represents two objectives. Similarly, three objectives, NC, NR and NL are considered for analyzing them in a fuzzy optimization framework termed O_3 scenario. Here O represents objectives, and 3 represents three objectives. The study's focus is to ascertain how different types of MF can influence outcomes and to assess their applicability to the present planning problem. In addition, the other focus point is to explore fuzzy logic-based optimization to WDN, which is a relatively new research area. HMF, EMF, and NMF are employed in SACSA-based fuzzy optimization model. Maximum and minimum values of each objective required for the development of MF are determined using SACSA. Outcomes are the optimal λ and pipe diameters in addition to objectives. The corresponding WDN designs are compared to published work wherever available. The impact of MF on the λ and objectives is also studied as part of the sensitivity analysis. A flow chart of the methodology is presented in Figure 1.

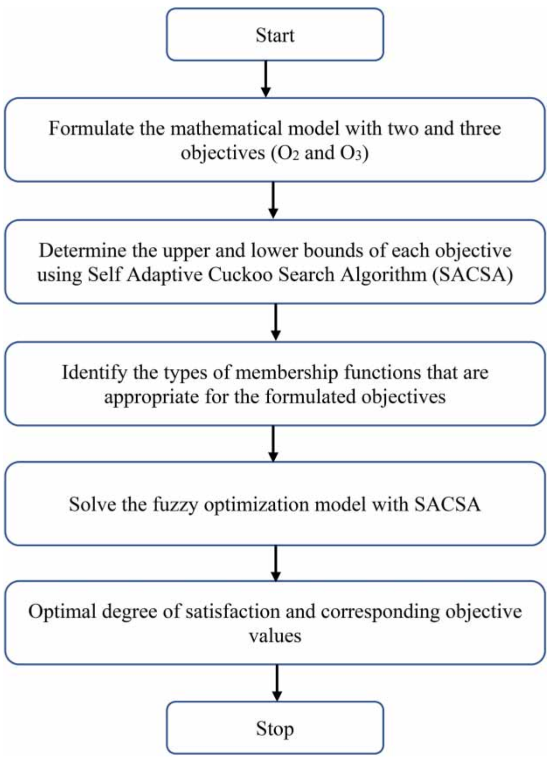

Figure 1 | Flowchart of the methodology.

2.1. Self-Adaptive Cuckoo Search Algorithm (SACSA)

The Cuckoo Search Algorithm (CSA) is a metaheuristic optimization technique based on swarm intelligence and cuckoo birds' breeding behavior (Yang & Deb 2009). These algorithms' convergence rate and efficacy depend on control parameters and are not the same for every problem. This challenge necessitates the best set of control parameters that are expected to provide the near-global optimal solution to decision-makers' satisfaction. One solution for this problem is to modify the initial control parameters during the iterative process of the optimization until termination criteria are met and termed as self-adaptive.

The present study focuses on applying a self-adaptive version of the CSA named the Self-Adaptive Cuckoo Search Algorithm (SACSA) for optimal WDN design. Governing parameters are (a) number of nests, (b) the step size control parameter and (c) the shifting parameter (Yang 2014). Initially, the locations of the nests are established by a randomly allocated set to each decision variable. Generation of new cuckoos is accomplished by Levy flights, utilizing local random walk and global random walk. Generation of new cuckoos and identifying alien eggs are alternately carried out until the chosen termination criteria are met. More details about SACSA are available from Pankaj *et al.* (2020).

2.2. Membership functions and fuzzy optimization model

2.2.1. Description of membership functions

Membership functions can be hyperbolic, exponential, non-linear, or any other suitable. Two types of MFs are employed. Non-decreasing is based on the hypothesis of 'more the better' (column 2 of Figure 2). Moreover, non-increasing is based on the philosophy of 'less the better' (column 3 of Figure 2) (Sasikumar & Mujumdar 1998). Z represents the objective function [refer to Equations (9)–(11) respectively for NC, NR, and NL], and Z_L and Z_U are the minima and maximum acceptable levels that objective Z can achieve. These are NC_L, NC_U for cost, NL_L, NL_U for leakages, and NR_L, NR_U for resiliency. β governs the type of MF. Here objective resilience falls under the category of non-decreasing, whereas cost and leakages fall under the category of non-increasing. Table 1 presents membership function equations for NC, NL, and NR for three different MF. In the case of NR, membership values of 1 and 0 are given for maximum desirable NR_U and minimum desirable levels NR_L (refer to column 5). It is vice versa for NL and NC (refer to column 5).

2.2.2. The mathematical framework of fuzzy optimization

In any optimization framework, decision space *SS* depends on objectives O and constraints *CS*. In fuzzy contexts, these are related (see Zimmermann 1991; Sasikumar & Mujumdar 1998):

$$\mu_{SS} = (\mu_O \cap \mu_{CS}) \tag{1}$$

Here μ_{SS}, μ_O, μ_{CS} are MF representing decision space, objectives, and constraints (refer to Figure 3). With several objective functions and constraints, Equation (1) can be transformed to:

$$\mu_{SS}(X) = [\mu_{O1}(X) \cap \mu_{O2}(X) \cap \ldots \cap \mu_{\mathrm{On}}(X) \cap \mu_{CS1}(X) \cap \mu_{CS2}(X) \cap \ldots \cap \mu_{CSm}(X)] \tag{2}$$

$$\mu_{SS}(X) = \mathrm{Min}[\mu_{O1}(X), \mu_{O2}(X), \ldots, \mu_{\mathrm{On}}(X), \mu_{CS1}(X), \mu_{CS2}(X), \ldots, \mu_{CSm}(X)] \tag{3}$$

In fuzzy logic, 'and' represents logical operator intersection ($\cap$), i.e., minimum:

$$\text{Optimum solution } \mu^*_{SS}(X) = \mathrm{Max}[(\mu_{SS}(X)] \tag{4}$$

The model can be worked out by establishing an auxiliary continuous variable, degree of satisfaction λ (Lence *et al.* 2017), by transforming Equation (4) into an equivalent single-objective optimization problem (Equations (5)–(8)). Here the goal is to find the best compromised unique solution x^* that represents the optimum λ [refer to Figure 3].

$$\text{Maximization } \lambda \tag{5}$$

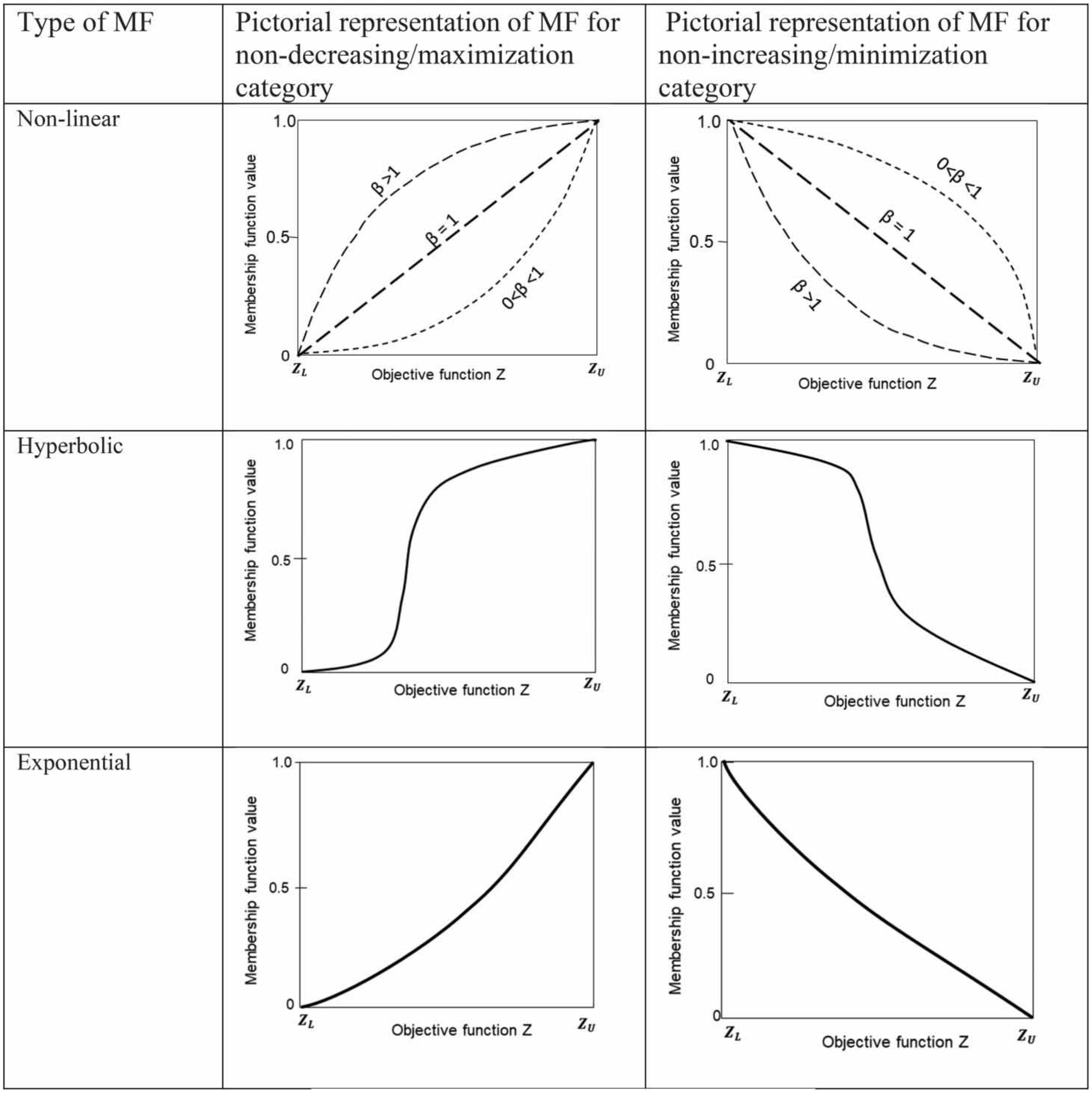

Figure 2 | Employed MF in the present study.

subject to:

$$\mu_{Oj}(X) \geq \lambda \quad j = 1, 2, \ldots, n \tag{6}$$

$$\mu_{CSi}(X) \geq \lambda \quad i = 1, 2, \ldots, m \tag{7}$$

$$0 < \lambda \leq 1 \tag{8}$$

and all the other case study-related constraints and bounds. Constraints 6–7 relate to the minimum degree of satisfaction λ. λ varies between 0 (implying that at least one objective has a null level of fulfilment, hence a conflict situation) and 1 (implying that all the objectives are entirely fulfilled, hence a no-conflict situation). Any intermediate value characterizes the

Table 1 | Membership function equations for three shapes with corresponding ranges

Objective	Non-linear membership function (NMF)	Hyperbolic membership function (HMF)	Exponential membership function (EMF)	Membership value for NMF, HMF, EMF for other ranges
Cost NC μ_{NC}	$\left[\frac{NC_U - NC}{NC_U - NC_L}\right]^{\beta}$ $NC_L \le NC \le NC_U$	$\frac{1}{2}\tanh\left[\left(\frac{NC_U + NC_L}{2} - NC\right) \times \frac{6}{NC_U - NC_L}\right] + \frac{1}{2}$ $NC_L \le NC \le NC_U$	$\left[\frac{e^{-S\left(\frac{NC - NC_L}{NC_U - NC_L}\right)} - e^{-S}}{1 - e^{-S}}\right]$ $NC_L \le NC \le NC_U$ S is a nonzero parameter $(0 < S \le 1)$	1 for $NC \le NC_L$; 0 for $NC \ge NC_U$.
Leakage NL μ_{NL}	$\left[\frac{NL_U - NL}{NL_U - NL_L}\right]^{\beta}$ $NL_L \le NL \le NL_U$	$\frac{1}{2}\tanh\left[\left(\frac{NL_U + NL_L}{2} - NL\right) \times \frac{6}{NL_U - NL_L}\right] + \frac{1}{2}$ $NL_L \le NL \le NL_U$	$\left[\frac{e^{-S\left(\frac{NL - NL_L}{NL_U - NL_L}\right)} - e^{-S}}{1 - e^{-S}}\right]$ $NL_L \le NL \le NL_U$ S is a nonzero parameter $(0 < S \le 1)$	1 for $NL \le NL_L$; 0 for $NL \ge NL_U$.
Resiliency NR μ_{NR}	$\left[\frac{NR - NR_L}{NR_U - NR_L}\right]^{\beta}$ $NR_L \le NR \le NR_U$	$\frac{1}{2}\tanh\left[\left(NR - \frac{NR_U + NR_L}{2}\right) \times \frac{6}{NR_U - NR_L}\right] + \frac{1}{2}$ $NR_L \le NR \le NR_U$	$\left[\frac{e^{-S\left(\frac{NR_U - NR}{NR_U - NR_L}\right)} - e^{-S}}{1 - e^{-S}}\right]$ $NR_L \le NR \le NR_U$ S is a nonzero parameter $(0 < S \le 1)$	0 for $NR \le NR_L$; 1 for $NR \ge NR_U$

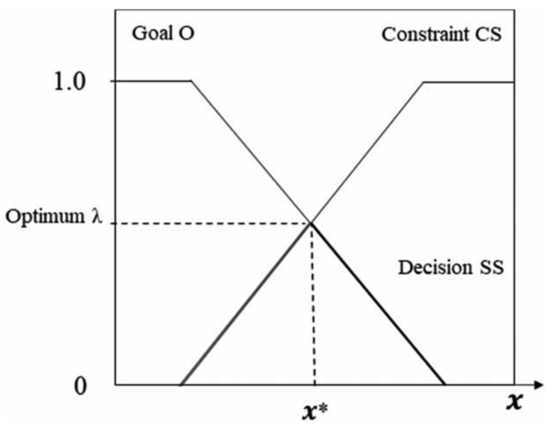

Figure 3 | Fuzzy logic decision framework.

corresponding level of conflict situation (Sasikumar & Mujumdar 1998). In the present study, we have considered uncertainty related to objective functions only.

3. CASE STUDIES AND MATHEMATICAL MODELING

Two case studies, Hanoi and Pamapur, were chosen for demonstrating the proposed methodology. Hanoi WDN comprises 32 nodes, and 34 pipes linking them, arranged in three loops as shown in Figure 4 (Fujiwara & Khang 1990). The Pamapur WDN (real-life case study located in Telangana, India) consists of 122 pipes, 102 demand nodes, and three tanks, as shown in Figure 5 (Pankaj *et al.* 2020).

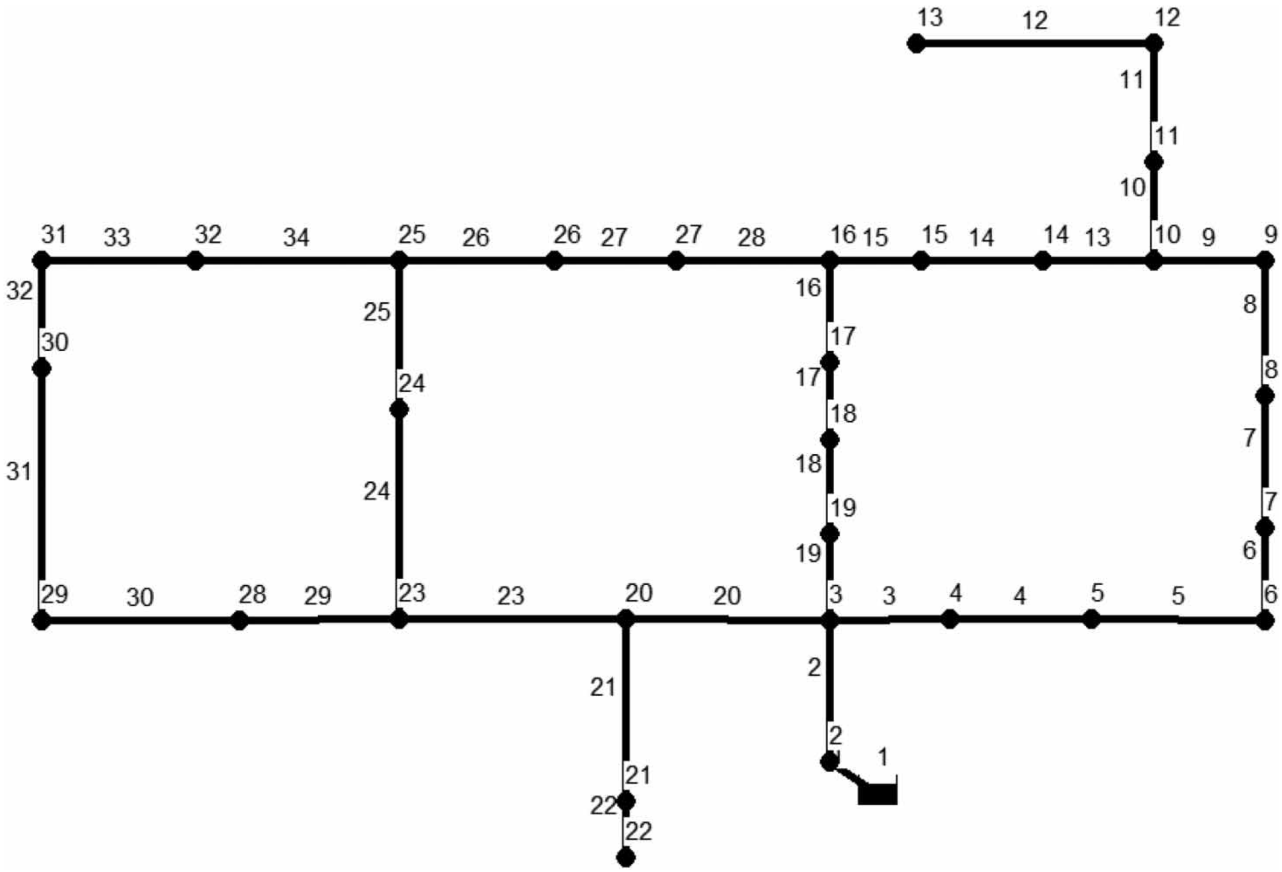

Figure 4 | Layout of Hanoi WDN.

The present study focuses on finding out the optimal set of WDN diameters while balancing the network hydraulically and satisfying minimum head requirements at each demand node. Mathematical representations of each objective are given below:

Cost of pipe is based on diameter and length, expressed as:

$$NC = \sum_{j=1}^{\text{nop}} (ucp)_j \times (L)_j \tag{9}$$

NR is the capacity of the system to meet the demands under failure or during maintenance that require surplus power. Modified resilience index is defined as (Todini 2000; Prasad & Park 2004):

$$(I_{nr}) = \frac{\sum_{j=1}^{nn} C_j Q_j (H_j - H_j^{\min})}{\left(\sum_{k=1}^{nr} Q_r H_r + \sum_{i=1}^{npu} \frac{P_i}{\gamma}\right) - \sum_{j=1}^{nn} Q_j H_j^{\min}} \text{ where } C_j = \frac{\sum_{i=1}^{npj} D_i}{npj \times \text{maximum}(D_i)} \tag{10}$$

NL is determined based on the pipe pressure and calculated as follows (Tucciarelli *et al.* 1999):

$$NL = (H_{i,t})^{\alpha} \times \sum_{j=1}^{npj} \frac{\pi}{2} \times D_i \times L_{ij} \times \theta_{ij} \tag{11}$$

where nop = number of pipes in the network, ucp_j = unit cost of jth pipe in the network, L_j = length of jth pipe in the network, nn = number of nodes, H_j = available head at demand nodes, Q_r = discharge at the reservoir, H_r = head at the reservoir,

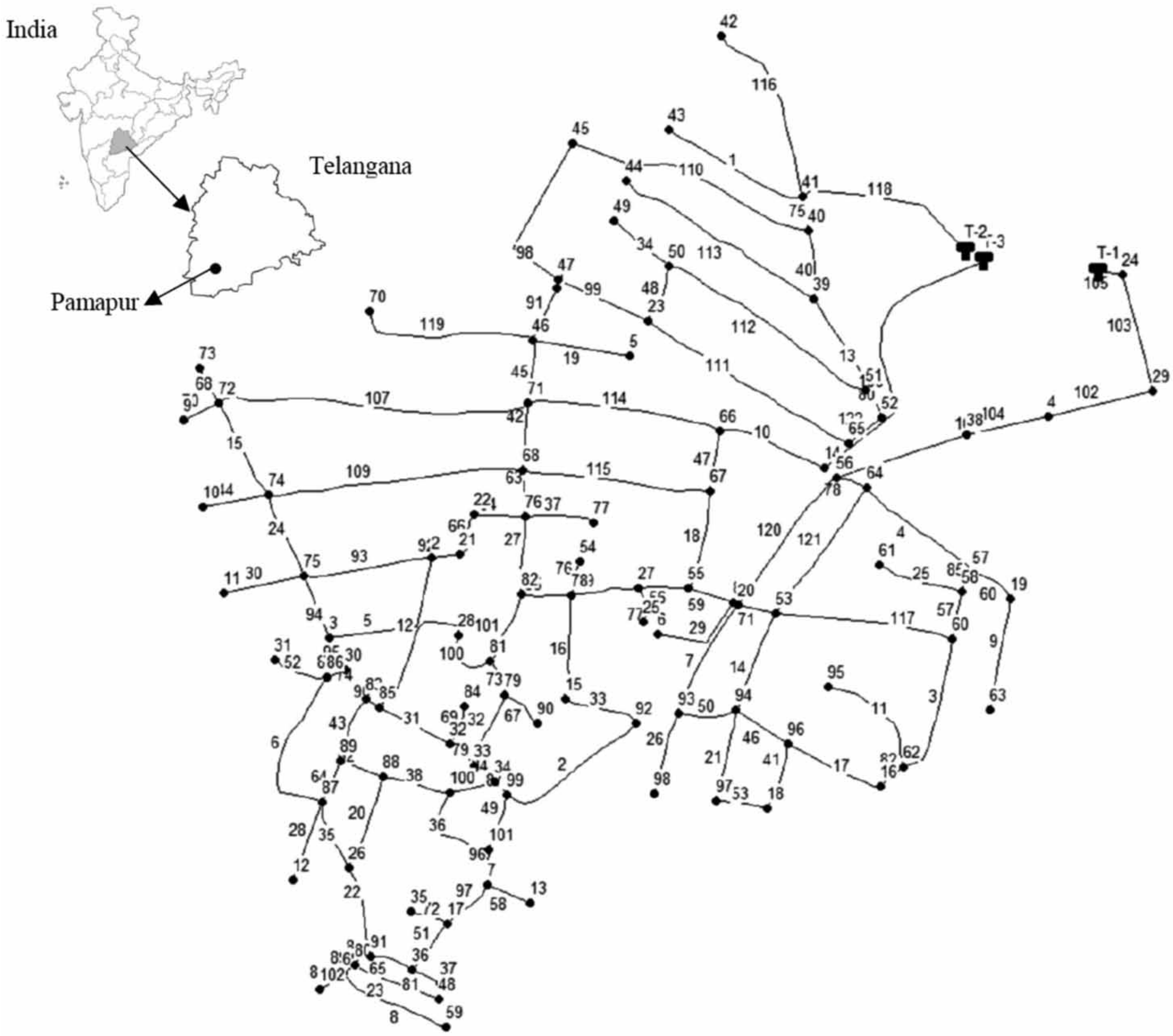

Figure 5 | Layout of Pamapur WDN.

$H_j^{\min}$ = minimum head required at demand node, Q_j = demand at nodes, npu = number of pumps, npj = number of pipes linked to node, D_i = diameter of ith pipe, γ = specific weight of water, L_{ij} = length of pipe linking nodes i and j, θ_{ij} = leak per unit surface of the pipe linking nodes i and j, α = loss exponent, and $H_{i,t}$ = calculated pressure at node i at time step t.

4. RESULTS AND DISCUSSION

The optimization-simulation framework (SACSA-EPANET 2.2) was established for accomplishing the optimal design of WDN (Rossman 2000). Continuity and energy conservation constraints were fulfilled externally via EPANET 2.2, whereas SACSA handled the discrete diameter constraints. Fifty nests with 2,000 iterations for Hanoi and Pamapur WDN were chosen (Yang & Deb 2009). For both case studies and scenarios, the algorithm is converged before chosen iterations. Initially, the model is solved independently using SACSA to obtain maximum and minimum values, Z_U, and Z_L (refer to Figure 2 and Table 1 for maximum and minimum values information). These are used as the basis while formulating HMF, EMF, NMF.

Table 2 | λ obtained for various MF and corresponding objective function values for Hanoi

Salient parameters (1)	Two objectives NC NR HMF (2)	NMF ($\beta = 0.8$ for all two objectives) (3)	EMF (S = 0.5 for all two objectives) (4)	Three objectives NC NR NL HMF (5)	NMF ($\beta = 0.8$ for all three objectives) (6)	EMF (S = 0.5 for all three objectives) (7)
NR	0.2969	0.2943	0.2961	0.2656	0.2642	0.2954
NC ($\times 10^6$ \$)	7.1220	7.0936	7.1059	6.7216	6.7469	7.1229
NL (m^3/sec)	–	–	–	0.0090	0.0089	0.0098
λ	0.968	0.823	0.737	0.886	0.730	0.734

Fuzzy optimization model for the chosen case studies are as follows:

$$\text{Maximization } \lambda \tag{12}$$

subject to

$$\mu_{NC} \geq \lambda \tag{13}$$

$$\mu_{NR} \geq \lambda \tag{14}$$

$$\mu_{NL} \geq \lambda \tag{15}$$

$$0 < \lambda \leq 1 \tag{16}$$

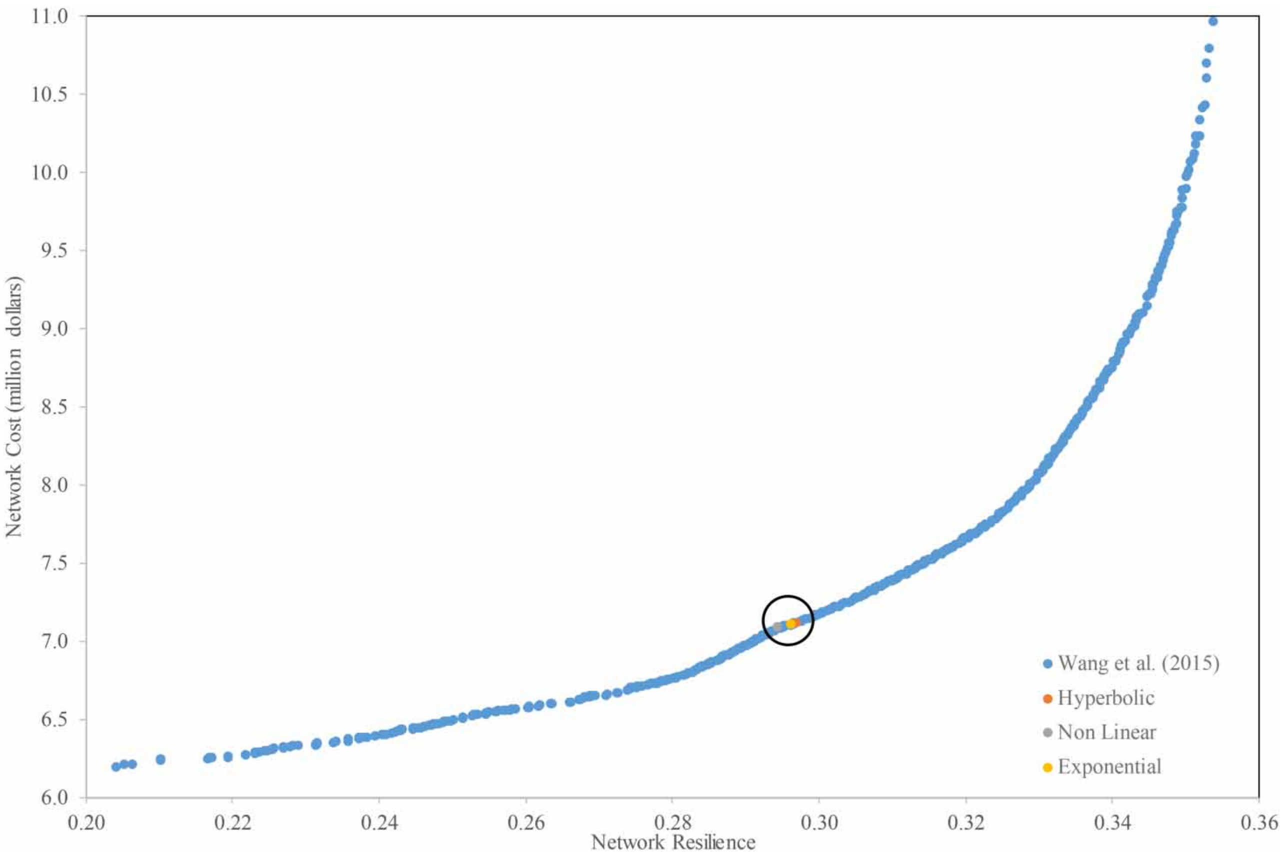

Figure 6 | Fuzzy optimization output marked on the Pareto front of Hanoi WDN (O_2 scenario).

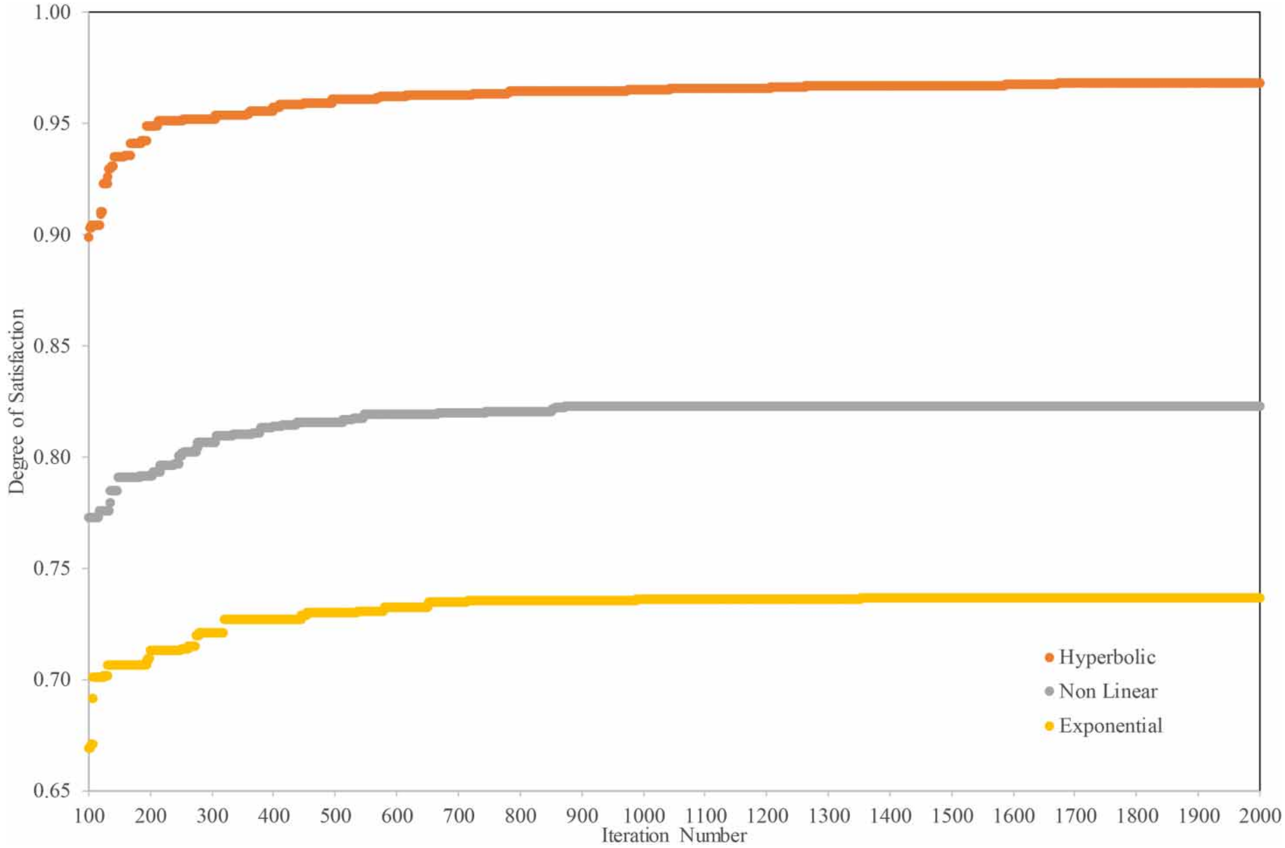

Figure 7 | Convergence graph of λ obtained by three MF for Hanoi WDN (O_2 scenario).

Here μ_{NC}, μ_{NR}, μ_{NL} are MF corresponding to cost, resilience, and leakage (refer to Table 1). These may be non-linear or hyperbolic, or exponential shapes. Equations (12)–(16) aim to maximize the level of satisfaction corresponding to minimum cost, minimum leakage, and maximum resiliency.

4.1. Hanoi WDN

Six commercially available pipes are considered, and the minimum pressure head needed at each node taken is 30 m. Table 2 presents λ obtained for various MF and corresponding objective values. Related results for O_2 and O_3 are as follows.

4.1.1. O_2 scenario

It is observed from Table 2 (columns 2–4) that λ values are in the decreasing trend, i.e., 0.968, 0.823, 0.737, respectively, for HMF, NMF, EMF. Values of NR and NC are almost similar, with a slight difference across all three memberships functions. The optimal WDN designs are compared with the previously published true Pareto front (Wang *et al.* 2015). The NR range in the true Pareto front is 0.2041–0.3538, and it is US\$ 6.195–10.97 $\times 10^6$ for NC. It is found from Figure 6 that the optimal WDN designs are located midway in the true Pareto front. As NR range is narrow compared to NC in true Pareto front, the obtained optimal WDN designs converged to a reasonable NR for a relatively low NC. It is observed from Figure 7 that the λ values show a steep increase up to 300 iterations, and after that, it is almost parallel to the x-axis in all three MF. As evident from Figure 8, the pipe diameters vary only in 13 out of 34 pipes (pipe numbers 8, 12, 14, 23, 24, 25, 26, 27, 29, 30, 32, 33, 34) in the three WDN designs obtained by HMF, NMF, and EMF.

4.1.2. O_3 scenario

It is observed from Table 2 (columns 5–7) that λ values are correspondingly lower (i.e., 0.886, 0.729, 0.734) as compared to the values in O_2 respectively for HMF, NMF, EMF. These trends are in the expected lines due to the conflicting nature of the objectives, which results in lower satisfaction levels. λ values for NMF and EMF are closer to each other. However, there is a wide variation in the values of the objectives. The range of NR, NC, and NL is wider among the three memberships functions than in

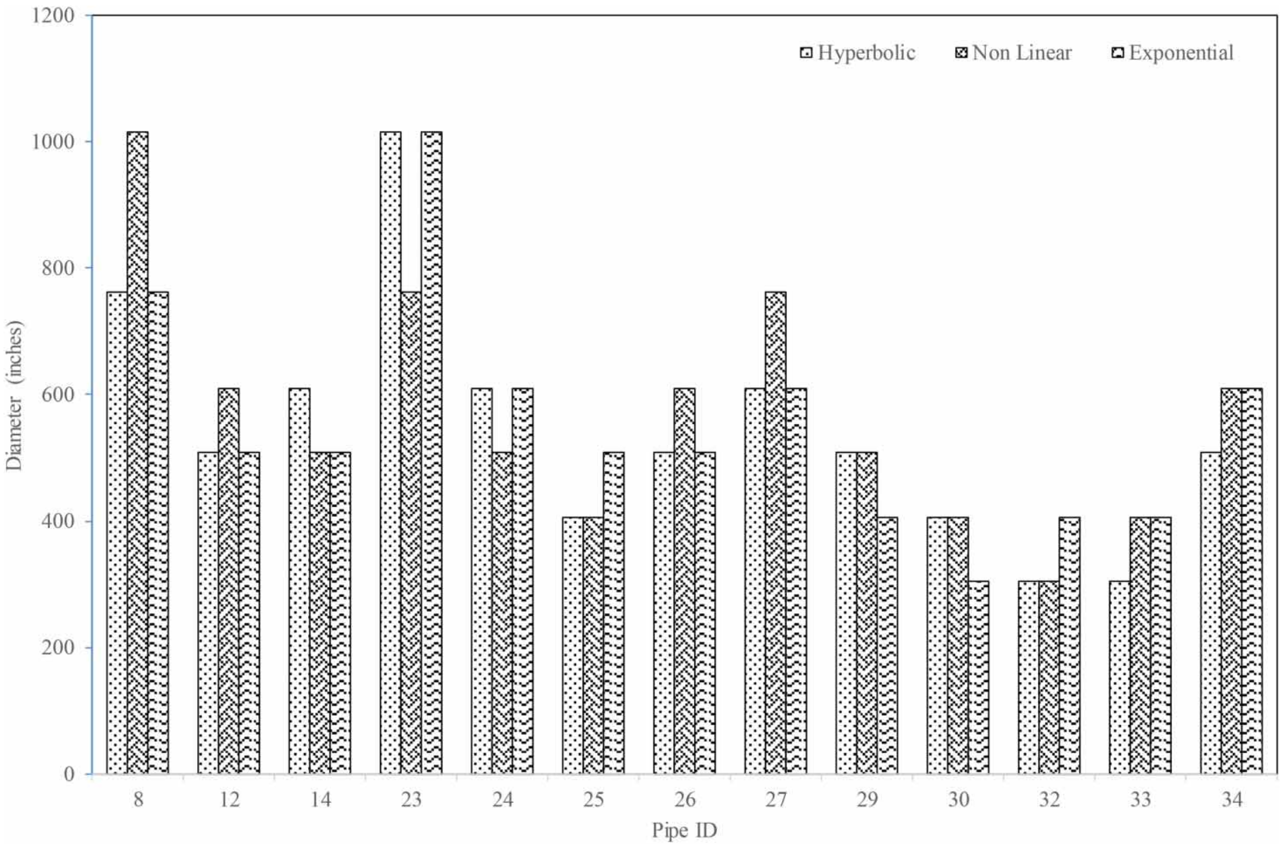

Figure 8 | Comparison of selected pipe diameters obtained by three MF for Hanoi WDN (O_2 scenario).

the O_2 scenario. It is observed from Figure 9 that the λ value is steeply increasing stepwise up to 300 iterations; thereafter, it is gradually rising to 1,428 and stabilizes in the case of HMF. In contrast, convergence trends of NMF and EMF are almost parallel with little variation in λ values. Out of 34 pipes, the pipe diameters vary only in 17 (pipe numbers 6, 7, 8, 9, 10, 11, 13, 14, 15, 23, 24, 26, 27, 28, 32, 33, 34) in the three WDN designs obtained by HMF, NMF and EMF (Figure 10).

4.2. Pamapur WDN

The minimum pressure head chosen is 6 m for all demand nodes. However, it is 5.75 m for node 22 (Pankaj *et al.* 2020). Table 3 presents the λ values obtained for various MF and corresponding objective values for Pamapur. Related results for O_2 and O_3 are as follows.

4.2.1. O_2 scenario

It is observed from Table 3 (columns 2–4) that the trend of λ values is the same as that of Hanoi O_2. However λ, values are more compared to Hanoi O_2. Optimal WDN designs obtained from three MF are compared to the previously published true Pareto front of Pankaj *et al.* (2020). It is found that the optimal WDN designs obtained are in line and towards the upper end of Pareto front of Pankaj *et al.* (2020), and evident from Figure 11. The optimal WDN design obtained by HMF, which represents a higher λ value, proposes a reasonable trade-off solution between NR and NC as compared to the designs obtained by NMF and EMF. NC and NR are the same for NMF and EMF, and are different in the case of HMF (columns 2–4 of Table 3). However, there is a slight variation in λ. It is observed from Figure 12 that λ value gradually increases in the case of HMF. In contrast, a steep increase is observed for NMF and EMF up to 600 iterations, which stabilizes after that.

4.2.2. O_3 scenario

It is observed from Table 3 (columns 5–7) that the trend of λ is the same as that of Hanoi O_3. The optimal WDN design obtained by HMF, which represents a higher λ value, has the best values in NC and NL compared to the designs obtained

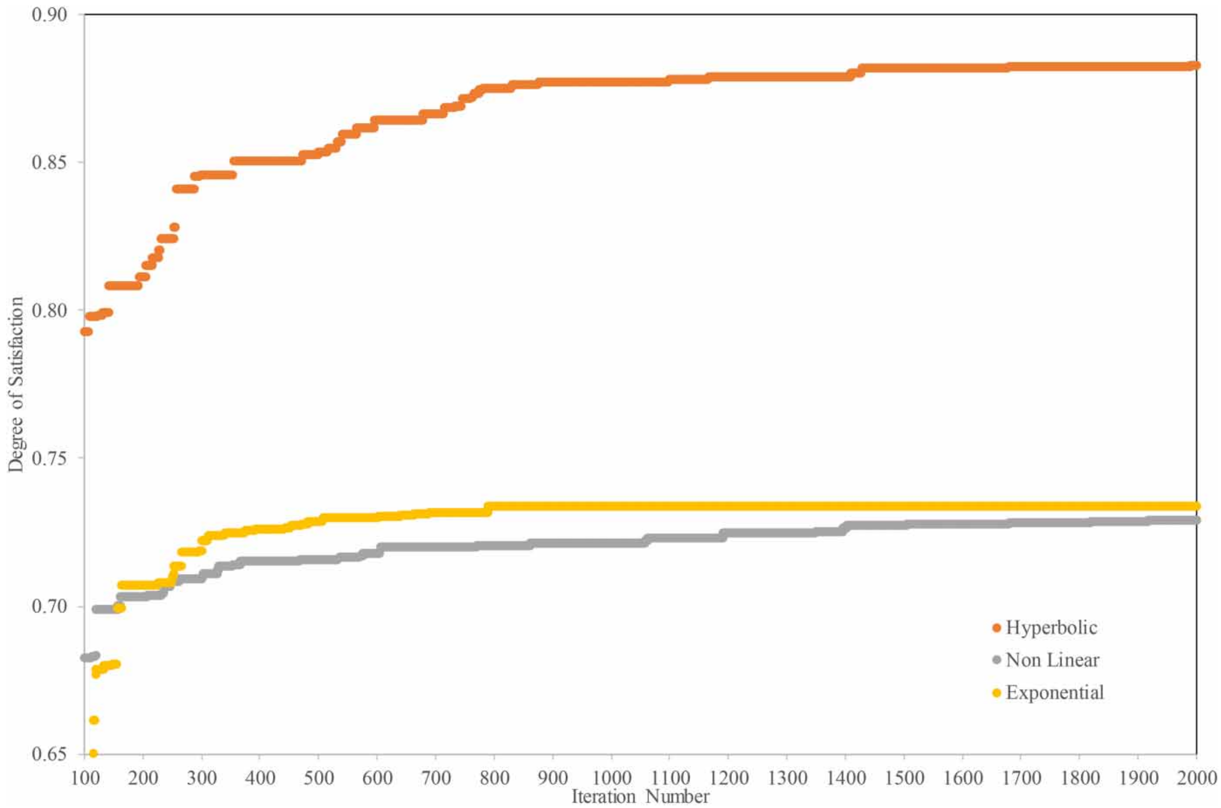

Figure 9 | Convergence graph of λ obtained by three MF for Hanoi WDN (O_3 scenario).

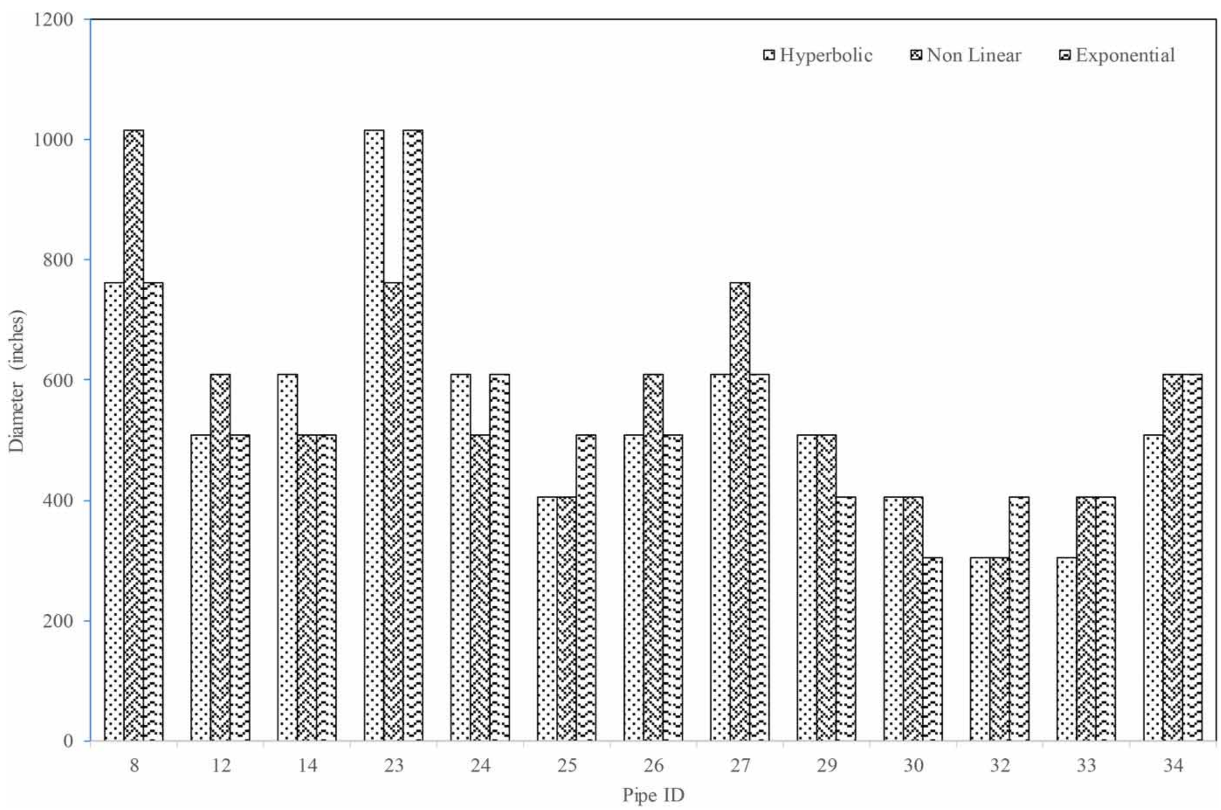

Figure 10 | Comparison of selected pipe diameters obtained by three MF for Hanoi WDN (O_3 scenario).

Table 3 | λ obtained for various MF and corresponding objective function values for Pamapur

	Two objectives (NC, NR)			Three objectives (NC, NR, NL)		
Salient parameters (1)	**HMF (2)**	**NMF ($\beta = 0.8$ for all two objectives) (3)**	**EMF (S = 0.5 for all two objectives) (4)**	**HMF (5)**	**NMF ($\beta = 0.8$ for all three objectives) (6)**	**EMF (S = 0.5 for all three objectives) (7)**
NR	0.8261	0.8565	0.8565	0.8220	0.8338	0.8332
NC ($\times 10^6$ \$)	0.0355	0.0441	0.0441	0.0343	0.0399	0.0396
NL (m^3/sec)	–	–	–	0.0016	0.0018	0.0018
λ	0.993	0.888	0.821	0.992	0.867	0.799

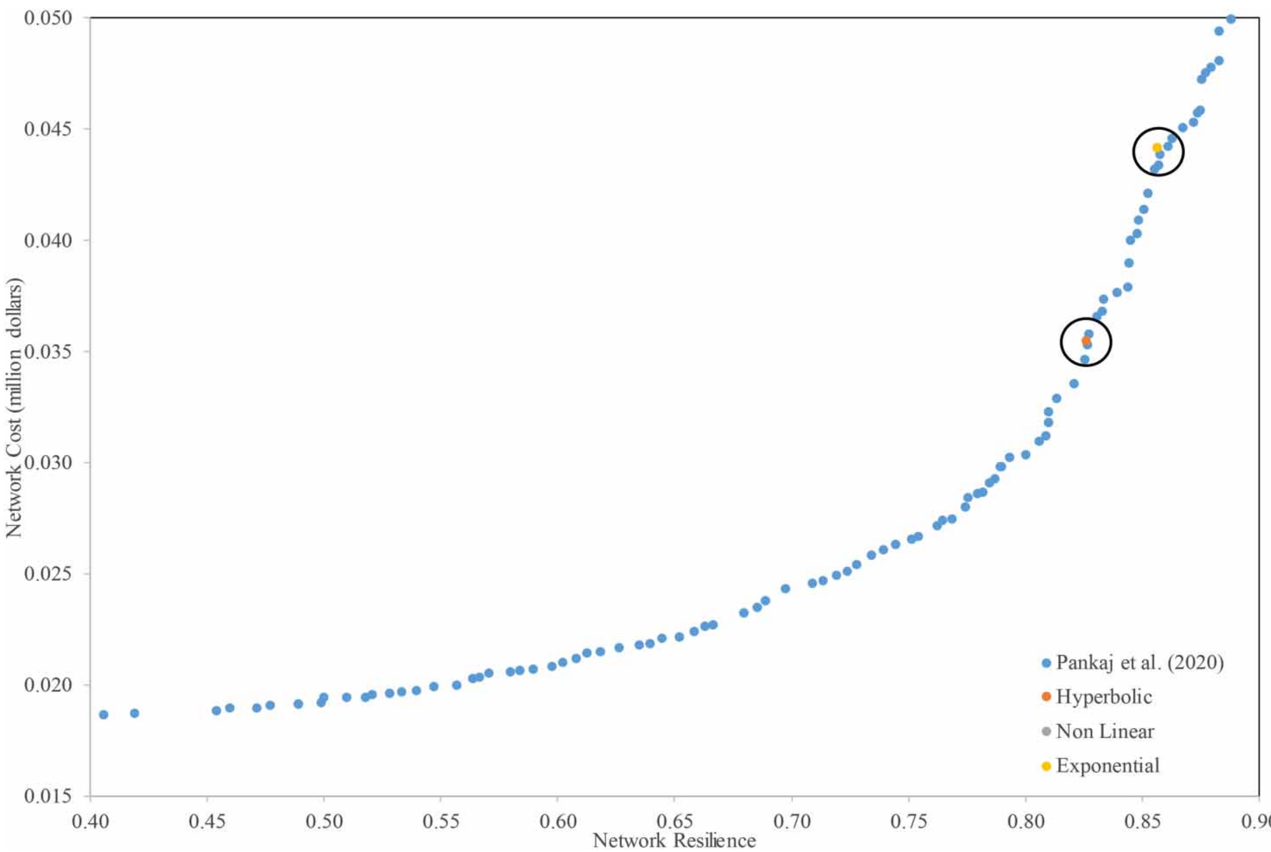

Figure 11 | Fuzzy optimization output marked on the Pareto front of Pamapur WDN (O_2 scenario).

by NMF and EMF. The values of all three objectives are almost the same for NMF and EMF, even though λ values are different for each MF. This may be due to the different mathematical frameworks of individual MF. Trends from the convergence graphs, as observed in Figure 13, are similar to Pamapur O_2. The λ values at iteration 100 are lower compared to the Pamapur O_2 scenario. No specific pattern is observed in the three WDN designs obtained by HMF, NMF, and EMF in O_2 and O_3 scenarios for the studied 122 pipes.

4.3. Sensitivity analysis

Multiple ways of handling fuzzy optimization problems are considered with all the three objectives, following (a) HMF, (b) EMF, (c) NMF, and (d) the number of other combinations. Accordingly, the impact of different membership parameters is studied (7 scenarios for O_3 and 2 scenarios O_2) for the Hanoi WDN. It is observed from Table 4 that the λ value is significantly affected with individual/different combinations of parameters. Range of λ, NC, NR, NL are 0.5275–0.8828, US\$6.4261–7.7982$\times 10^6$, 0.2318–0.324, 0.0083–0.0107 m^3/s as evident from Table 4. However, an interesting aspect is that

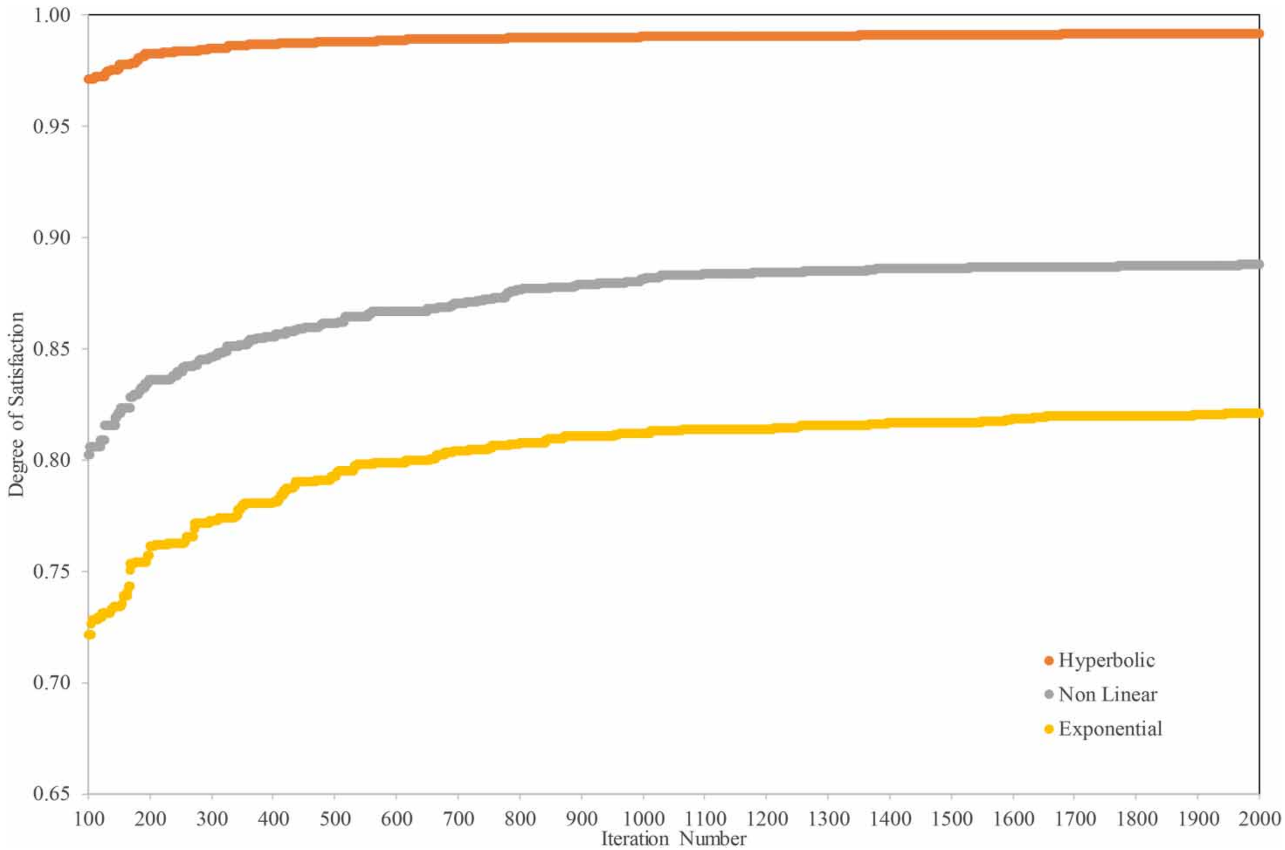

Figure 12 | Convergence graph of λ obtained by three MF for Pamapur WDN (O_2 scenario).

the objective values are not impacted considerably by this development. Similar results can be expected for Pamapur, as understood from the number of runs made for Hanoi.

5. CONCLUSIONS

The study presents a fuzzy optimization approach to determine optimal WDN design in a multiobjective framework for Hanoi and a Pamapur WDN. The proposed approach expressed the objectives fuzzified and explored the Pareto optimal front to find the most attractive compromise solution with much ease and less computational complexity. In this process, a multiobjective problem transforms into single-objective optimization to maximize the degree of satisfaction. Resulted objective values correspond to the optimal degree of satisfaction. The performance of the proposed approach has been tested on two scenarios, i.e., formulated mathematical model with two objectives (O_2) and three objectives (O_3). Three MF, i.e., HMF, EMF and NMF, are employed in the SASCA-based fuzzy optimization model to identify the most suitable WDN design among the possible non-dominated solutions for any multiobjective problem.

The results show that the λ value is significantly affected with individual/different combinations of parameters and MF. Reduction of λ is observed from O_2 to O_3 scenario for HFM, NMF, and EMF in Hanoi. In O_2, these values are 0.968, 0.823, 0.737; in O_3, these are 0.886, 0.730, 0.734. A similar trend is observed for Pamapur. Pipe diameters vary only in 13 pipes and 17 pipes out of 34, respectively, for O_2 and O_3 in the case of Hanoi. However, no specific pattern is observed for O_2 and O_3 for 122 pipes studied in the case of Pamapur. The optimal WDN designs in the O_2 scenario for both the case studies fell on the true Pareto front. HMF is found suitable for O_2 and O_3 of Hanoi and Pamapur WDN based on the highest λ, which has provided optimal WDN design for each problem.

Real-world application problems are often complex, challenging, and have mostly been multiobjective. As further research progresses, many more objectives might be identified to represent the actual situation in the field better. The proposed fuzzy optimization approach may be applied to determine the best possible WDN design in such cases that simplifies the decision-

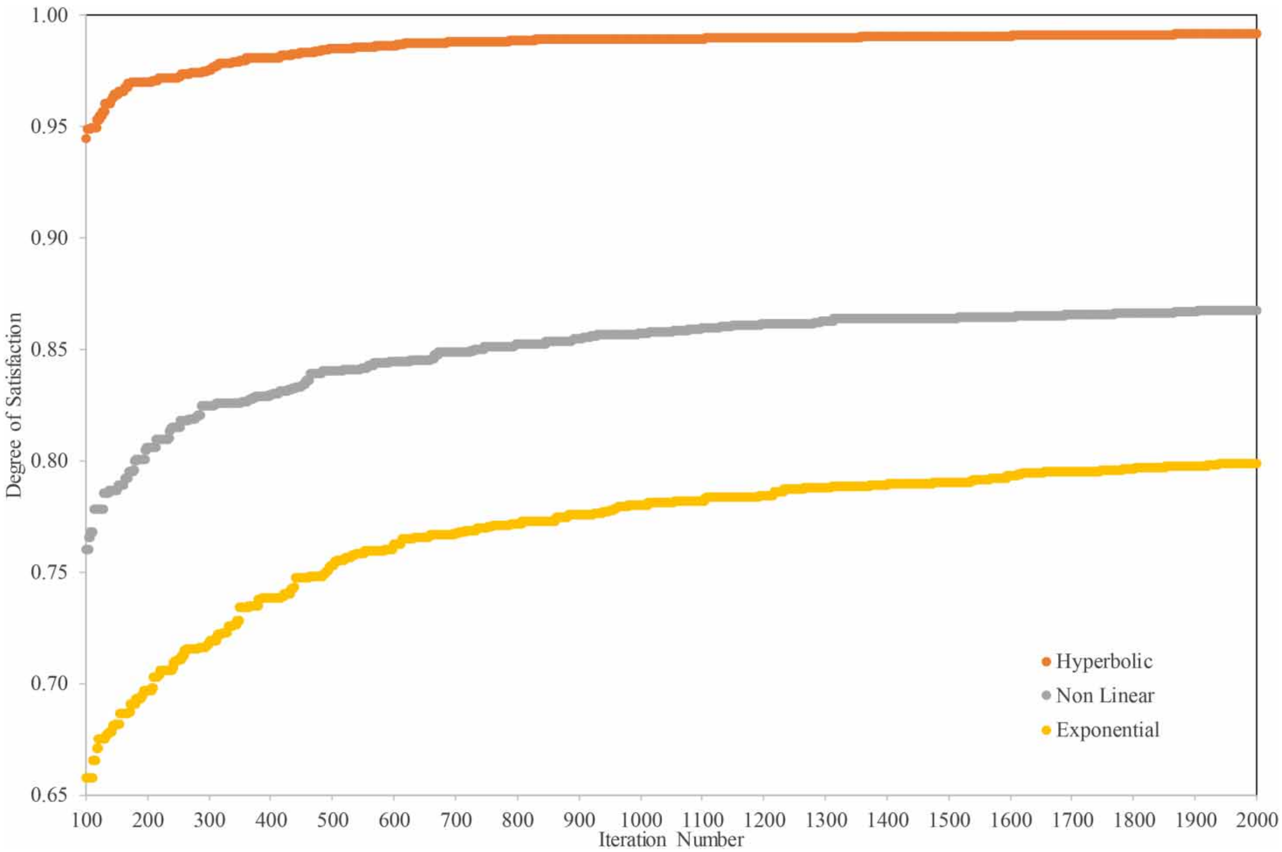

Figure 13 | Convergence graph of λ obtained by three MF for Pamapur WDN (O_3 scenario).

Table 4 | Impact of various parameters employed in MF on the λ and objective values for Hanoi

Scenario	Salient parameters	λ	Network cost ($\times 10^6$ \$)	Network resilience	Network leakages (m^3/sec)
1	NMF ($\beta = 0.3$ for NC, NR and NL)	0.8828	7.0060	0.2564	0.0090
2	NMF ($\beta = 1.5$ for NC, NR and NL)	0.5275	7.1544	0.2564	0.0091
3	EMF (S = 0.2 for NC, NR and NL)	0.6506	6.7987	0.2619	0.0089
4	EMF (S = 0.8 for NC, NR and NL)	0.5806	6.8531	0.2616	0.0089
5	NMF [($\beta = 1.5$), EMF (S = 0.8), HMF respectively for NC, NR and NL]	0.7088	7.0969	0.2887	0.0097
6	HMF, EMF (S = 0.8), NMF ($\beta = 1.5$) respectively for NC, NR and NL	0.5666	6.7941	0.2546	0.0089
7	NMF ($\beta = 1.5$), HMF, EMF (S = 0.8) respectively for NC, NR and NL	0.6911	6.4261	0.2318	0.0083
8	HMF, EMF (S = 0.8) respectively for NC, NR	0.8536	7.7982	0.3240	0.0107
9	NMF ($\beta = 1.5$), EMF (S = 0.8) respectively for NC, NR	0.7086	7.0420	0.2925	0.0096

making of the design engineer/manager. Also, the fuzzy multiobjective model can be further extended in the future also with fuzzification of the constraints to account for uncertainties in pipe roughness and nodal demands of larger WDN.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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