A performance comparison of differential evolution and genetic algorithm variants applied to water distribution system optimization

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Abstract: The differential evolution (DE) algorithm has been received some attention recently in terms of water distribution system (WDS) optimization. The DE is potentially becoming an alternative optimization tool for WDS design due to its satisfactory search performance. This paper presents a systematic performance comparison between the DE algorithm and the frequently used genetic algorithms (GAs). Two DE variants and two GA variants are compared in this paper in terms of optimizing the design of WDSs. These include the traditional DE, the dither DE algorithm, the traditional GA and the creeping mutation GA. Two well-known benchmark water distribution case studies are used in this study, which are the New York Tunnels Problem and the Hanoi Problem. The results show that the DE variants significantly outperform the GA variants in terms of both the solution quality and efficiency.

Keywords

Differential evolution, genetic algorithm, water distribution systems, optimization

Introduction

Over the past two decades, evolutionary algorithms (EAs) have been introduced to find the least-cost design for the water distribution systems (WDSs). The advantages of EAs are (i) they are able to handle discrete search spaces directly, (ii) they are less likely to be trapped at local optima and (iii) they can provide a number of similar cost solutions while being different designs. The search strategy of EAs differ to deterministic optimisation techniques (such as linear programming and nonlinear programming) in that they explore the search space broadly based on stochastic evolution rather than on gradient information. A number of EAs have been developed for optimizing the WDS design and the first significant publication of each EA is given in Table 1. These EAs have been successfully applied to a number of WDS design optimization problems and results obtained showed that they were able to yield better quality solutions compared to the deterministic optimization techniques. Among these EAs, genetic algorithms (GAs) have gained popularity due to their easy implementation and satisfactory performance.

Table 1 Types of previously used EAs applied to WDS optimization

Algorithm	First reference
Genetic algorithm (GA)	Simpson et al. (1994)
Simulated annealing (SA)	Loganathan et al. (1995)
Tabu search (TS)	Lippai et al. (1999)
Harmony search (HS)	Geem et al. (2002)
Shuffled frog leaping algorithm (SFLA)	Eusuff and Lansey (2003)
Ant colony optimisation (ACO)	Maier et al. (2003)
ANN metamodels	Broad et al. (2005)
Particle swarm optimisation (PSO)	Suribabu and Neelakantan (2006)
Scatter search (SS)	Lin et al. (2007)
Cross-entropy algorithm (CE)	Perelman and Ostfeld (2007)
Differential evolution (DE)	Suribabu (2010)
Honey-Bee Mating Optimisation (HB)	Mohan and Babu (2010)

Differential evolution (DE) is an optimization technique that has been received attention recently (Storn and Price 1995) in terms of WDS optimization. Three operators are involved in the DE during optimization, which are mutation, crossover and selection operators. The process names are similar to the commonly used genetic algorithm (GA), however, there are significant differences in the order of application and form of these operators. The DE differs significantly from a GA in the mutation process whereby the mutant solution is generated by adding the weighted difference between several random population members to another random member. Three parameters need to be pre-specified for the use of the DE including the population size (N), mutation weighting factor (F), and crossover rate (CR). In addition to these three parameters, a particular mutation strategy needs to be selected for the use of DE among a number of availabilities (Price et al. 2005).

Vasan and Simonovic (2010) and Suribabu (2010) applied DE to the optimization of WDSs, and concluded that the DE was able to find the optimal solutions with great efficiency. Zheng et al. (2011a) developed a DE combined with the NLP method for optimizing WDS design. Zheng et al. (2011b) investigated the sensitivity of the control parameters of DE algorithm in terms of optimizing WDSs. It was concluded in their work that the performance of the DE heavily relies on the control parameter values used. Zheng et al. (2011c) have undertaken an analysis on investigating the effect of various mutation strategies of DE algorithm for WDS design and found that the DE/rand/1 mutation strategy was overall the most effective among the five most frequently used mutation strategies.

In terms of comparing the performance of the DE with other EAs on non-WDS problems, Vesterstrom and Thomsen (2004) have undertaken a comparative study of DE, particle swarm optimization (PSO) and GAs based on a total of 34 numerical benchmark problems. It was found that, from the results obtained, DE was by far more efficient and robust compared to PSO and GAs. However, this conclusion cannot necessarily be directly transferred to the WDS optimization since the search space landscape of numerical optimization problems differs significantly to that of the WDS optimization problem.

Suribabu (2010) concluded that the DE has at least the same, if not better, performance than GAs in terms of WDS optimization. In contrast, Dandy et al. (2011) reported that GAs had overall better performance than the DE in terms of solution quality and efficiency based on testing for two WDS case studies. This contradiction may be explained that different parameter values including N, F and CR were selected in these DE applications. These comparisons are not reasonable as the parameter values of the DE were not appropriately selected. Thus there is still a lack of a systematic comparison between the DE algorithm and the frequently used GAs.

The aim of this paper is to compare the performance of four optimization algorithms in terms of WDS optimization. These include standard differential evolution (SDE), dither differential evolution (DDE), a standard genetic algorithm (SGA) and a creeping mutation genetic algorithm (CGA).

Differential evolution algorithm variants

The description of the standard DE algorithm (SDE) for WDS design was introduced by Zheng et al. (2011a) and hence is not repeated in this paper. Karaboga and Ökdem (2004) proposed a dither DE (DDE) where the value of mutation weighting factor (F) was randomized in a given range rather than specified a fixed value. For the DDE, the randomly produced F in a given range was applied at the generational level, which is the same with the SDE. Subsequently, Das et al. (2005) developed another DDE that the F value was also randomly generated in a given range but applied at the individual level rather than the generational level. Das et al. (2005) reported significant improvements of their DDE compared to the SDE and the DDE proposed by Karaboga and Ökdem (2004) in terms of convergence speed and the robustness. In the later discussion of this paper, the DDE is referred as the dither differential evolution proposed by Das et al. (2005) that the F is applied at the individual level.

For both of the SDE and DDE, the DE/rand/1 mutation strategy was used since it has been demonstrated to be the most effective (Zheng et al. 2011c). Constraint tournament selection was used for these two DE variants to deal with the head constraints (Deb 2000).

Genetic algorithm variants

A standard genetic algorithm (SGA) and a creeping mutation genetic algorithm (CGA) are used in this paper to compare with the DE variants. The integer coding, two-point crossover (P_c) and constraint tournament selection were used for the SGA and CGA. The only difference between the SGA and the CGA is that the bitwise mutation (P_m) is used in the SGA while the creeping mutation is employed by the CGA. The creeping mutation algorithm is given as follows: for each coded string in the CGA, each bit of this string has a given particular probability (P_{cm}) to be selected for creeping mutation. The selected bit has a probability of P_d of being mutated to the adjacent bit below and a probability of 1-P_d of being mutated to the adjacent bit above. For a bit that is already at the smallest or largest integer number, only upward or downward mutation is allowed respectively.

Case studies

All these four optimization algorithms have been coded using C++ and the EPANET2.0 tookit was used to perform the hydraulic simulation. Two well-known benchmark WDS case studies, the New York Tunnels problem and the Hanoi Problem were used to enable the performance comparison for the four algorithms.

The NYTP network has 21 existing tunnels and 20 nodes fed by the fixed-head reservoir as shown in Figure 1. All the details of this network including the head constraints, pipe costs and water demands can be found in Dandy et al. (1996). The objective of this case study is to determine which of the least cost set of tunnels that should be installed in parallel with the existing tunnels while satisfying the minimum head requirement at all nodes. There are 15 tunnel diameters that can be selected for the NYTP. In addition, a zero tunnel size provides a total of 16 options (15 actual tunnel diameters plus a zero tunnel size) for each link. Thus the total search space is 16^{21} (approximately 1.934×10^{25}).

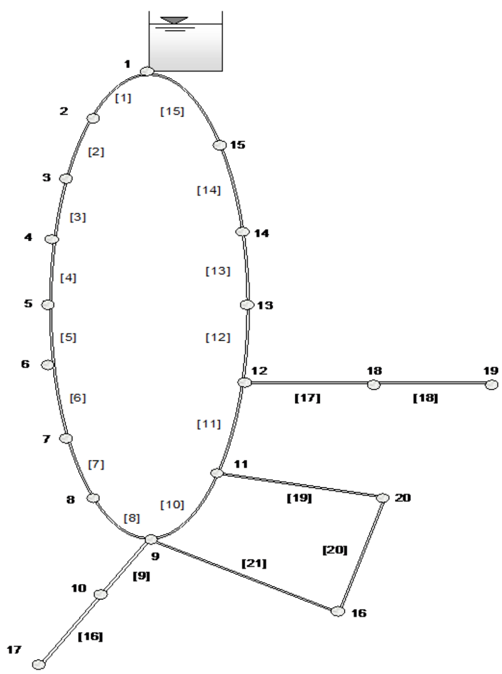

Figure 1 The layout of the New York Tunnel network

The Hanoi Problem (HP) is a network design where all new pipes are to be selected. The network is composed of 34 pipes and 32 nodes which are fed by a single reservoir with the head of 100 meters as shown in Figure 2. The minimum head requirement of the other nodes is 30 meters. A total of six pipe diameters of {12, 16, 20, 24, 30, 40} inches may be selected for each new pipe. The total search space is $6^{34} \approx 2.8651 \times 10^{26}$. The details of this network and the formulation of the cost for pipes are found in Fujiwara and Khang (1990).

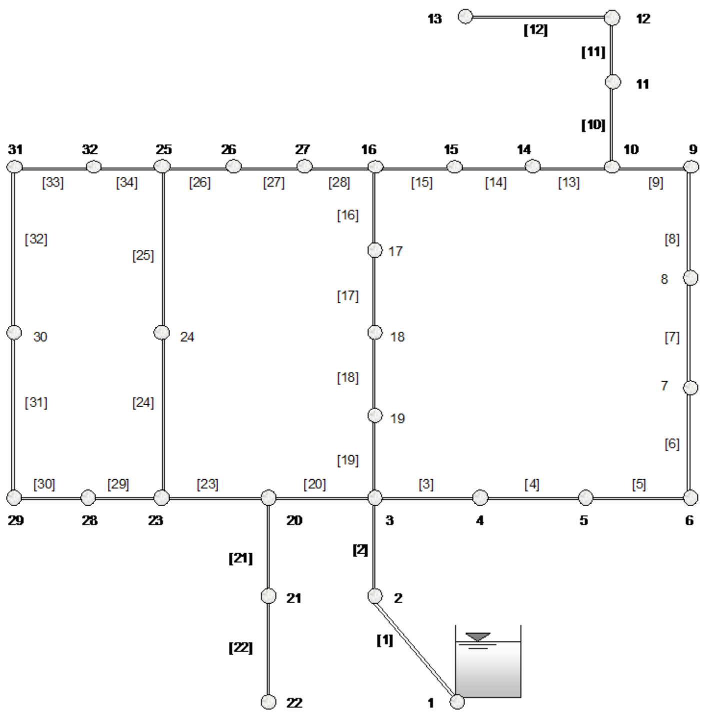

Figure 2 The layout of the Hanoi problem network

A preliminary analysis was undertaken to determine appropriate parameter values for each algorithm applied to these two case studies, which are given in Table 2. As shown in Table 2, a population size of 100 was consistently used for each algorithm. For each algorithm, a total of 100 runs with different random number seeds were performed for each case study to enable the reliable performance comparison. The maximum numbers of allowable evaluations for NYTP and HP case studies are 200,000 and 500,000 respectively.

Table 2 Parameter values for each algorithm applied to two case studies

Algorithms	NYTP	HP
SDE	N=100, F=0.5, Cr=0.6	N=100, F=0.7, Cr=0.8
DDE	N=100, F=[0.3 0.9], Cr=0.6	N=100, F=[0.3 0.9], Cr=0.8
SGA	N=100, P_c=0.6, P_m=0.03	N=100, P_c=0.5, P_m=0.02
CGA	N=100, P_c=0.6, P_d=0.6, P_{cm}=0.05	N=100, P_c=0.6, P_d=0.5, P_{cm}=0.03

Results and discussion

New York Tunnels Problem

Figure 3 presents a comparison of the convergence properties of four algorithms (best solution versus the evaluations) when applied to NYTP case study. These four typical runs used the same starting random number seeds.

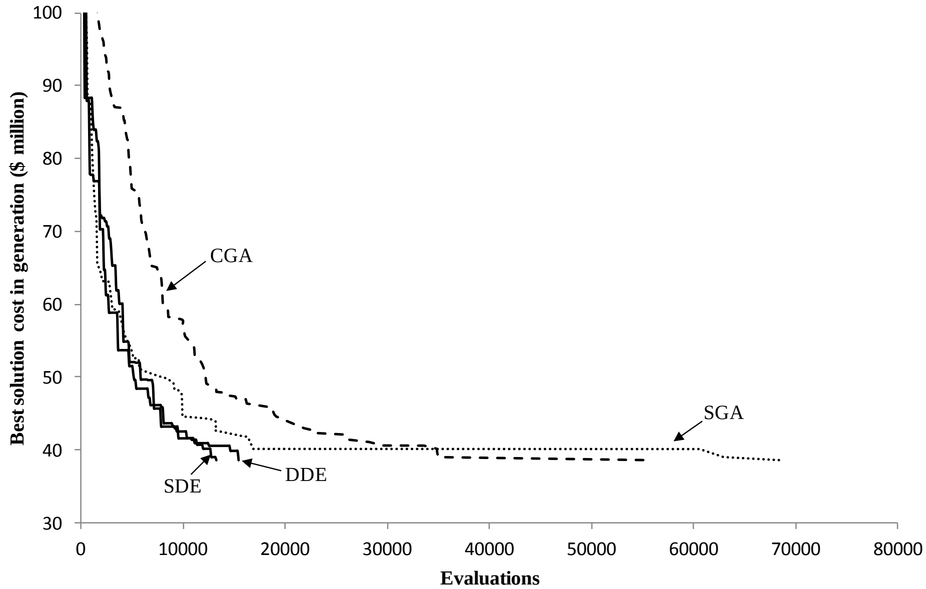

Figure 3 A convergence comparison for four algorithms applied to the NYTP case study

The current best known solution for the NYTP case study with a cost of $38.64 million was first reported by Maier et al. (2003). This best known solution was found by the runs of the four algorithms presented in Figure 3. As shown in Figure 3, the DE variants (SDE and DDE) exhibit clearly faster convergence speed than the GA variants. This is proven by the fact that the DE variants converged to the final solution ($38.64 million) using significantly less evaluations than the GA variants.

It is very interesting to note that the CGA converged slower than the SGA at the early generations while faster than the SGA at the later generations. This is because that the creeping mutation GA has less exploration strength than the SGA at the early stages as the creeping mutation focuses more on the local exploitation. While at the later stage, more exploitation is preferred to seek optimal solutions and hence the CGA shows faster convergence speed than the SGA. The convergence behavior of SDE and DDE is similar as displayed in Figure 3. The statistical results of the four algorithms applied to the NYTP case study are given in Table 3.

As shown in Table 3, the SDE and DDE found the current best known solution for the NYTP case study with a success rate of 97% and 93% respectively, which is significantly higher than those of SGA and CGA. The SGA performed the worst in terms of the percent of trials with the best solution found as it produced the lowest success rate to find the current best known solution for the NYTP case study.

Table 3 Performance comparison of four algorithms applied to the NYTP case study

Algorithms	Number of different runs	Best solution ($M)	Percent of trials with the best solution found[1]	Average cost ($M)	Maximum allowable evaluations	Average evaluations required to find the best solutions
SDE	100	38.64	97	38.65	200,000	12,855
DDE	100	38.64	93	38.66	200,000	13,214
CGA	100	38.64	50	39.04	200,000	44,324
SGA	100	38.64	45	39.25	200,000	54,789

[1]Results are ranked based on this column.

In terms of efficiency, the DE variants substantially outperformed the GA variants. This is reflected by the fact that the average number of evaluations required by the DE variants to find the optimal solutions is only around 30% of that used by the GA variants. This implies that the DE variants are overall three times faster than the GA variants in finding optimal solutions for the NYTP case study.

The Hanoi Problem

Figure 4 provides a convergence comparison for the four algorithms with the same starting random number seeds applied to the HP case study. The current best known solution for the HP case study was $6.081 million (Reca and Martínez 2006). This current best known solution was located by both DE variants. The best solutions generated by the SGA and CGA were $6.181 and $6.170 million, which are larger than the current best known solution.

It is clearly shown in the Figure 4 that the DE variants are able to find optimal solutions for the HP case study with a significantly improved efficiency than the GA variants. As for the NYTP case study, the CGA for the HP case study converged more slowly at the early stages than the SGA while faster than the SGA at the later generations for the HP case study. As shown in Figure 4, the DDE was able to converge slightly more quickly than the SDE for the HP case study. The results of the four algorithms are presented in Table 4.

As shown in Table 4, the GA variants were unable to find the current best known solution for the HP case study based on 100 different runs. While the DE variants found the best known solution with success rates of 92% and 80%. This shows that for this relatively more complex case study, the DE exhibits a superior performance than the GA variants in terms of robustness. In terms of comparing the convergence speed, the DE variants were overall four times faster than the GA variants.

Another observation can be made based on Figure 3 and 4 is that the GA variants converge quickly at the early generations while exhibit extremely slow convergence speed at the later generations. This implies that the GA variants are effective in initially exploring the whole search space while tending to stagnate at the later generations. In contrast, the DE variants consistently show good convergence speed throughout the whole search process as shown in Figure 3 and 4. This is a significant difference in search behavior found in this study between the DE variants and GA variants.

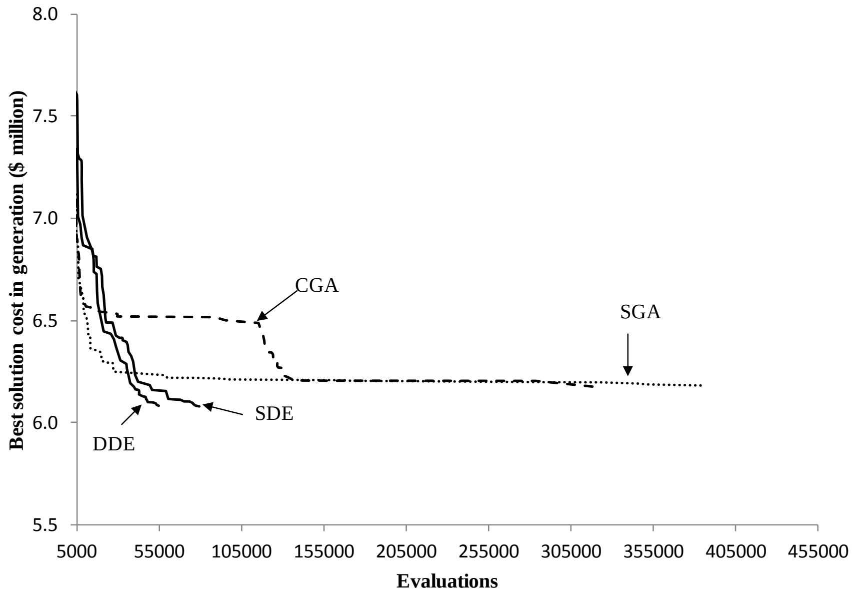

Figure 4 A convergence comparison for four algorithms applied to the HP case study

Table 4 Performance comparison of four algorithms applied to the HP case study

Algorithms	Number of different runs	Best solution ($M)[1]	Percent of trials with the best solution found	Average cost ($M)	Maximum allowable evaluations	Average evaluations required to find the best solutions
SDE	100	6.081	92	38.65	500,000	77,220
DDE	100	6.081	80	38.66	500,000	63,700
CGA	100	6.109	0	6.274	500,000	321,170
SGA	100	6.112	0	6.287	500,000	384,942

[1]Results are ranked based on this column.

Conclusions

Analyzing the results obtained from these two case studies, the following conclusions can be made:

1. The DE variants consistently outperformed the GA variants in terms of solution quality and efficiency. The advantage of the DE variants over the GA variants is more significant when dealing with relatively more complex case studies. The DE variants were able to find optimal solutions approximately three times faster than GA variants.

2. The dither DE (DDE) has similar performance with the standard DE (SDE) with the calibrated parameter values. However, the mutation weighting factor used in the DDE was randomly selected from a given range rather than pre-specified by a particular value. This alleviates the effort required to tune the parameter values during the trial-and-error process, which is an advantage compared to the SDE.
3. The creeping mutation GA performed slightly better than the SGA based on the two case studies in this study.

Based on this study, it is concluded that the differential evolution algorithms are more suitable for water distribution network optimization when compared with genetic algorithms.

Reference

Broad, D. R., Dandy, G. C., and Maier, H. R. (2005). "Water distribution system optimization using metamodels." *Journal of Water Resources Planning and Management*, 131(3), 172-180.

Dandy, G. C., Simpson, A. R., and Murphy, L. J. (1996). "An improved genetic algorithm for pipe network optimization." *Water Resources Research*, 32(2), 449-457.

Das, S., Konar, K., and Chakraborty, U. K. (2005). "Two improved differential evolution schemes for faster global search." In *proceedings of conference on genetic and evolutionary computation (GECCO 2005)*, 991-998.

Dandy, G. C., Wilkins, A., and Rohrlach, H. (2010). "A methodology for comparing evolutionary algorithms for optimizing water distribution systems." *Proceedings of the 12th Water Distribution System Analysis Symposium*, Tucson, Arizona

Deb, K. (2000). "An efficient constraint handling method for genetic algorithms." *J Comput. Methods Appl. Mech. Engrg*., 186,311-338.

Eusuff, M. M., and Lansey, K. E. (2003). "Optimisation of water distribution network design using shuffled frog leaping algorithm." *J. Water Resources Planning and Management*, 129(3), 210-225.

Geem, Z. W., Kim, J. H., and Loganathan, G. V. (2002). "Harmony search optimization: application to pipe network design." *Int. J. Model. Simulat*., 22(2), 125-133.

Mohan, S., and Babu, K. S. J. (2010). "Optimal water distribution network design with honey-bee mating optimization." *Journal of Computing in Civil Engineering*, 24(1), 117-126.

Karaboga, D., and Okdem, S. (2004). "A simple and global optimization algorithm for engineering problems: differential evolution algorithm." *Turkish Journal of Electrical Engineering & Computing Science*, 12(1), 53-60.

Lin, M.-D., Liu, Y.-H., Liu, G.-F., and Chu, C.-W. (2007). "Scatter search heuristic for least-cost design of water distribution networks." *Engineering Optimization*, 39(7), 857 - 876.

Lippai, I., Heaney, J. P., and Laguna, M. (1999). "Robust water system design with commercial intelligent search optimizers." *Journal of Computing in Civil Engineering*, 13(3), 135-143.

Loganathan, G. V., Greene, J. J., and Ahn, T. J. (1995). "Design heuristic for globally minimum cost water-distribution systems." *Journal of Water Resources Planning and Management*, 121(2), 182-192.

Maier, H. R., et al. (2003). "Ant colony optimization for the design of water distribution systems." *J. Water Resources Planning and Management*, 129(3), 200-209.

Perelman, L., and Ostfeld, A. (2007). "An adaptive heuristic cross-entropy algorithm for optimal design of water distribution systems." *Engineering Optimization*, 39(4), 413 - 428.

Price, V. K., Storn, M. R., and Lampinen, A. J. (2005). *Differential Evolution: A practical approach to global optimization*, Springer, Berlin.

Reca, J., and Martinez, J. (2006) "Genetic Algorithms foe the design of looped irrigation water distribution networks." *Water Resources Research*, 42, W05416,doi:10.1029/2005WR004383.

Simpson, A. R., Dandy, G. C., and Murphy L. J. (1994). "Genetic Algorithms compared to other techniques for pipe optimization." *J. Water Resources Planning and Management*, *120(4)*, 423-443.

Storn, R., and Price, K. (1995). "Differential Evolution-A Simple and Efficient Adaptive Scheme for Global Optimization over Continuous Space." *Technical Report*, International Computer Science Institute, Berkeley, CA.

Suribabu, C. R., and Neelakantan T. R. (2006). "Design of water distribution networks using particle swarm optimization." *Urban Water J.*, 3(2), 111-120.

Suribabu, C. R. (2010). "Differential evolution algorithm for optimal design of water distribution networks." *Journal of Hydroinformatics*, 12 (1), 66-82.

Vesterstrom, J., and Thomsen, R. (2004) "A comparative study of differential evolution, particle swarm optimization, and evolutionary algorithms on numerical benchmark problems." *Proc., Evoluti. Comput., CEC2004. Congress on*, 1980-1987 Vol.1982.

Vasan, A., and Simonovic, S. P. (2010). "Optimization of water distribution network design using differential evolution." *Journal of Water Resources Planning and Management*, 136(2), 279-287.

Zheng, F., Simpson, A. R., and Zecchin, A. C. (2011a). "A combined NLP-differential evolution algorithm approach for the optimization of looped water distribution systems." *Water Resour. Res.*, 47(8), W08531.

Zheng, F., Simpson, A. R., and Zecchin, A. C. (2011b) "Parametric analysis of differential evolution applied to water distribution system optimization." *Proc., 11th International Conference on Computing and Control for the Water Industry (CCWI 2011)*, Exeter, UK.

Zheng, F., Simpson, A. R., and Zecchin, A. (2011c) "Performance Study of Differential Evolution with Various Mutation Strategies Applied to Water Distribution System Optimization." *Proc., World Environmental and Water Resources Congress 2011*, ASCE, 166-176.