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OPTIMAL DESIGN OF A WATER DISTRIBUTION NETWORK USING SIMULATION–BASED MULTI-OBJECTIVE OPTIMIZATION

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ABSTRACT

The design of water distribution networks is aiming at a good compromise between reliability and costs. Because such networks commonly serve for several objectives, multi-objective optimization approaches are the appropriate methods for this purpose. In this paper, the results of a simulation-based multi-objective optimization (MO-CMA-ES-EP) approach which couples a multi-objective covariance matrix adaptation evolution strategy (MO-CMA-ES) with Epanet are presented. The new method was tested with two published benchmark cases, the two-loop network and the Hanoi water network. The objective functions used in this study are aiming at the minimization of initial capital cost and maximization of network resilience. The results reveal that MO-CMA-ES-EP is able to determine the true Pareto optimal front of cost and network resilience index which serves as a tool for decision makers of water networks design.

KEYWORDS: optimal design, water distribution network, multi-objective optimization, simulation–based optimization.

INTRODUCTION

A water distribution network (WDN) represents one of the most important infrastructures in urban and regional economic development. An adequate network layout, the selection of components and the dimensioning of the distribution system are amongst the major challenges when setting up a water supply network. Calculating the hydraulic properties for each network configuration is commonly considered as "the balancing" between flows, head losses, velocities and pressures.

For optimal design of a water distribution network most of studies try to minimize cost by reducing pipe diameter while reliability was quantified as a constraint. Consequently, such network may not able to provide sufficient demand at some nodes if there is a local failure or a demand change occurs. Therefore, the reliability of WDN has received more attention. The reliability of a WDN can be understood as the ability of the network, which providing adequate demands both normal and abnormal condition (Farmani et al., 2006).

Generally, an increasing network reliability will cause an increase in cost. In this case, multi-objective optimization is useful for quantifying the relationship between the conflicting objectives, i.e. minimize cost function and maximize network reliability which is referred to as Pareto front.

Traditional practice still employs a trial and error approach for minimizing the design parameters (such as pipe diameters, suitable netowrk layout) while satisfying all pre-defined requirements (for example, required nodal head, flow velocity, water quality). This approach is very time consuming and depends mainly on designer's experiment.

In order to tackle this limits many optimization models have been developed to search for the optiaml/near optimal solution of a water distribution network, for instant, genetic algorithms - GAs (Simson et al., 1994), ant-colony optimization algorithm – ACOA (Afshar, 2007), simulated annealing – SA (Tospornsampan et al., 2007), differential evolution – DE (Suribabu, 2010), particle swarm optimization - PSO (Suribabu & Neelakantan, 2006), harmony search - HS (Geem et al., 2006). Studies show that these algorithms are able to produce overwhelming results in terms of robustness, flexibility, general application, and capability of solving large combinatorial problems. However, each optimization algorithm possesses its own set of controlled parameters that affects its performance in terms of solution quality and processing time.

Recently, simulation–based multi-objective optimization models that link a simulation model with a nonlinear optimization algorithm, has been developed as an efficient method for solving WDN design problems. Farmani et al. (2006) applied non-dominated sorting genetic algorithm (NSGA II) coupling with Epanet for solving multi-objectives including minimizing total cost, maximizing minimum resilience index and minimizing maximum water age on the Anytown water distribution network. Vasan et al. (2010) introduced the DENET model which applied differential evolution to Epanet for solving multi-objective optimization problems of the New York water network including cost function and network resilience based on the work of Prasad and Park (2004). Chandramouli et al. (2011) developed a combination of genetic algorithms and Epanet to optimize cost and network reliability of the benchmark two loop network using fuzzy concepts based on the residual pressure available at junction nodes. Baños et al. (2011) used the Strength Pareto Evolutionary Algorithm 2 (SPEA 2) and coupled it with Epanet to solve multio-bjective optimization problems including cost function and three different resilience indexes: resilience index, network resilience, and a modified resilience index which based on resilience index in order to determine whether the solutions become infeasible under a large number of over demand scenarios.

In this paper, a simulation–based multi-objective optimization framework which combines the Epanet (Rossman, 2000) with the multi-objective covariance matrix adaptation evolution strategy (MO-CMA-ES) developed by Igel et al. (2007) for solving mono and multi-criteria optimization problems (Figure 1) is presented. Considering the trade-off between initially capital cost and network reliability the resulting simulation–based multi-objective optimization model has been developed and analyzed using two published benchmark cases - the two loop network proposed by Alperovits & Shamir (1977) and the Hanoi network proposed by Fujiwara and Khang (1990).

MATERIALS AND METHODS

1. Formulation of the multi-objective problem

When designing a water distribution network, a wide range of concerns may have to be considered. During operation, a WDN can suffer the internal hydraulic surplus, even if some segments are out of service caused by a failure in the network. Thus, the design of the WDN considers in this study an initial cost function and network reliability. The network cost is minimized as:

$$MinimizeCOST = min \sum_{i=1}^{np} L_i .C(D_i) \tag{1}$$

COST: total initial capital cost

L_i: length of pipes i^{th}

C(D_i): unit length cost of candidate pipe diameter D_i

np: number of pipes in the network

There are many alternatives to define the network reliability, however, most of them basically derive from resilience index definition. The resilience index (I_r) of a network was introduced by Todini (2000) based on concept that the power input into a network is equal to the power lost internally to tackle the friction and the power that is delivered at demand nodes, and its form is given below:

$$I_r = \frac{\sum_{j=1}^{nn} q_j(h_j - h_j^*)}{\left[\sum_{k=1}^{nr} Q_k .H_k + \sum_{p=1}^{npu} Q_P .H_P \right] - \sum_{j=1}^{nn} q_j h_j^*} \tag{2}$$

q_j: demand at node j

h_j and h_j^*: actual head and required head at which q_j is supplied

nn, nr and *npu*: number of nodes, number of reservoirs and number of pumps

Q_k, H_k: flow and pressure head, respectively, corresponding to each reservoir node k.

Q_p, H_p: power and head supplied by pump p, respectively

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Prasad and Park (2004) found that though maximization of the resilience index which can be achieved by an increase of head surplus or power at any junction node, the effect of redundancy is not reflected. Consequently, a reliability network, called network resilience (I_n), has been proposed, that combines the effect of both surplus power and reliable loops. The surplus power at any node j is given by:

$$P_j = \gamma . q_j \left(h_j - h_j^* \right) \tag{3}$$

Reliable loops can be ensured, if the pipes connected to a node are not widely varying in diameter. The general form is given by:

$$C_j = \frac{\sum_{i=1}^{np} (D_i)}{np_j \cdot max(D_i)} \tag{4}$$

np_j is the number of pipes connected to node j

The combined effect of both surplus power and nodal uniformity of node j, called weighted surplus power, is expressed as:

$$X_j = C_j P_j \tag{5}$$

This equation may be normalized by dividing with maximum surplus power to get network resilience as:

$$I_n = \frac{X}{X_{max}} = \frac{\sum_{j=1}^{n} C_j . q_j (h_j - h_j^*)}{\left[\sum_{k=1}^{nr} Q_k . H_k + \sum_{p=1}^{npu} Q_P . H_p \right] - \sum_{j=i}^{nn} q_j . h_j^*} \tag{6}$$

According to theory it is $0 \leq I_n \leq 1$ but in real world application, the value of I_n can not reach one due to two problems: (1) the inequality between supplied heads and actual demand heads and (2) the diversity of pipe diameters in a network. An advantage of the use of network resilience (I_n) as an objective instead of the resilience index is that it produces more robust designs and clearly meets reliable loops of equally pipe sizes by penalizing sudden changes in pipe diameter (Raad et al., 2009). In addition, with a more complex water distribution network, network resilience responds slightly better than resilience index (Banos et al., 2011). Consequently, network resilience index is used in this paper as the second objective function for the water distribution network design:

$$Maximize\ Reliability = Max(I_n) \tag{7}$$

In general, the design of a WDN implies constraints for the decision variables as given below:

Bounds on pipe diameters, D_i :

$D_i \in D$ (D denotes the set of commercial available diameter set). (8)

Nodal pressure head bounds:

$$H_j^{min} \leq H_j \leq H_j^{max} \tag{9}$$

Bounds on water velocity in the pipe:

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{10}$$

The node flow continuity relationship must be satisfied at all sources and demand nodes:

$$\sum_{x\_connected\_to\_j} Q_x + q_j = 0, \quad \text{for all demand nodes} \tag{11}$$

The loop head loss relationship must be satisfied for all loops of the network:

$$\sum_{loop} h_x = 0, \quad \text{for all loops} \tag{12}$$

2. Methodlogy

2.1. Outline of the proposed method

Based on the general structure of simulation-based optimization (Mays, 2000), a novel simulation-based optimization approach, MO-CMA-ES-EP, has been developed and verified (Figure 1). The approach couples a hydraulic model (Epanet) with the covariance matrix adaptation evolution strategy (CMA-ES).

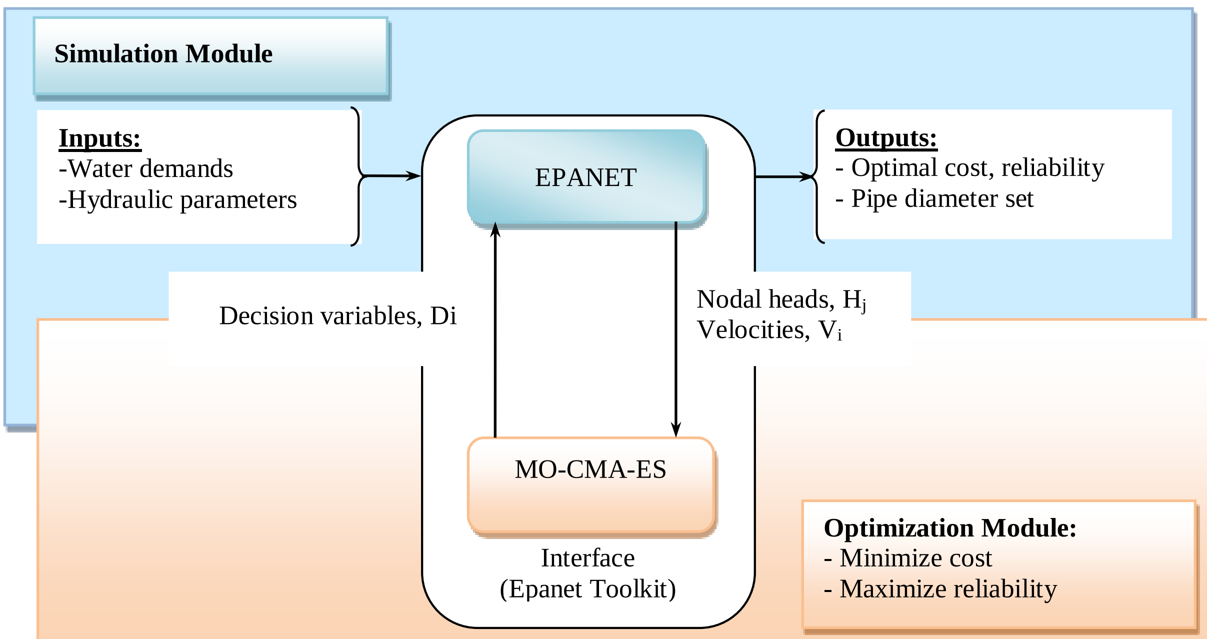

Figure 1: Structure of simulation-based optimization MO-CMA-ES-EP model

The general principle of the new technique can be described as follows: objective functions associated with a range of decision variables, constraints and other parameters will be mathematically interpreted in the interface module. The set of initial decision variables, which are arbitrarily assigned using optimization model, is firstly denormalized and transferred to the Epanet. Epanet solves the hydraulic processes based on the laws of conservation of mass and energy and then produces the hydraulic parameter values such as discharge, flow velocities, head losses in pipes, nodal heads (or pressures) and so on. These values are then transferred back to the optimization mode and to be checked in terms of given constraints and then, at the end of an iteration, objective function(s) can be estimated. The forth and back transference of these decision variables and parameters between these two modes is done through the interface module (Epanet Tookit) programmed in Matlab language. Whenever there is a violation of any given constraint (for instance, minimum required nodal pressures, limits of velocity, design parameters, constraint related to optimal layout, etc…), the penalty function will be added to the objective function value. By comparing to the previous objective value, the decision variables are automatically adjusted afterwards to move to a better solution. The process continues until any defined stop criterion is met. Finally, the optimal decision variables for designing PWDN will be selected which must satisfy all given constraints.

2.1. Epanet toolkit

The epanet toolkit is a dynamic link library (DLL) of functions which connecting a programming language that can call functions with a windows DLL to the solver hydraulic software Epanet. These functions can read all characteristics of a water network described in a suitable format file and write results in an output file as well (Eliades, 2009).

2.2. Multi-objective covariance matrix adaptation evolution strategy (MO-CMA-ES)

The MO-CMA-ES, was developed by Igel et al. (2007). This approach is a combination between the strategy parameter adaptation and multi-objective selection mechanism which is based on non-dominated sorting approach (Deb et al., 2000). The major working principles of the approaches are to force the solutions toward the Pareto optimal front which includes trade-offs solutions between objectives and to maintain the diversity among solutions in the Pareto front.

By using the concept of Pareto efficiency, accordingly, any two solutions x_1 and x_2 may have one of two possibilities: one dominating the other, or neither dominating the other. A solution, for instant x_1, is considered to dominate the other solution, x_2, if both the following conditions are satisfied (Prasad and Park, 2004):

(i) The solution x_1 is no worse than x_2 in all objectives, and

(ii) The solution x_1 is thoroughly better than x_2 in at least one objective.

If there is any condition violated, x_1 is considered to be dominated solution, otherwise x_1 is a non-dominated solution

2.3. Box constraint handling method associated with MO-CMA-ES

The box constraint handling is associated with the algorithm in order to guarantee that each evaluated solution must lie within feasible space (X_f). The feasible search space is a hypercube defined by the lower and upper boundary values for each decision variable. The algorithm influences individually the computation of the solutions and requires the steps as follows (Hansen et al., 2008):

(i) An infeasible solution x, from the infeasible search space (X) can be mapped to the nearest feasible point (*feasible(x)*) in feasible search space (X_f) in the following way in the handling box constraint:

$$feasible(x) = (min(max(x_1, x_1^l), x_1^u), \ldots, min(max(x_n, x_n^l), x_n^u) \quad \text{with} \quad x \in R^n \tag{13}$$

Hence, the feasible solution is evaluated itself and the infeasible is evaluated on the boundary of the feasible space. The new feasible solution is then used for the evaluation on objective function and for computing a penalty function.

(ii) A penalty function is added objective function penalizing infeasible solutions. In this study, to save computational time, the Squared Euclidean death penalty of the infeasible candidates computed directly by (Eq.14) is used in the MO-CMA-ES:

$$f_m^{penalty} = \alpha \sum_{i=1}^{n} (x_i - feasible(x)_i)^2 + \beta \tag{14}$$

where the penalty factor α and the offset β will be experientially chosen.

RESULTS AND DISCUSSION

1. Case study 1: Two – loop network

The network was the first introduced by Alperovits and Shamir (1977) which encompasses 8 pipes, 6 junction nodes and is supplied by a single fixed head reservoir R1 (Figure 2). The pipes in the network are all 1000m long and a Hazen – William friction factor of $C_{H\text{-}W}$ = 130 is used as the same other studies before for the sake of comparison. The minimum required pressure for all junction nodes are equally 30 m.

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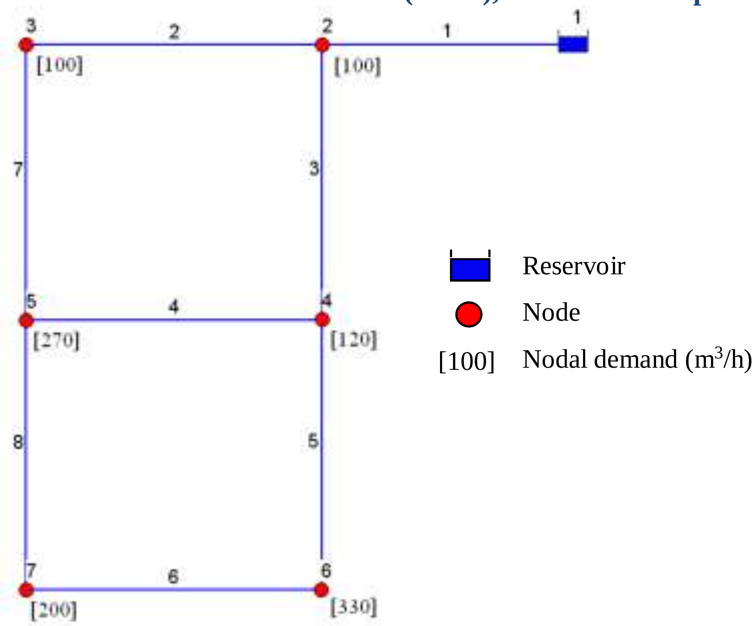

Figure 2: Two - loop benchmark network

Decision variables are the diameters of the eight pipes. Each pipe diameter has to be chosen from a commercially available set of pipes consisting of 14 different values. Hence, there is a total of 14^8 possible solution combinations for this network. This study also used maximum velocity $V_{max} = 2m/s$ (Todini, 2000) as another constraint.

In this application, the number of parents = 20, number of initial chromosomes = 8, penalty factor α = 1E05, and offset parameter β = 1E06 are used. Figure 3 shows the results obtained by MO-CMA-ES-EP. The blue x-marks represent all cadidate solutions while the red circles represent the Pareto optimal solutions obtained by solving simultaneously the optimization problems (1) and (7) using the proposed model.

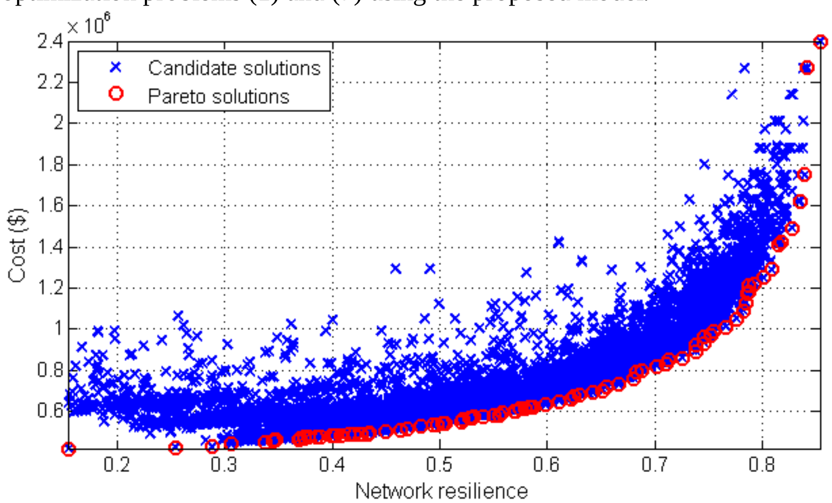

Figure 3: Pareto front of cost and network resilience optimization for two-loop network

Compared with previous studies as reflected in Table 1, the least cost produced by MO-CMA-ES-EP in Column 7 is lower than the results produced by Linear Programming LPG (Column 1); GA and ACCL (Columns 2 and 3); and is exactly equal to the optimum results obtained from GEO, GANEO, and ACOC (Columns 4, 5, and 6). MO-CMA-ES-EP produces the optimal result with an acceptable number of function evaluations (NFEs) of 3,670 compared to the other approaches as well as compared to the total possible solution combinations ($14^8 = 1.48*10^9$). The NFEs has proved the effectiveness of the new proposed approach.

Table 1: Comparison of alternative solutions for two - loop network

Authors and Methods	Alperovits and Shamir (1977)	Abebe and Solomatine (1998)		Wu (2001)	Dijk et al. (2008)	Afshar (2009)	Current study
	LPG (1)	GA (2)	ACCOL (3)	GEO (4)	GANEO (5)	ACOA (6)	CMA-ES-EP (7)
Cost ($)	497,525	424,000	447,000	419,000	419,000	419,000	419,000
NFEs	-----	3,381	1,810	7,467	100,000	3,000	3,670

2. Case study 2: Hanoi water network

The 34 pipes, 32 nodes network is supplied by a single fixed head source at elevation of 100 m introduced by Fujiwara and Khang (1990). The nodal minimum required pressure is determined to be 30m. The set of commercially available diameters in inches encompasses [12, 16, 20, 24, 30, 40] and corresponding cost per unit length can be implied from: $1.1 \times D^{1.5}$. The value of Hazen – William friction coefficient $C_{H\text{-}W} = 130$ is also used for all pipes. Model coefficients are used in this case including: number of parents = 100, number of initial chromosomes = 3400, α = 2E05, and β = 3E07. The maximum velocity, $V_{max} = 2m/s$, was also used as additional constraint.

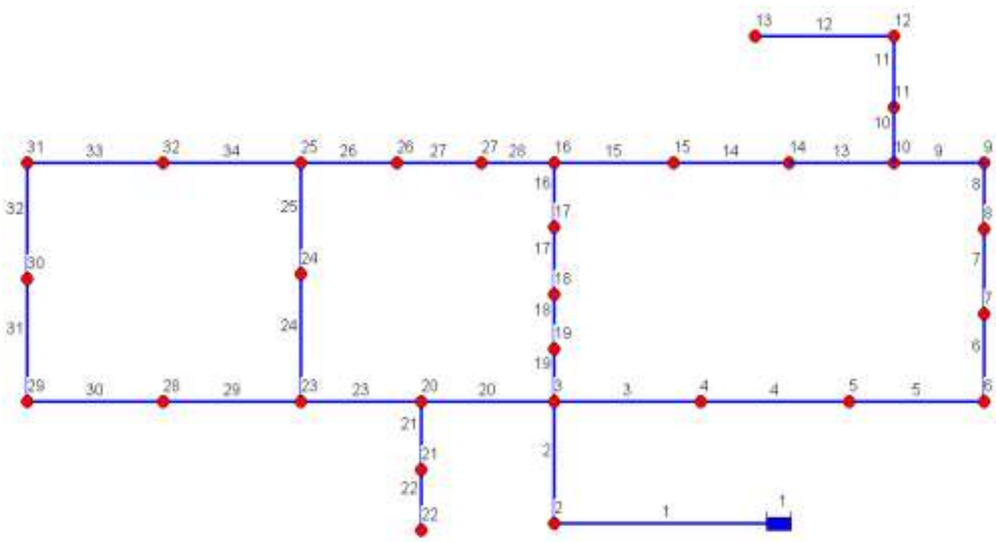

Figure 4: Hanoi water distribution network

For analyzing a more complex water distribution network (Hanoi network), Figure 5 shows all representative solutions obtained by MO-CMA-ES-EP. The Pareto efficient values for cost and network resilience can be taken from the solutions at Pareto front (red circles). It is confirmed that these solutions are also good approximation, since the least cost solution for this network of Mi.$ 6.046 is the best solution so far (as shown in Table 2).

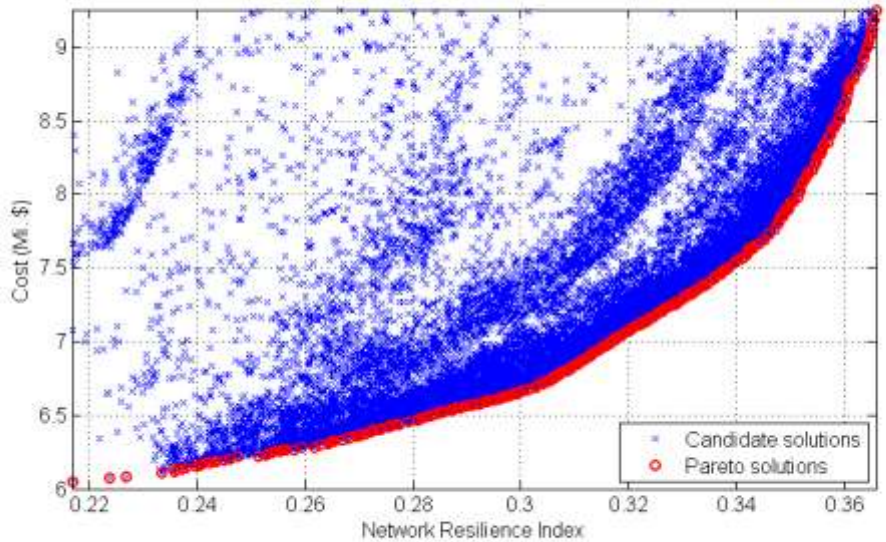

Figure 5: Pareto front of cost and network resilience optimization for Hanoi network

Table 2: Comparison of nodal pressure for best solution of the Hanoi water network

Method / Node	Previous studies					Current Study
	Savic &Walters (1997)	Abebe & Solomatine (1998)		Cunha & Sousa (1999)	Perelman et al (2009)	
	GA1	GA	ACCOL	SA	GA	
NFE	\	16,910	3,055	53,000	\	12,481
Cost (Mi.$)	6.073	7	7.8	6.056	6.055	6.046

CONCLUSION

New method simulation – based multi-objective optimization framework MO-CMA-ES-EP is successfully tested on two - loop network and Hanoi water network. The problem is defined here as a multi-objective optimization of initial capital cost and network resilience. Using this method, all candidate pipe diameters are analyzed in MO-CMA-ES-EP. The model is capable making set of pipe diameter automatically vary at every iteration in order to get as many Pareto optimal solutions as possible.

Identified Pareto efficient solutions are validated by comparison with previous studies. With respect to the two-loop network, the obtained solution as the same the least cost produced by previous study. When dealing with a more complex network, e.g. the Hanoi water network, MO-CMA-ES-EP particularly produces a more economic design than those of compared previous state-of-the-art single and multi-objective methods. Thus, it can be concluded that the proposed method is able to determine the true Pareto front between the initial capital cost and network resilience. In future studies, MO-CMA-ES-EP should be further developed for the application to more complex networks including pumps, tanks, and multiple water sources.

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