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Multi Objective Evolutionary Algorithms for Pipe Network Design and Rehabilitation: Comparative Study on Large and Small Scale Problems

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Abstract

This paper deals with comparative search performance of a number of well-established multiobjective evolutionary algorithms on water distribution network design. Evolutionary methods include strength Pareto evolutionary algorithm (SPEA), non-dominated sorting genetic algorithm (NSGA), Pareto archived evolution strategy (PAES), population-based incremental learning (PBIL) and particle swarm optimisation (PSO). The optimisation methods, with the use of binary and real codes resulting in eight optimisation strategies, are implemented on two problems of pipe network design and rehabilitation. The multiobjective optimisation problems are classified as being large- or small-scale based on number of design variables. Design objectives are minimising cost and increasing network resilience of the network whereas discrete design variables are pipe diameters. The obtained numerical results using various optimisation strategies are compared and discussed. By utilising pareto frontier and hypervolume values in performance test, for the large-scale problem RNSGA and RSPEA are the first and the second best respectively. However, in the small-scale problem, RMPSO is the best while RNSGA is the second. Hence, the evolutionary algorithm that gives the best overall results for both large- and small- scale problems is RNSGA while the second best methods are RMPSO and RSPEA. The BPBIL method is suitable for small-scale problems. The binary-code versions of NSGA, SPEA and PAES are totally outperformed by their real-code counterparts.

Keywords: Pipe network design, Multiobjective evolutionary algorithms, Pipe network rehabilitation, Large-scale problem, Hypervolume indicator

1. Introduction

Practical engineering design problems are usually assigned to find the best solution of design variables that result in optimum design objectives and feasible design constraints. Recently, multiobjective evolutionary algorithms (MOEAs) (1) have been developed as multiobjective optimisers. Initially, well-known methods were vector evaluation genetic algorithm (VEGA) (2), multiobjective genetic algorithm (MOGA) (3), non-dominated sorting genetic algorithm (NSGA) (4), Pareto archived evolution strategy (PAES) (5-6) and strength Pareto evolutionary algorithm (SPEA) (7). Since then, numerous new algorithms have been developed e.g. multiobjective population-based incremental learning (PBIL) (8) including the upgrade of some previously mentioned methods such as NSGAII (9) and SPEA2 (10). One of the most popular techniques is a multiobjective particle swarm optimiser (MPSO) (11), which is a population-based method using real design variables. Some work on comparing their performance has been done e.g. in references (12) and (13). Various comparative performance of evolutionary algorithm studies lead to the conclusion that the performance of evolutionary algorithms depends on the type of optimisation problem. For example, crossover-based methods are effective to be used with global optimisation (8) while mutation-based methods are very useful for solving a large-scale topology optimisation (14). Therefore, the benchmarks of MOEAs performance for every type of optimisation problem should be defined. Moreover, a development of new approaches, improvement of the existing algorithms, and implementation of these methods on real world applications are still greatly challenging.

The work in this paper covers the implementation of the established MOEAs i.e. PAES, NSGAII, SPEA2, PBIL and PSO using binary and real codes (designated as B and R respectively) on the design and rehabilitation of a water distribution network. The current pipe network of Yasothorn city centre in Thailand is chosen for a numerical experiment. The design problems are optimising the network cost and network resilience to meet predefined constraints. Using the above mentioned criteria as bi-objective functions in the numerical experiment, pipe network efficiencies were investigated in terms of cost and reliability. The network cost was determined from length and diameter of pipes of the network while the network resilience was obtained in term of pressure power balance to overcome the friction at the demand points. Design variables, which are discrete, consist of selected pipe diameters. The multiobjective problems can be classified as being large-, and small-scale depending on the number of design variables.

2. Materials and Methods

Piping or a water distribution network is one of the most important engineering systems in daily life. A study of network models is formulated in a system of mixed linear and nonlinear equations with term of discharge being the unknown parameters. In this work, the software EPANET was employed for this pipe network analysis. The optimisation process can be achieved by interfacing EPANET into MATLAB since the optimisation codes had been developed in the MATLAB environment. The diagram of function evaluations is shown in Figure 1. In practice, pipe network design is accomplished by taking into account of economic, safety, maintenance and public health considerations. The common design criteria include the network cost, the network reliability, total head loss in pipes, pressure in pipes, water quality, network infrastructure etc. The optimisation process is not only applied to the design of a new network but also used in the rehabilitation of the existing network. A particular multiobjective design problem of a pipe network can be written as

$$\underset{\mathbf{x}}{Min} : [f_1(\mathbf{x}),..., f_m(\mathbf{x})] \quad (1)$$

Subject to

$V_i(\mathbf{x}) \le \overline{V_i}; i = 1,..., N_p$

$H_i(\mathbf{x}) \le \overline{H}_i; i = 1,..., N_p$

where x is the vector size N×1 of discrete design variables

f_i are the objective functions

V_i are pipe velocities are allowable velocities (set to be 1.5 m/s)

H_i denote hydraulic gradients in the pipes and $\overline{H}_i$ are allowable hydraulic gradients (set to be 10 m).

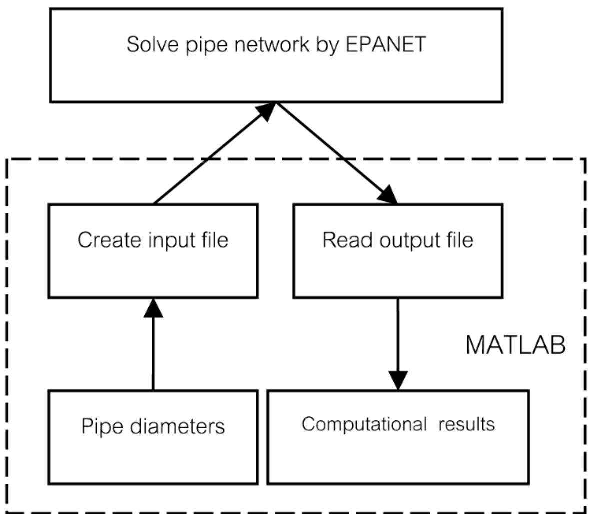

Figure 1. EPANET and MATLAB interface

Two objective functions were chosen for this numerical experiment consisting of network cost and network resilience. The cost minimisation is more or less taken into consideration for any engineering system. The network resilience, presented in (15) was claimed to be a good measure of network reliability which should be maximised.

A chosen water distribution network was the city centre of Yasothorn province in Thailand (shown in Figure 2). The network consisted of one tank and 426 pipes with 337 junctions. Two sets of design variables were:

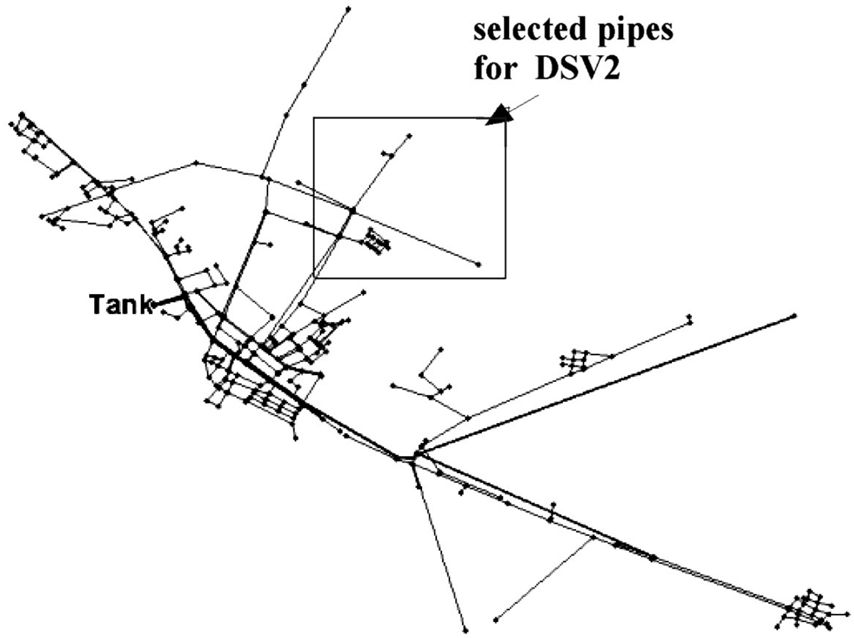

Figure 2. Water distribution network of Yasothorn province, Thailand

DSV1: 422 pipe diameters. All of the pipes excluding the 4 main pipes are selected

DSV2: 40 pipe diameters, the selected pipes are located in the sub-region as shown in Figure 4.

The main network, namely DSV1, is the main network while DSV2 is the small network merged within the main network DSV1. The efficiency of DSV1 is always maintained while DSV2 which is the rehabilitation network can be modified. Even though a small change has been made, the re-design of the whole network still has to be employed for the system to be functioned as the design objectives. The set of pipe diameters and their prices are similar to those used in (15) with some modification as detailed in Table 1 along with their integer representation. As a result, it can be concluded that the rounded-off design variables are round(x) $\in I^N$ where $I = \{1, 2, \ldots, 12\}$. Multiobjective is assigned to minimise the cost of pipes and maximise the resilience. Note that, sets of design variables and objective function sets, F11 stands for the optimisation problem using the DSV1 and F21 stands for the optimisation problem using the DSV2.

Table 1. Integer encoding, pipe diameters and prices

Integer	Diameter (mm)	Price ($/m)
1	25	2
2	50	5
3	75	8
4	100	11
5	150	16
6	200	23
7	250	32
8	300	50
9	350	60
10	400	90
11	450	130
12	500	170

All the optimisation methods addressed in the previous section were implemented on the proposed multi-objective design problems. The non-dominated sorting concept for constrained optimisation proposed in (16) was used to handle design constraints. The number of generation, the population size, and the external archive size used for the design problem are given in Table 2.

Table 2. Numbers of loops and population size

Design problem	No. of generation	Population size	External archive size
F11	250	200	200
F21	100	100	100

For the Pareto archive evolution strategy, the ($\mu+\lambda$)-PAES version in (6) which is adapted from the (1+1)-PAES was used. For the optimisation strategy that uses binary code, a pipe diameter value was encoded as 10 bits of a binary string. The lower and upper bounds are ai = 1 and bi = 12 respectively. The probabilities of crossover and mutation for NSGA and SPEA are 1.0 and 0.5 respectively. For each testing problem, the optimisation methods used the same initial population. Each method was employed to solve each problem over 6 runs while on each operation the non-dominated solutions of the final iteration were taken as the optimal front. The performance assessment was reasonably similar to the work presented in (12). The performance tests in this study were using the Pareto frontier and hypervolume (HV) value (17) which is one of the best performance indicators in MOEAs comparison. Note that the hypervolume indicated the distribution of the solutions lined in the frontier. A higher HV means a larger distance between a frontier and a reference point. The frontier with highest HV is the best. In the whole testing the ranking of HV value was shown for each problem. Results were discussed and concluded for the best of MOEA.

3. Results and Discussion

There are totally 8x6x2 non-dominated fronts from the 6 runs of the 8 multiobjective evolutionary optimisers used for solving the 2 design problems. The illustration and comparison of the first numerical experiment are shown in Figures 3-5. Figure 3 displays the plots of approximate Pareto fronts of F11 obtained from various optimisers. The fronts are rather contiguous. Network resilience is multiplied by -1 before plotting so that it is viewed as minimisation, and simple in observing and comparing. The zoom-in of the rectangle region in

Figure 3 is presented in Figure 4. The fronts of RNSGA and BPBIL were the best. Most of the non-dominated fronts were better than the original network with the exception of the front from BNSGA and BSPEA.

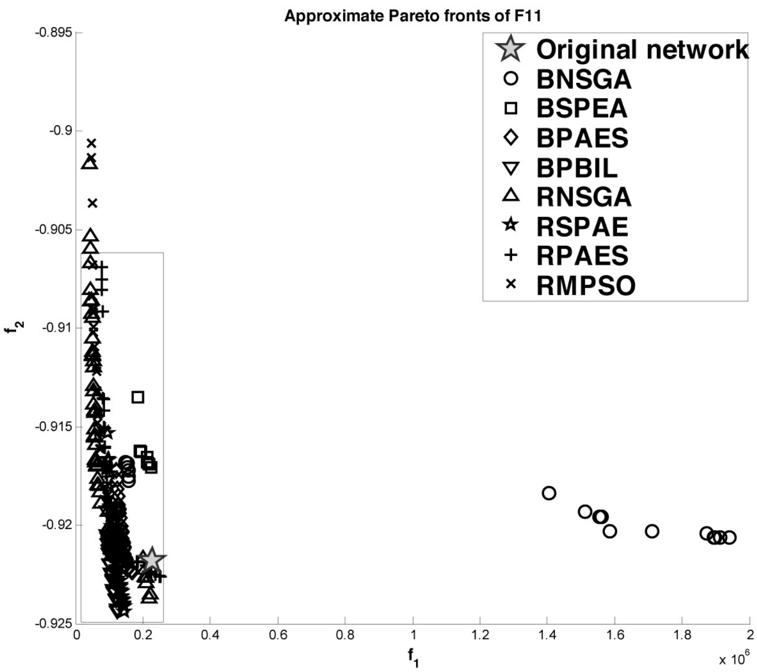

Figure 3. Approximated Pareto fronts of F11 obtained from the various MOEAs

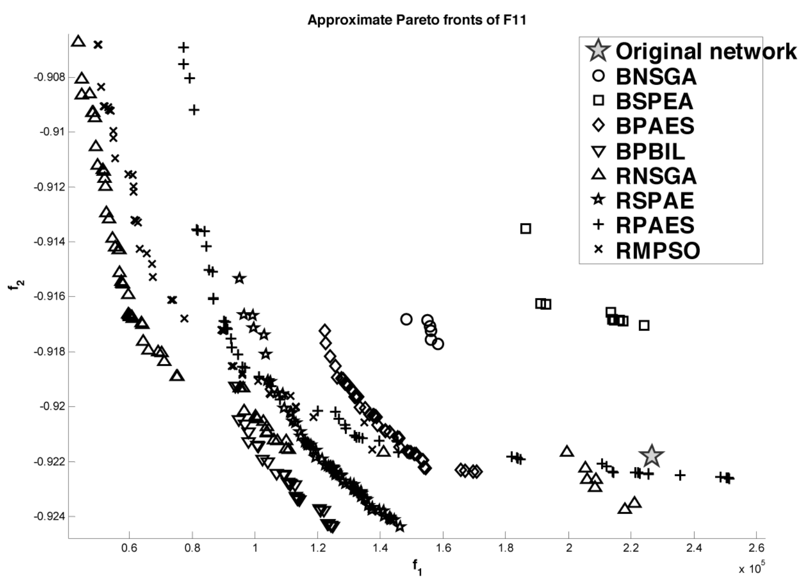

Figure 4. Zoom-in of Figure 3

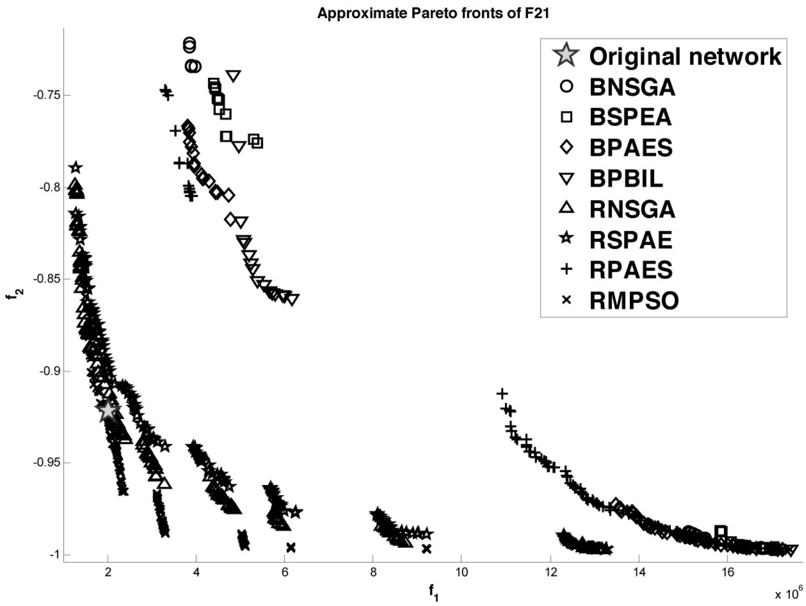

Figure 5. Approximated Pareto fronts of F21 obtained from various MOEAs

For the large-scale cases, Figure 5 demonstrates plots of non-dominated fronts of F21 obtained from the various optimisers. The fronts are non-contiguous.The front of RMPSO is the best while the second best is the front obtained from RNSGA. Only the best approximate Pareto front, which is obtained from using RMPSO, is not dominated by the original network. From Figures 3-5, it is shown that RNSGA, RMPSO and RSPEA provide the best distributed and extended fronts.

Tables 3 and 4 list the ranking of HV-values and ranking for both cases of study. These tables also pose HV values of MOEA methods. The method with higher value of HV is better. Ranking by HV of each method is related to ranking by Pareto in section 2 except for RSPEA and BPBIL. However, the HV values of RSPEA and BPBIL methods are very close to each other. Therefore, similarly to pareto, HV value can be used for indicating a performance of the method.

Table 3. HV-values and ranking for a large-scale problem (F11)

MOEAs	HV for F11	Ranking
RNSGA	0.901	1
RSPEA	0.852	2
BPBIL	0.839	3
RMPSO	0.719	4
RPAES	0.632	5
BPAES	0.608	6
BNSGA	0.296	7
BSPEA	0.085	8

Table 4. HV-values and ranking for small-scale problem (F21)

MOEAs	HV for F21	Ranking
RMPSO	0.953	1
RNSGA	0.928	2
RSPEA	0.878	3
RPAES	0.420	4
BPAES	0.311	5
BPBIL	0.236	6
BNSGA	0.081	7
BSPEA	0.057	8

At this stage, the using of Hypervolume concept can give more detailed in MOEAs performance tests than using pareto frontier consideration. However, the both methods lead to a suitable discussion and conclusion in this study.

4. Conclusion

Based on several comparative studies, it can be concluded that most of the employed multiobjective evolutionary algorithms are powerful tools for dealing with the design and rehabilitation problems of water distribution networks especially the real-code evolutionary algorithms. The non-dominated sorting scheme for constrained multiobjective optimisation in (16) can effectively deal with the assigned constraints. All of the optimisation strategies can deal with both large- and small- scale design problems. The evolutionary algorithm that gives the best overall results for both large- and small- scale problems is RNSGA while the second best methods are RMPSO and RSPEA. The BPBIL method is suitable for the small-scale problem which is the best method among the binary-code algorithms. The binary-code versions of NSGA, SPEA and PAES are totally outperformed by their real-code counterparts. This can be fairly concluded that the real code crossover and mutation operators are efficient in exploring a Pareto front of water distribution network design problems.

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