Design of water distribution systems using an intelligent simple benchmarking algorithm with respect to cost optimization and computational efficiency

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ABSTRACT

The increasing stress on the water distribution network (WDN) considering demand satisfaction with minimum cost has inspired designers to apply various optimization techniques to meet the consequent challenges. The traditional way of using optimization methods, e.g. stochastic meta-heuristic algorithms, have come along with various constraints to explore an optimum solution. In this study, a newly developed meta-heuristic algorithm called the Simple Benchmarking Algorithm (SBA) is used to optimize pipe size. A modified approach with SBA having interfaces with the EPANET 2.0 hydraulic simulation model is used to compute the minimum cost of the two-loop network and the Hanoi benchmark WDN. Results show that SBA is more efficient in obtaining the least possible cost with fast convergence.

Key words | algorithms, EPANET, hydraulic design, optimization, water distribution network

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INTRODUCTION

The crucial characteristic of a water distribution network (WDN) is to perform adequately under financial limitation. Traditional approaches in design are based on the minimization of cost factors considering various hydraulic constraints. With the advent of computer-aided design, the application of meta-heuristic algorithms, also called intelligent optimization algorithms (IOA), for WDN design has shown promising success for finding the economic expenditure; yet there is no guarantee that a global optimum will be found from a stochastic approach. To ensure that the solution evaluated is an optimum, extensive trial runs are required. For a large network, the computation time for excessive iterations is very high. Numerous designs for WDN have been reported in the literature considering the minimum cost (Savic & Walters 1997; Geem 2009; Sayyed 2017).

In the past two decades, various meta-heuristic optimization tools have been proposed in different branches of water resources engineering (Chau 2017; Moazenzadeh *et al.* 2018; Mosavi *et al.* 2018; Yaseen *et al.* 2019). In the optimum design for WDN, these include heuristic methods, e.g. Genetic Algorithm (GA) (Savic & Walters 1997), Simulated Annealing (SA) (Cunha & Sousa 1999), Particle Swarm Optimization (PSO) (Geem 2009), Shuffled Complex Algorithm (SCA) (Eusuff & Lansey 2003), Non-dominated Sorting GA (NSGA-II) (Sayyed 2017), Honey-Bee Mating Optimization (HBMO) (Mohan & Babu 2010), etc. Some advantages and disadvantages are associated with such traditional approaches. Difficulties are associated with formulation ease, fast convergence, handling non-linearity, handling discrete diameter, etc. Such limitations have led researchers to use these algorithms with some deterministic mathematical-based approaches. There has been experimentation with various combinations of GA, PSO, SA, NSGA, etc., along with their modified versions, in WDN optimization (Wu *et al.* 2001; Neelakantan & Suribabu 2005; Kadu *et al.* 2008; Geem 2009; Sayyed 2017). These investigations demonstrated that deterministic models were better from a computational efficiency point of view when compared with various stochastic algorithms, yet the dominant factor

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of the probability rules of the operator affects the global search solution.

Recently, a new approach to the optimization strategy has been introduced, called the Simple Benchmarking Algorithm (SBA). SBA (Xie 2018; Xie & Mu 2018) adopts an intelligence strategy to find the best solution during a global search, in which 'intellect' is based on operational rules, probability equations and mathematical formulation. The individuals within the solution space learn from each other and emulate a good example according to the organizing tactic. A modified approach with the SBA algorithm, termed 'SiBANET', is introduced to optimize the design cost of the WDN by considering two well-established benchmark cases. For this purpose, SiBANET uses the EPANET 2.0 (Rossman 2000) hydraulic simulation model. Results are verified for the optimum cost and a number of iterations. The prime objective of the proposed investigation is to check the efficiency of SiBANET in search of a global optimum solution. Additional objectives are:

1. to apply SBA for WDN design;
2. to compare the performance of SBA and other IOA algorithms;
3. to investigate the state-of-the-art hybrid framework and identify its advantages.

METHODOLOGY

The optimum design of a WDN is investigated to assess the combination of pipe diameters for the least cost. Various hydraulic parameters at different nodes are computed with the assistance of the EPANET 2.0 hydraulic network solver. The objective function is the cost constraint by pipe diameter selection as a decision variable. The total network cost to be minimized is expressed below:

$$\textit{Cost minimization} = f(D_1, D_2, \ldots\ldots D_n) \tag{1}$$

in which D = pipe diameter and n = total number of links. The total cost of the WDN can be expressed as:

$$\textit{Total cost} = \sum_{i=1}^{n_i} L_i \times c(D_i) \tag{2}$$

where n = total number of links and $c(D_i)$ = cost per unit length of the ith link in the distribution system of length L. As pipe lengths are fixed for a given network, the pipe diameters are decision variables. The basic hydraulic equations involved in EPANET are the loop energy balance and nodal mass balance, which are expressed as:

$$Q_{\text{ext}} = \sum Q_{\text{in}} - \sum Q_{\text{out}} \tag{3}$$

where Q_{ext} is external nodal demand, Q_{in} is nodal inflow and Q_{out} is the respective outflow.

For each closed loop, the energy conservation gives:

$$\sum_{i \in \text{loop } p} h_{\text{f}_i} = \Delta H_i \qquad \forall p \in N_{\text{L}} \tag{4}$$

where h_{f_i} = frictional head loss, N_{L} = number of loops in the network and ΔH = difference between node heads. The Hazen–Williams equation to estimate head loss due to friction (Savic & Walters 1997) is:

$$h_f = \omega \frac{L_i}{C_{\text{HW}}^{1.85} D_i^{4.87}} Q_i^{1.85} \tag{5}$$

In Equation (5), Q_i is the ith pipe flow and C_{HW} is the Hazen–Williams roughness constant. Here, ω is a dimensionless factor for conversion. Different values of ω are found in the literature ranging between 10.431 to 10.903. The average value of ω, i.e. 10.667, is used. The head loss in the ith pipe, which is located between the jth and kth junctions, is:

$$\Delta H_i = H_j - H_k \tag{6}$$

$\Delta H = 0$ if the network's path is closed. To meet the minimum pressure requirement of a network, the pressure head at all demand nodes should be greater than the allowable minimum pressure head ($H_{\min}$) at all nodes, i.e.:

$$H_n \geq H_{\min} \tag{7}$$

where H_n is pressure head at node n.

Formulation of the model

A simulation–optimization model 'SiBANET' is developed in this study to optimize the WDN. The single objective that is considered here is the network cost. The optimization is explored by the SBA algorithm framework. The algorithm is externally supported by EPANET.

The hydraulic constraints that are considered for the WDN design are:

$$D_{\min} \leq D_i \leq D_{\max} \qquad i = 1, \ldots, N_i \tag{8}$$

$$V_{\min} \leq V_i \leq V_{\max} \qquad i = 1, \ldots, N_i \tag{9}$$

$$P_{\min} \leq P_j \leq P_{\max} \qquad j = 1, \ldots, N_j \tag{10}$$

where $D_i =$ available commercial diameters, $V_i =$ flow velocity, $P_j =$ pressure in node j and N is the total number of nodes in the WDN.

Simple Benchmarking Algorithm

The advancement of SBA is based on the Benchmark Learning Algorithm (Xie 2014) theory that is typically used in business management. Benchmarking is a kind of management approach which consists of various implicit rules for optimization. It is a strategy in the corporate sector where various companies correlate their merchandise, processes, marketing etc. with leading firms in a similar domain. In other words, the gaps are found by comparing the best product and quickly covered by studying, analysing and mimicking. In this way, the company will take the leading edge over its competitors by adopting the best possible solution.

Therefore, when benchmarking philosophy is considered, the existing good solution will be implemented. This is an iterative process, which involves studying and emulating gradually from a sub-optimal solution to an optimal and ultimately reaching the best solution (Xie & Mu 2018). Repeated assessment of progress for setting new benchmarks is essential to achieve the best solution during optimization. Such a searching process offers a certain degree of intelligence. SBA offers an intelligent approach whose framework depends on self-organizing learning strategies instead of excessive emphasis on probability and operational rules (see Appendix, available with the online version of this paper).

SiBANET method and hydraulic model application

SiBANET is a collective simulation–optimization model developed in this study, which is tested for two benchmark WDN cases available in the literature. The simulation is performed by EPANET as the inner driver model having a source code with a dynamic link-library function for customizing the network to a specific need. The SBA algorithm, on the other hand, is an outer driver model, which works in conjunction with EPANET for network optimization. MATLAB R2016a is used to implement the SBA algorithm in conjunction with EPANET. SBA is deployed to compute the design cost of the WDN and update the input file with new diameters. This process is continued until the best individuals in the ecological system (E_s) are found as the best possible solution.

A systematic approach is illustrated with a two-loop network (Alperovits & Shamir 1977) and Hanoi WDN (Fujiwara & Khang 1990). The optimized solutions are obtained by implementing the SiBANET methodology. Pipe diameters are the only decision variable with a single objective of cost optimization. The computation time required for a number of function evaluations is also reported to gauge its efficiency.

The two-loop network

A well-known benchmark problem in WDN optimization study termed the two-loop network (TLN) is used here for demonstration. TLN is a small-size network generally referred to as a benchmark to test the WDN for optimization. All nodes are required to meet a minimum pressure demand for 30 m. For the proposed network, a Hazen–Williams coefficient of 130 is used for all pipes. The cost data for pipes is well documented in Alperovits & Shamir (1977).

The TLN consists of eight pipes, for each of which 14 discrete diameter sets are available. Therefore, the search space consists of 14^8 design combinations. At each node, EPANET handles demand and pressure as decision variables implicitly. However, SiBANET works explicitly over the eight pipes as decision variables to explore the optimum cost of the network. Figure 1 shows the convergence characteristics for the two-loop network.

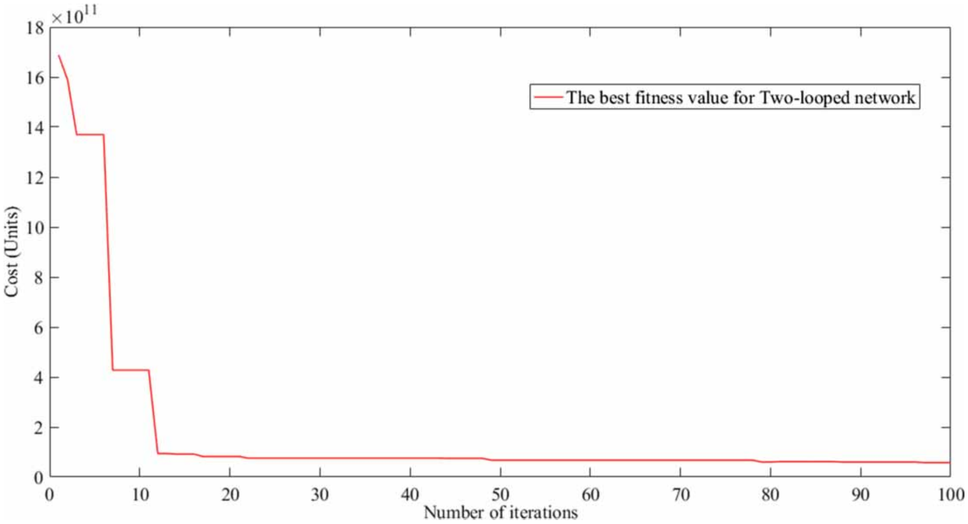

Figure 1 | Evaluation of optimal design solution for TLN.

Table 1 | Optimum solutions for two benchmark WDNs

			Two-loop network			**Hanoi network**		
Sr. no.	**Authors**	**Technique used**	**Least cost solution (units)**	**No. of funct. eval.**	**Time (s)**	**Least cost solution (units)**	**No. of funct. eval.**	**Time (s)**
1.	Wu *et al.* (2001)	fmGA	419,000	7,467	–	6,182,000	113,626	–
2.	Eusuff & Lansey (2003)	SLFANET	419,000	11,155	–	6,073,000	26,987	–
3.	Neelakantan & Suribabu (2005)	MGA	420,000	58,380	86	6,081,087	1,234,340	1,800
4.	Suribabu & Neelakantan (2006)	PSONET	419,000	5,138 (mean)	2	6,093,470	6,600	9
5.	Geem (2009)	PSHS	419,000	204	–	6,081,087	17,980	–
6.	Mohan & Babu (2010)	HBMO	419,000	1,293	–	6,117,000	15,955	–
7.	Sayyed (2017)	NSGA-II	419,000	400	8	6,081,087	18,400	–
8.	Present study	SiBANET	419,000	100	3.28	6,081,087	600	236.78

The least cost obtained using discrete diameters is 419,000 units with 114.701, 70.563, 109.193, 49.457, 101.787, 75.791, 74.865 and 14.106 mm pipe respectively for links 1 through 8. Various authors have also assessed the solution for the TLN using different optimization techniques. The SiBANET method also explores a similar solution for the TLN, yet with fewer iteration numbers. The solution is listed in Table 1 for comparison. Table 1 indicates the efficiency of SiBANET, which takes 3.28 seconds of CPU time with 100 iterations for function evaluation. The algorithm uses the Windows 10 operating system on an Intel i7-7700 K CPU@4.20 GHz for computation. Different permutations and combinations within E_s are performed. These trials involve a number of niche populations, initial solutions, number of individuals within each niche population at the initial stage and a maximum number of iterations within the cycle of environmental change. During several trial runs, it is noticed that the size of the niche population and the number of individuals in each niche plays a vital role in reaching the global optimal solution. The analysis is also repeated with various cycles of environmental change. However, this does not affect the

Table 2 | Solution for Hanoi water distribution network with optimized candidate diameters (mm)

Link	Diameter	Link	Diameter	Link	Diameter	Link	Diameter
1	604.75	10	541.61	19	418.43	28	223.22
2	600.67	11	498.42	20	619.04	29	266.53
3	604.45	12	406.08	21	383.76	30	185.45
4	601.98	13	177.22	22	179.99	31	199.67
5	666.43	14	241.54	23	609.46	32	299.96
6	603.17	15	391.10	24	556.27	33	311.06
7	712.93	16	399.01	25	544.91	34	332.53
8	569.02	17	411.76	26	348.61		
9	513.59	18	550.68	27	180.52		

overall performance of optimization. Table 2 shows the solution for the Hanoi water distribution network with optimized candidate diameters. By comparing SiBANET results with other meta-heuristic optimization algorithms (see Table 1), it is evident that the proposed methodology performs efficiently because it has an intelligent approach to locate the global optimum solution. Nowadays, it is essential to explore more efficient and fast-converging algorithms that can handle large-size problems. In the next section, a relatively larger-size network is configured for further investigation.

The Hanoi network

The Hanoi benchmark network was proposed for Hanoi city by Fujiwara & Khang (1990). It is a three-loop network having 32 demand nodes, 34 links and one reservoir (see Figure 2). The Hanoi network is a widely used benchmark problem in large WDN design (Wu *et al.* 2001; Prasad & Park 2004; Neelakantan & Suribabu 2005; Sayyed 2017). The hydraulic design of the Hanoi network is limited to six commercial diameter pipes (for pipe cost data, see Fujiwara & Khang 1990). Therefore, a huge solution space,

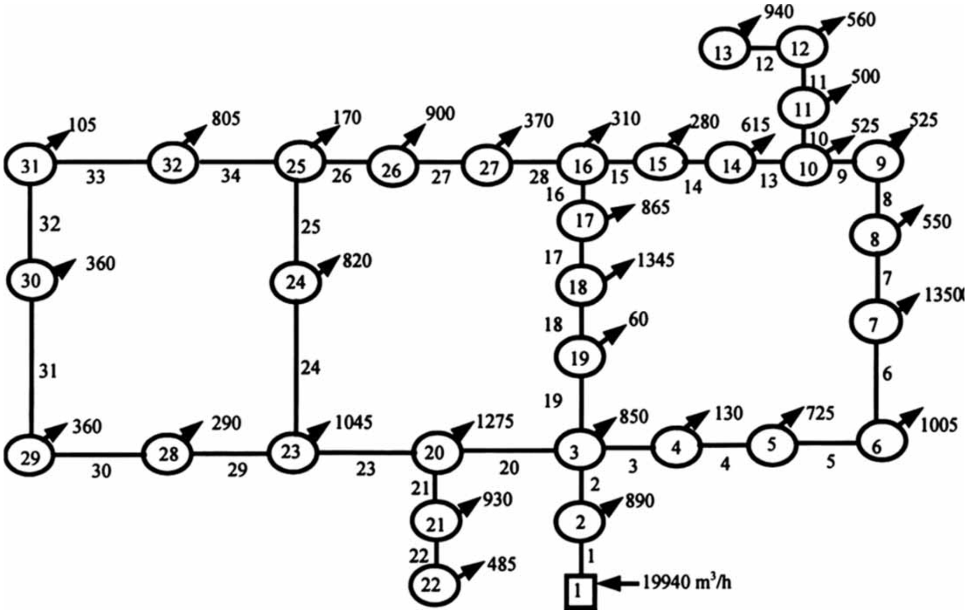

Figure 2 | Network of Hanoi water distribution system (Kadu *et al.* 2008).

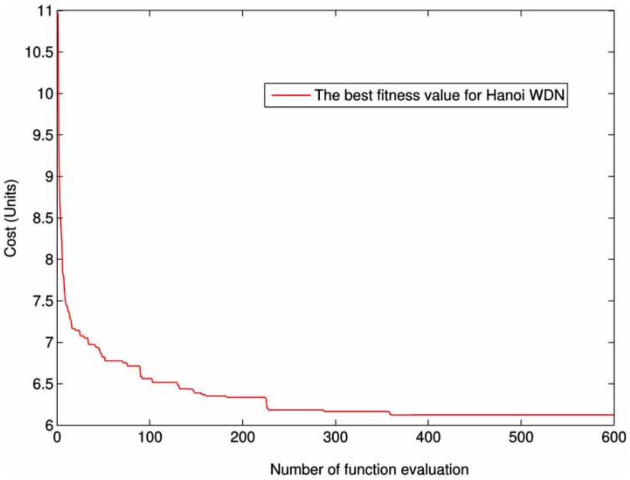

Figure 3 | Convergence of optimal solution for Hanoi WDN design.

i.e. 6^{34} (2.87×10^{26}) outcomes is available for optimization as compared with TLN.

Overall 34 discrete decision variables are required to be handled by SBA. In the investigation, different permutations and combinations of various components of the E_s are performed. Similar methodology is adopted from previous examples of TLN to assess the global optimal solution.

From this solution, the optimum cost for the Hanoi Network, i.e. 6,081,087 units, is obtained within 600 function evaluations.

Table 1 shows that the optimization takes 237 seconds for convergence. Here, only those techniques that have deployed EPANET as a hydraulic solver are used for comparison. Figure 3 represents the evaluation of the global optimal solution for the Hanoi network. The fast convergence characteristics can be observed from the graph.

The solution obtained by the present method is marginally higher than that of Eusuff & Lansey (2003) for a large network whereas there is similar cost computation for a small-size network. It is essential to explore the fast-converging algorithm strategies which will be more appropriate in handling large-size problems. Furthermore, Geem (2009) evaluated cost with the lowest iteration number when it comes to a larger network of Hanoi and SiBANET converges faster than all listed IOAs. Though these independent results cannot be compared directly as randomness plays a vital role in reaching the optimum solution, the number of function evaluations and CPU time are significantly less in the case of SiBANET. While traditional optimization methods have a limitation towards NP-hard problems, the intelligence-based SBA algorithm is more promising due to its organizing strategy.

CONCLUSIONS

WDN design is a constrained optimization problem for hydraulic requirements along with cost. It is necessary to incorporate new methodologies that ease the hydraulic design. When a meta-heuristic optimization technique is used to achieve an optimum solution, constraint handling is a priority. An intelligent approach named SiBANET is formulated which is comprised of the EPANET 2.0 hydraulic solver. This new methodology is verified through TLN and the Hanoi network for assessing minimum cost. The results of the analysis indicate that it is the most robust algorithm in handling discrete constraints wherein the global solution can be achieved with fewer functional evaluations. It is also found that the CPU time is less than for other IOAs. The SiBANET model has the desired results in WDN problems as it has the ability to handle discrete pipe diameters along with fast convergence. The main reason for the lesser number of function evaluations required is the intelligent exploration and exploitation strategy of SBA to locate a global optimum solution with its organizing tactics rather than the probability rules of the operator. This study is the first effort to optimize a WDN by utilizing an SBA intelligent approach with a meta-heuristic algorithm, hence only pipe-sizing optimization with a single objective is considered. Optimization of the complex looped networks with multiple objectives is highly recommended for further research.

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