



Research article

Multiobjective evolutionary optimization of water distribution systems: Exploiting diversity with infeasible solutions

Tiku T. Tanyimboh^{*}, Alemtsehay G. Seyoum

Department of Civil and Environmental Engineering, University of Strathclyde, James Weir Building, 75 Montrose Street, Glasgow G1 1XJ, UK

ARTICLE INFO

Article history:

Received 3 April 2016

Received in revised form

17 August 2016

Accepted 19 August 2016

Available online 30 August 2016

Keywords:

Water supply

Dynamic simulation

Constraint handling

Minimum solution vector

Maximum solution vector

Infrastructure planning

ABSTRACT

This article investigates the computational efficiency of constraint handling in multi-objective evolutionary optimization algorithms for water distribution systems. The methodology investigated here encourages the co-existence and simultaneous development including crossbreeding of subpopulations of cost-effective feasible and infeasible solutions based on Pareto dominance. This yields a boundary search approach that also promotes diversity in the gene pool throughout the progress of the optimization by exploiting the full spectrum of non-dominated infeasible solutions. The relative effectiveness of small and moderate population sizes with respect to the number of decision variables is investigated also. The results reveal the optimization algorithm to be efficient, stable and robust. It found optimal and near-optimal solutions reliably and efficiently. The real-world system based optimization problem involved multiple variable head supply nodes, 29 fire-fighting flows, extended period simulation and multiple demand categories including water loss. The least cost solutions found satisfied the flow and pressure requirements consistently. The best solutions achieved indicative savings of 48.1% and 48.2% based on the cost of the pipes in the existing network, for populations of 200 and 1000, respectively. The population of 1000 achieved slightly better results overall.

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1. Introduction

An effective solution method that is reliable and easy to use is required for the optimization of water supply systems that provide an essential service in the communities they serve worldwide. Optimization addresses not only the capital and operating costs along with hydraulic performance and reliability but also increasingly the efficient management of energy and scarce water resources and other environmental concerns (Allam et al., 2016; Cherchi et al., 2015; Kurek and Ostfeld, 2013; Matrosova et al., 2015; Ren et al., 2016; Wang et al., 2016).

Genetic algorithms are used frequently in the optimization of water distribution systems. Generally, genetic algorithms require additional case-specific and/or external procedures to solve optimization problems that have constraints and the execution times can be excessive when applied to large optimization problems involving real-world water distribution networks with hundreds of pipes, especially those that require extended period simulation.

This paper investigates the computational efficiency of constraint handling in multi-objective evolutionary optimization algorithms for water distribution systems based on the coexistence and simultaneous development including crossbreeding of subpopulations of cost-effective feasible and infeasible solutions that are non-dominated. This yields a boundary search approach that also promotes diversity in the gene pool throughout the progress of the optimization by exploiting the full spectrum of non-dominated infeasible solutions.

Results for a real-world network with variable-head supply nodes, variable demands, multiple demand categories and operating conditions including fire-fighting flows are included to illustrate the methodology. The relative merits of small and moderate population sizes compared to the number of decision variables were investigated also. The multiobjective genetic algorithm formulation we developed does not require any additional case-specific or external procedures for the minimum node pressure constraints. Embedded in the genetic algorithm, the hydraulic analysis model can simulate realistically both feasible and infeasible solutions, with fitness directly related to the hydraulic properties.

Many optimization models have been proposed previously including mathematical programming approaches such as linear

^{*} Corresponding author.

E-mail addresses: tiku.tanyimboh@strath.ac.uk (T.T. Tanyimboh), alemtsehay.seyoum@strath.ac.uk (A.G. Seyoum).

and non-linear programming with the design variables assumed to be continuous (Alperovits and Shamir, 1977). Evolutionary algorithms have gained widespread acceptance in recent years. Some examples include genetic algorithms (Dandy et al., 1996), ant colony optimization (Ostfeld and Tsubaltzev, 2008), particle swarm optimization (Montalvo et al., 2008), simulated annealing (Marques et al., 2015), shuffled frog leaping (Eusuff and Lansey, 2003), differential evolution (Zheng et al., 2015), harmony search (Geem, 2006) and tabu search (Cunha and Ribeiro, 2004). Genetic algorithms are used extensively in the optimization of water distribution systems in areas such as pump operation scheduling (Rao and Salomons, 2007), leakage minimization (Creaco and Pezzinga, 2015) design and rehabilitation (Bi et al., 2015), water quality optimization (Farmani et al., 2006) and service reservoir location, design and operation (Prasad, 2010; Siew et al., 2016).

Inspired by Darwin's theory of evolution, genetic algorithms use natural selection as the driving force. A genetic algorithm involves a population of individuals that are represented as chromosomes, each consisting of a set of genes that describe a solution. Individuals are selected from the population to create a mating pool based on their respective fitness levels. Individuals with a higher fitness level have a higher probability of being selected to produce offspring that represent new solutions. A very small proportion of the offspring will mutate after reproduction. Genetic operators consist of selection, crossover and mutation. Crossover involves the creation of new offspring by transforming two or more individuals. Mutation randomly changes an individual to help increase genetic diversity. Selection drives the search towards the regions with the fittest individuals i.e. the best solutions. Roulette wheel and tournament selection (Goldberg and Deb, 1991) are examples of selection operators. Tournaments are often preferred as the roulette wheel operator is characterised by rapid loss of genetic diversity that may cause premature convergence (Goldberg and Deb, 1991). An assessment of the operators applied in evolutionary algorithms is available in McClymont et al. (2015).

There have been many attempts to enhance genetic algorithms. Examples include Gray coding (Dandy et al., 1996), real coding (Vairavamoorthy and Ali, 2000), integer coding (Barlow and Tanyimboh, 2014), creeping or adjacency mutation (Barlow and Tanyimboh, 2014; Dandy et al., 1996), variable mutation rate (Kadu et al., 2008) and the mapping of redundant binary codes to closed pipes (Saleh and Tanyimboh, 2014). Referring to the above-mentioned schemes, the candidate solutions in a genetic algorithm may be represented in different ways. Binary coding is a common scheme where problem variables are represented by bit combinations of 0s and 1s. Gray coding is similar to binary coding, but differs in that only a single bit changes in the representation of adjacent values of the decision variables. In real and integer coding, genes are represented as real numbers and integers, respectively.

A simulation model helps ascertain the fitness of every individual in the population of solutions. Vairavamoorthy and Ali (2000) used a regression model that approximates the hydraulic properties. Vairavamoorthy and Ali (2005) and Kadu et al. (2008) used solution space reduction methods that limit the scope of the search, to reduce the execution times of the algorithms. Also, parallel algorithms have been used to improve the execution times in examples such as Balla and Lingireddy (2000) for model calibration, Ewald et al. (2008) for the location of booster chlorination stations and Barlow and Tanyimboh (2014) for pipe sizing.

Constraints in the optimization problems are often addressed using penalty functions based on the severity of constraint violation, as in Kougias and Theodossiou (2013), for example. Many researchers have attempted to address the difficulties associated with penalty functions (Dridi et al., 2008). For example, Khu and Keedwell (2005) considered node pressure constraints as

additional objectives. Prasad (2010) used a constraint dominance tournament (Deb et al., 2002). Wu and Simpson (2002) developed a self-adaptive penalty method. Farmani et al. (2005) proposed a self-adaptive fitness procedure that does not require parameter calibration. Saleh and Tanyimboh (2013, 2014) developed a penalty-free approach for joint topology and pipe size optimization.

The optimization of real-world water distribution systems involves multiple objectives that tend to be in conflict, e.g. minimizing capital and operating costs whilst simultaneously maximizing hydraulic performance and reliability. A multi-objective optimization approach is suitable for such problems as it produces a set of non-dominated solutions that are equal in rank. Such solutions are said to be Pareto-optimal as it is not possible to improve the solutions in any objective without making at least one of the other objectives worse. Pareto-optimal solutions are practical as they offer flexibility, since the final choice of the decision maker is a trade-off.

Evolutionary optimization approaches such as genetic algorithms are suited to multiobjective optimization problems (Konak et al., 2006). Strength Pareto Evolutionary Algorithm (Zitzler and Thiele, 1998), Nondominated Sorting Genetic Algorithm II (Deb et al., 2002) and Pareto Archived Evolution Strategy (Knowles and Corne, 2000) are some of the common multiobjective evolutionary algorithms. Elitism is one of the key factors for successful application of multiobjective evolutionary algorithms that helps to prevent the loss of good solutions and achieve better convergence (Bekele and Nicklow, 2005; Kollat and Reed, 2006; Zitzler et al., 2000). The Nondominated Sorting Genetic Algorithm NSGA II is popular due to its efficient nondominated sorting procedure and strong global elitism that preserves all elites from both the parent and child populations.

An additional advantage of NSGA II is that it requires few user-specified parameters (Dridi et al., 2008). Its use in the optimization of water distribution systems is widespread. For example, Farmani et al. (2006) optimised the design and operation of a network that included pump scheduling and tank location and design. Jayaram and Srinivasan (2008) optimised design and rehabilitation based on whole-life costing. Jeong and Abraham (2006) optimised operational response strategy to mitigate the consequences of deliberate attacks. Preis and Ostfeld (2008) and Weickgenannt et al. (2010) optimised sensor placement for contamination detection. Nicolini et al. (2011) optimised leakage management. Additional applications of NSGA II in water distribution systems include Saleh and Tanyimboh (2013, 2014) who optimised topology and pipe sizing and Zheng and Zecchin (2014) who investigated a two-stage optimization approach.

Furthermore, evolutionary algorithms can potentially locate the neighbourhood that has the global optimum in the solution space while local search methods can find local optima more rapidly. For example, Haghghi et al. (2011) incorporated integer linear programming while Barlow and Tanyimboh (2014) included local search and cultural improvement operators. Wang et al. (2015) have compared the performance of two hybrid search procedures to NSGA II while other algorithms investigated previously include ParEGO, LEMMO and PESA-II (di Pierro et al., 2009).

This article investigates the computational efficiency of constraint handling in multiobjective evolutionary optimization algorithms for water distribution systems based on the co-existence and simultaneous development including crossbreeding of subpopulations of cost-effective feasible and infeasible solutions that are non-dominated. This yields a practical boundary search approach that also promotes diversity in the gene pool throughout the progress of the optimization by exploiting the full spectrum of non-dominated infeasible solutions. The results revealed insights on the relative merits of small and moderate population sizes

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