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A coupled binary linear programming-differential evolution algorithm approach for water distribution system optimization

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Abstract: A coupled binary linear programming-differential evolution (BLP-DE) approach is proposed in this paper to optimize the design of water distribution systems (WDSs). Three stages are involved in the proposed BLP-DE optimization method. In the first stage, the WDS that is being optimized is decomposed into trees and the core using a graph algorithm. Binary linear programming (BLP) is then used to optimize the design of the trees during the second stage. In the third stage, a differential evolution (DE) algorithm is utilized to deal with the core design while incorporating the optimal solutions for the trees obtained in the second stage, thereby yielding near-optimal solutions for the original whole WDS. The proposed method takes advantage of both BLP and DE algorithms: BLP is capable of providing global optimal solution for the trees (no loops involved) with great efficiency, while a DE is able to efficiently generate good quality solutions for the core (loops involved) with a reduced search space compared to the original full network. Two benchmark WDS case studies and one real-world case study (with multiple demand loading cases) with a number of decision variables ranging from 21 to 96 are used to verify the effectiveness of the proposed BLP-DE optimization

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approach. Results show that the proposed BLP-DE algorithm significantly outperforms other optimization algorithms in terms of both solution quality and efficiency.

CE Database subject headings: Optimization; Water distribution systems; Binary linear programming; Differential evolution

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INTRODUCTION

A number of deterministic optimization techniques have previously been applied to the optimization design problem of water distribution systems (WDSs). These include a complete enumeration approach (Gessler 1985); linear programming (LP) (Alperovits and Shamir 1977; Sonak and Bhave 1993; Guercio and Xu 1997); and non-linear programming (NLP) (Lansey and Mays 1989; Fujiwara and Khang 1990). Each deterministic method offers advantages, but also has disadvantages in terms of optimizing WDS design. The complete enumeration approach guarantees that the global optimal solution will be found, for example, but the computational overhead is extremely intensive as this method evaluates every possible combination of discrete pipe diameters for a WDS. In most cases, this is an impossible task. LP and NLP converge quickly, on the other hand, but only a local optimum is located. In addition, split pipe sizes are usually allowed by a LP solution and continuous pipe diameters are normally included in a NLP solution, neither of which is practical from an engineering perspective.

Samani and Mottaghi (2006) proposed a binary linear programming (BLP) approach for WDS design optimization, in which the objective function and constraints were linearized using zero-one variables. Four steps are involved for their BLP method, which are step 1: each pipe in the water network to be optimized is initially assigned a commercially available pipe diameter; step 2: a hydraulic solver is performed for the known network configuration to obtain water flows for each pipe; step 3: a BLP model is formulated and solved for the water network based on the known flows at each pipe and solved while satisfying the head constraints at each node and step 4: the resulting pipe sizes obtained in step 3 are compared with the assumed pipe diameters in step 1. If they are the same, the optimization process has converged and the resulting pipe sizes are the final solution, otherwise, the resulting pipes sizes are assigned to the water network and steps 2, 3 and 4 are repeatedly performed until the convergence (where resulting pipe sizes in step 3 are the same as the those used in step 2) is achieved.

Samani and Mottaghi (2006) used two relatively small WDS case studies to verify the effectiveness of their proposed BLP method, and reported that the performance of the BLP method was satisfactory in terms of accuracy and convergence based on results of two WDS case studies.

The advantage of the BLP developed by Samani and Mottaghi (2006) over LP and NLP is that it is able to handle the discrete search space, thereby providing discrete pipe diameter solutions. However, the BLP approach is compromised by extreme inefficiency when dealing with relatively large WDS case studies (Savic and Cunha 2008). In addition, the global optimum for a looped WDS cannot be guaranteed as the final solution reached by this BLP approach is dependent on the initially assumed pipe diameters (Martínez 2008).

In addition to deterministic optimization techniques (LP, NLP and BLP), evolutionary algorithms (EAs), as stochastic approaches, have also been employed to optimize the design for WDSs. Simpson et al. (1994) first applied a genetic algorithm (GA) to tackle the water network optimization problem. Afterwards, a number of other evolutionary algorithms were developed and applied to WDS design. These include simulated annealing (Cunha and Sousa 2001); harmony search (Geem et al. 2002); the shuffled frog leaping algorithm (Eusuff and Lansey 2003); Ant Colony Optimization (Maier et al. 2003); the modified GA (Vairavamoorthy and Ali 2005); particle swarm optimization

(Suribabu and Neelakantan 2006); cross entropy (Perelman and Ostfeld, 2007); scatter search (Lin et al. 2007); HD-DDS (Tolson et al 2009) and differential evolution (Suribabu 2010). These EAs have been applied to a number of WDS case studies and exhibit good performance in terms of finding optimal solutions.

The advantages of EAs over deterministic optimization methods are (i) EAs are able to deal with the discrete search space directly and (ii) EAs explore the search space broadly and are therefore more likely to provide good quality solutions. However, a major issue pertaining to the application of EAs for WDS design is the computational intensity. This is a severe limitation for EAs dealing with real-world WDS optimization, for which, a large number of pipes are normally involved. Zheng et al. (2011a) reported that EAs perform well on relatively small case studies in terms of solution quality, whereas solution quality deteriorates for EAs when dealing with larger networks. Thus, it is desirable to develop advanced optimization techniques to overcome these limitations to enable a more generic application of optimization techniques for WDS design. The development of hybrid optimization methods is a way of overcoming the problems outlined above.

Recently, EAs have been combined with deterministic optimization methods in attempts to overcome the disadvantages of both optimization techniques when optimizing the design of WDSs. Krapivka and Ostfeld (2009), for example, proposed a coupled GA-LP method for the WDS optimization. In their technique, all possible spanning trees for a looped water network are first evaluated to identify the least-cost spanning tree. The chords of the tree are assigned with the minimum allowable pipe diameters. The coupled GA-LP technique is then used to further polish the optimal solution of the least-cost spanning tree, in which a GA is used to update the flow distribution, while LP is employed to optimize the tree for a given flow distribution. However, this GA-LP method is limited by the fact that split pipe sizes are allowed in the final solution and it is computationally expensive to evaluate all possible spanning trees for a large WDS.

Tolson et al. (2009) developed a hybrid discrete dynamically dimensioned search algorithm (HD-DDS) for WDS design optimization. In the HD-DDS, a stochastic algorithm is combined with two local search methods (one-pipe search and two pipes search algorithms). These two local search methods are carried out using complete enumeration. Efficiency improvements were reported by Tolson et al. (2009) when this method was compared to other optimization algorithms in terms of optimizing WDSs.

Zheng et al. (2011b) developed a combined NLP-DE approach to deal with WDS optimization problems. In the NLP-DE method, graph decomposition is first employed to identify the shortest-distance tree for a looped WDS. NLP is then used to optimize the shortest-distance tree and an approximately optimal solution is obtained for the original full network. Finally, a DE is seeded in the vicinity of the approximately optimal solution rather than the whole search space in order to optimize the original full network. It was reported by Zheng et al. (2011b) that the combined NLP-DE method was able to find good quality solutions for the WDSs with great efficiency based on four case studies.

Haghighi et al. (2011) combined a simple GA with BLP for WDS optimization design. In this GA-BLP method, a water network is first converted to a tree by removing one pipe from each primary loop and hence a total of *NL* pipes are removed, where *NL* is the number of loops in the water network. Then a set of *N* diameter combinations for the *NL* pipes are randomly generated using commercially available pipe diameters to form the initial population of the GA, where *N* is the population size of the GA. For each GA individual with different diameter combinations for the *NL* pipes, an iterative procedure using BLP combined with a hydraulic solver (EAPNET) is utilized to optimize the remaining tree (the *NL* pipes are not included in the BLP optimization).

The optimum pipe diameters obtained from the iterative BLP optimization for the tree are returned to the GA along with corresponding cost. This cost in combination with the cost of the *NL* pipes handled by the GA provides the total cost of the original water network. This total cost is used to calculate the fitness of the GA individual. Subsequently, the GA operators (selection, crossover and mutation) are performed to evolve the initial solutions to achieve the final optimal solutions.

In the GA-BLP method (Haghighi et al. 2011), the GA was only used to deal with the *NL* pipes, while BLP was employed to tackle the optimization of the tree that was obtained by removing *NL* pipes. Thus, efficiency of the GA optimization is expected to be improved as the GA only handles the *NL* pipes rather than the total number pipes in the original whole network (*NL* is normally significantly smaller than the total number pipes). However, the computational effort for iterative BLP optimization in this GA-BLP approach is massive when dealing with large water networks since BLP has been found to be extremely inefficient when tackling large optimization problems (Savic and Cunha 2008; Martínez 2008).

In the current paper, a novel hybrid optimization approach that combines BLP and DE is proposed for optimizing the design of WDSs. Three stages are proposed in the BLP-DE method. In the first stage, the full water network that is being optimized is decomposed into trees and the core using a graph decomposition algorithm. In the second stage, the trees of the original full network are individually optimized by BLP. In the third stage, the core of the original full network is optimized by a DE algorithm and the optimal solutions for the trees obtained in the second stage are incorporated during the DE optimization. The proposed BLP-DE method has been verified by two benchmark case studies each with a single demand loading case and a larger real-world network with multiple loading cases. The details of the proposed BLP-DE method are given in the next section

THE PROPOSED BLP-DE METHOD

The first stage: water network decomposition

Deuerlein (2008) introduced the novel idea of decomposing a water network based on its connectivity properties, using terms and concepts drawn from graph theory; and describe how a full WDS could be decomposed into forests, blocks and bridges. This decomposition allowed various types of systems analysis to be conducted on water supply networks. In the first stage of the proposed method, the full water network is decomposed into two main components, rather than the forest, blocks and bridges. These two components are trees and the core, where trees are the outer component of the network, while the core is the inner component of the network (Deuerlein 2008).

Figure 1 represents the network layout of the New York tunnels problem (NYTP), a case study often used to test methods of WDS optimization. The NYTP is a pipe duplication optimization problem, the details of which are given by Dandy et al. (1996).

Normally, a WDS can be described as a graph $G(V,E)$, in which, vertices (V) of the graph represent the nodes of the WDS, and edges (E) of the graph represent links between nodes. For the NYTP network $G(V,E)$ given in Figure 1, V={1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20} and E={[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21]}.

In graph theory, a connected graph without any loops is referred as a tree (T) (Deo 1974). Based on the decomposition method proposed by Deuerlein (2008), the trees (T_s) and the core (C) of the NYTP network $G(V,E)$ (see Figure 1) are obtained and shown in Figure 2, where $G(V,E)= T_s \cup C$. As shown in Figure 2, two trees are identified after decomposition, including T_1={10, 17, [9], [16]} and T_2={18, 19, [17], [18]}, where 10, 17, 18 and 19 are nodes, and [9], [16], [17] and [18] are links in Figure 1. The remaining nodes and pipes form the core (C) of the NYTP network, where C={1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 13, 14, 15, 16, 20, [1], [2], [3], [4], [5], [6], [7], [8], [10], [11], [12], [13], [14], [15], [19], [20], [21]}. As can be seen from Figure 2, the trees and the core (C) overlap at the nodes 9 and 12, i.e., $T_1 \cap C$=9 and $T_2 \cap C$ =12. The nodes that connect the core and the trees in the original water networks are defined as root nodes r (Deuerlein 2008). Thus, for the NYTP network given in Figure 1, nodes 9 and 12 are root nodes, i.e., $r(T_1)$=9 and $r(T_2)$=12, as shown in Figure 2.

The second stage: BLP optimization for the trees

In the proposed method, binary linear programming (BLP) is employed in the second stage to optimize the design of the trees obtained at the end of the first stage. Since the WDS optimization problem is mathematically nonlinear due to the nonlinearity of the head loss equation, during BLP, zero-one variables are used as decision variables in order to convert the optimization problem from a nonlinear to a binary linear system. The trees of the original full network are individually optimized by BLP in the proposed method. The BLP formulation for tree optimization is given as follows.

Objective function of BLP

The objective function involved for the least-cost WDS design is normally the sum of the construction cost of each pipe in the WDS. The objective function F for a tree in BLP is given by:

$$F = \sum_{i=1}^{N} \sum_{j=1}^{P} X_{ij} L_i \, C(D_j) \quad (1)$$

where N is the total number of pipes that needs to be optimized; P is the total number of commercially discrete pipe diameters that can be used; L_i is the length of pipe i; $C(D_j)$ is the unit length cost of the pipe diameter D_j and X_{ij} is the zero-one variable.

In Equation (1), X_{ij}=1 indicates that the diameter D_j is selected for pipe i while X_{ij}=0 indicates that the diameter D_j is not selected for pipe i. No nonlinear terms are involved in the objective function F,

Constraints of BLP

Normally, when designing a WDS the hydraulic balance for the water network (including a continuity equation at each node and the energy conservation for each primary loop and required path) and the head requirement for each node are usually constraints that need to be satisfied. In the proposed method, however, BLP is only employed to deal with the trees of the original full network. Therefore, the hydraulic balance does not need to be considered as a constraint since no loops are involved in the

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trees and the flows at each pipe in the trees can be determined for each demand loading case before BLP optimization is carried out.

The head requirement for each node still needs to be considered as a constraint for the BLP optimization in the second stage of the proposed method. The Hazen-Williams or Darcy-Weisbach formula may be used during the BLP to determine the head loss for each pipe. For the Hazen-Williams formulation,

$$h_{fi}^{n} = \sum_{j}^{P} \omega \frac{L_i X_{ij}}{C_j^{\alpha} D_j^{\beta}} (q_i^n)^{\alpha} \qquad n \in TN, i \in T \tag{2}$$

where h_{fi}^{n} is the frictional head loss for pipe i for demand loading case n in the tree (T) that is being optimized; q_i^n=flows in pipe i for demand loading case n; TN= total number of demand loading cases; P=total number of available pipe diameters; ω=numerical conversion constant which depends on the units of flows and diameters; α , β =coefficients; C_j=Hazen-Williams coefficient of pipe diameter D_j.

As can be seen from Equation (2), for pipe i, each pipe diameter D_j is considered as its potential option. The final diameter for pipe i is selected by using X_{ij} (the zero-one variables), where X_{ij}=1 implies that diameter D_j is used for pipe i and then the h_{fi}^{n} is based on the selected diameter D_j; a value of X_{ij}=0 means that diameter D_j is not selected for pipe i and no head loss is involved for the diameter D_j.

The only unknown in Equation (2) is X_{ij} (the zero-one variables) since q_i^n is already determined for each link in the tree and each commercially available pipe diameter is known. Consequently, by utilizing the zero-one decision variables X_{ij} and the known flows in the tree network, the nonlinear Hazen-Williams formula is converted to a linear formula.

In the proposed BLP, the constraint for each node k is that the total head loss used by the pipes involved in the water supply path from source node R to node k should be less than the value of the head at the source node minus the head requirement at node k for each demand loading case, which is given by:

$$\sum_{m}^{W_{k\text{-}R}} h_{fm}^{n} \leq H_R\text{-}H_{k,n}^{\min} \quad k \in T, m \in W_{k-R} \tag{3}$$

where H_R is the available head provided by the source node (R) of the tree that is being optimized by BLP; $H_{k,n}^{\min}$ is the minimum head requirement for node k in the tree (T) for demand loading case n; $W_{k\text{-}R}$ is the water supply path from source node R to node k (only one path is available for each node k to receive water demand from the source node R in a tree). $\sum_{m}^{W_{k\text{-}R}} h_{fm}^{n}$ is total head loss involved in water supply path $W_{k\text{-}R}$ for demand loading case $n \in TN$.

An additional constraint in BLP is that the sum of X_{ij} for each link i must be equal 1 as only one pipe diameter is selected for each link, which is given by:

$$\sum_{j=1}^{P} X_{ij} = 1 \tag{4}$$

BLP optimization for the trees

It is noted that no supply sources (R) are available for trees that are obtained by decomposing the original whole network and hence H_R is unknown in Equation (3). For the trees T_1 and T_2 given in Figure 2, no supply source is available for these two trees obtained by decomposition. For the purposes of the proposed optimization method, however, the root nodes r are assumed as the supply source nodes for the trees. This is because the root nodes are the connection of the trees and the core and all the water demands required by a particular tree are delivered via its corresponding root node. As such, the supply source nodes for T_1 and T_2 in Figure (2) are $r(T_1)$=9 and $r(T_2)$=12 respectively.

The water demands at the root nodes are not considered when conducting the tree optimization using BLP. A series of assumed H_R values are used for each root node to enable BLP optimization of the corresponding tree. In the proposed method, H_R values are selected from a pre-specified head range with a particular interval (of say 1 foot or 0.1 meters). The lower boundary of the head range is the maximum value of the head requirement across the whole tree ($H_{min}=\max(H_k^{\min})$), while the upper boundary of the head range is the head provided by the supply source node of the original full network ($H_{max}=H_s$). T_1 of the NYTP network given in Figure 2 is used to illustrate the proposed BLP optimization algorithm. For the NYTP case study, a single demand loading case was specified as per the original paper (Schaake and Lai 1969)

For T_1, H_{min}=272.8 ft and H_{max}=300 ft, where 272.8 ft is the maximum value of the minimum allowable head requirement of all nodes contained within T_1 (nodes 10 and 17 as shown in Figure 2) and 300 ft is the allowable head provided by the reservoir given in Figure 1 (the head information is given by Dandy et al. 1996).

A series of values of H_R ($H_R \in [272.8, 300]$) with an increment of 1 ft is used for root node $r(T_1)$. BLP is formulated (see Equations (1), (2) and (3)) for each H_R value and solved. The final solutions for T_1 with different H_R assigned for $r(T_1)$ are presented in Table 1.

As can be seen from Table 1, a lower cost solution was found by BLP when a higher head was assigned for $r(T_1)$. When H_R is equal to or larger than 280.8 ft, no pipes need to be duplicated and hence the solution is zero in cost since NYTP is a pipe duplication optimization problem.

The fourth column of Table 1 displays the minimum pressure head excess H_e across the tree for each optimal solution obtained by BLP. For each optimal solution, the corresponding H_R can be further reduced by its corresponding H_e while still maintaining its feasibility. For example, there is a minimum pressure excess of 0.09 ft (H_e =0.09 ft) for the optimal solution with H_R =273.8 ft at $r(T_1)$ (as shown in the third row of Table 1). This H_R value can be reduced to 273.71 ft while still guaranteeing the feasibility of the optimal solution. The reduced H_R value is denoted as H_R^*, which is the minimum head required at $r(T_1)$ to maintain the feasibility of its corresponding optimal solution ($H_R^* = H_R - H_e$). H_R^* values for all the optimal solutions for T_1 are provided in the fifth column of Table 1. It should be noted that for each optimal solution, the H_e value varies for different demand loading cases and the H_R^* value is therefore different for each loading case.

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A solution choice table is developed for T_1 (denoted as $S(T_1)$) including the H_R^* values, the optimal solution costs and the pipe diameters of the optimal solutions. In $S(T_1)$, each unique H_R^* is associated with a unique optimal solution (including the cost and the pipe diameters for each link of T_1). In addition, H_R^* in the solution choice table is sorted from the smallest to the largest, while the optimal solution cost is sorted from the largest to the smallest. For each tree of the original full network, a solution choice table is constituted during the second stage of the proposed optimization method. For a water network having a total of TN demand loading cases, the solution choice table is composed of the optimal costs, pipe diameters for each optimal solution and $H_{R,n}^*$ ($n \in TN$) values for each demand loading case. In the solution choice table, each demand loading case is associated with a different set of $H_{R,n}^*$ values but the same optimal costs and the pipe diameters for the tree.

The third stage: DE optimization for the core

During the third stage of the proposed optimization method, a differential evolution (DE) algorithm is employed to optimize the design for the core of the original full network. The water demands at the root nodes in the core have to be increased by the total water demands of their corresponding trees before DE optimization for each demand loading case. For the example given in Figure 2, the water demands of T_1 and T_2 are added to the demands at node $r(T_1)$=9 and $r(T_2)$=12 in the cores respectively. Furthermore, during the DE optimization of the core, the optimal solutions obtained for the trees during the second stage are incorporated. The proposed DE optimization algorithm for the core is given as follows.

(1) A total of N solutions (pipe diameter combinations for the core) are randomly generated for the core to initialize the DE search, where N is the population size of the DE algorithm. It should be noted here that only the pipes in the core are handled by the DE algorithm in the third stage of the proposed method.

(2) For each individual solution, a hydraulic solver (EPANET2.0 [Rossman 2000]) was used in this study) is used to obtain the head at each node for each demand loading case. The head at each root node in the core for demand loading case n is tracked (denote as $H^{\#}_{R,n}$).

(3) The total pipe cost of the core *(PC)* is computed for each individual solution of the DE algorithm. In addition, a penalty cost *(PE)* is computed for the solution that has head deficits at the nodes in the core.

(4) The optimal solutions for the trees during in the second stage are now incorporated into the DE process. The optimal solutions of trees are selected from their corresponding solution choice tables based on the head at the root nodes. The selection of the optimal solution for each tree from its corresponding solution choice table is guided by one of two possible sets of circumstances:

(i) If any head value at a root node for loading case $n \in TN$ ($H^{\#}_{R,n}$) in the core obtained by a hydraulic solver is smaller than the minimum $H^{*}_{R,n}$ value associated with its corresponding demand loading case n in the solution choice table of its corresponding tree, the optimal solution cost associated with the minimum $H^{*}_{R,n}$ is added to the *PC*. Additionally, a penalty cost is added to the *PE* for this individual solution as no feasible solution is found for this tree to satisfy the head constraints for all demand loading cases.

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(ii) If all $H^{\#}_{R,n}$ values in the core are greater than the minimum $H^{*}_{R,n}$ values of their corresponding demand loading cases in the solution choice table, the minimum optimal solution in terms of cost in the choice table that has all $H^{*}_{R,n}$ values smaller than their corresponding $H^{\#}_{R,n}$ values is selected and added to PC.

The total pipe cost is obtained, therefore, by combining the selected optimal solution cost for each tree and the cost for the core. The total penalty cost is achieved by adding the penalty cost for each tree (if applicable) and the penalty cost of the core (if applicable).

(5) The objective function value is obtained for each individual solution of the DE by adding the total pipe cost and the total penalty cost. Then the mutation, crossover and selection operators of the DE are carried out to generate the offspring.

(6) Steps (2) to (5) are performed iteratively until the convergence criterion is satisfied.

During the DE optimization, real continuous values for the pipe diameter are created in the mutation process although discrete pipe diameters are used to initialize the search. In the proposed method, the real diameter values are rounded to the nearest commercially discrete pipe diameters after the mutation operator of the DE is performed. It is noted that rounding the diameters to the nearest discrete diameters may generate some infeasible solutions (Vasan and Simonovic 2010; Marchi et al. 2012). However, these infeasible solutions will be removed by the selection operator of the DE algorithm. Since the optimal solutions for the trees are included when the DE is optimizing the core, the final solution obtained is actually the optimal solution for the whole original network. However, the decision variables handled by the DE are only the pipes in the core as the solutions for the trees are selected from their existing solution choice tables. The DE, therefore, has a significantly reduced search space to explore, as defined by the core, while optimal solutions are provided for the whole network. This is the great benefit of the proposed optimization method.

CASE STUDIES

Two benchmark WDS case studies each with a single demand loading case are used to demonstrate the effectiveness of the proposed coupled BLP-DE method. These studies are the New York Tunnels problem (NYTP) and the Hanoi Problem (HP). A real-world WDS case study with multiple demand loading cases is then used to further verify the effectiveness of the BLP-DE method in terms of dealing with a relatively large and more complex case study. The DE algorithm and the BLP formulation were coded using Matlab 7.5 and the BLP was solved by the 'bintprog' function in the Matlab 7.5. It is noted that the EPANET2.0 was used in this paper to enable the hydraulic simulation. The Hazen-Williams equation (Equation (2)) was used. The coefficients of Hazen-Williams equation used in this paper according to those used in EPANET 2.0 were ω=10.670 (SI units used in this study); α =1.852 and β=4.871. For the NYTP and HP benchmark case studies, all the previously published results presented in this paper have used EPANET2.0 as the hydraulic simulation model and hence utilized the same coefficients of Hazen-Williams equation as those used in the proposed method. This therefore enables a fair comparison between the proposed BLP-DE method and other previously published algorithms.

Case study 1: New York Tunnels Problem (21 decision variables)

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The layout of the NYTP and the decomposition results of the NYTP were given in Figure 1 and 2 respectively. Two trees were identified for the NYTP network and a series of values of H_R ($H_R \in [272.8, 300]$) with an increment of 1 foot was used for $r(T_1)$=9 to enable the BLP optimization for T_1. For T_2, a series of values of H_R ($H_R \in [255, 300]$) with an increment of 1 foot was used for $r(T_2)$=12 to conduct BLP optimization. A solution choice table was generated for each tree of the NYTP case study in the second stage of the proposed BLP-DE approach. Figure 3 gives the H_R^* value versus the optimal solution cost in the solution choice table for each tree.

As shown in Figure 3, only seven different optimal solutions were found for T_1 with a large range of assumed heads at root node $r(T_1)$, while 23 different optimal solutions can be located for T_2. For each tree, the optimal solution cost decreases as the head value at the root node increases. These optimal solutions are used to generate solution choice tables that are used during the third stage of the proposed method

The number of decision variables in the core is 17, compared to 21 decision variables in the original full NYTP, as four pipes are located in the trees. A population size (N) of 50, a weighing factor (F) of 0.5 and a crossover rate (Cr) of 0.5 are used for the DE applied to the core optimization in the third stage of the proposed method. The number of maximum allowable evaluations ($NMAE$) is 7,500 and 100 runs with different starting random number seeds are performed for the DE applied to the core. The results of the proposed BLP-DE method and other optimization algorithms that have previously been applied to the NYTP case study are presented in Table 2.

The current best known solution for the NYTP case study is \$38.64 million and the diameters of the tunnels for this best known solution were presented by Maier et al.

(2003). In the current study, this best solution was found with a 100% success rate by the proposed BLP-DE method over 100 different runs. The rate at which the best known solution is found by the new BLP-DE method is higher than all the other optimization algorithms in Table 2. The most noticeable advantage of the proposed BLP-DE method over other optimization algorithms is the efficiency improvement. The proposed BLP-DE approach required only an average of 3,486 equivalent full network evaluations over 100 different runs to find the optimal solutions, which is significantly less than those required by all the other algorithms given in Table 2. It can be concluded that, for the NYTP case study, the proposed BLP-DE outperformed all the other optimization algorithms given in Table 2 in terms of percent with the current best solution found and efficiency.

It should be noted that all the computational overhead of the proposed BLP-DE method (including the BLP optimization for the trees and the DE optimization for the core) was converted to the equivalent number of full NYTP network evaluations using the same computer configuration. In particular, the full network was run 1000 times with randomly selected pipe configurations using the Matlab code developed for this proposed method. The average computational time for each full network simulation was obtained. Then the total computational time used by the core optimization and the BLP optimization applied to the trees was converted to the equivalent time for full network simulations. This allows a fair comparison between the proposed BLP-DE method and other optimization algorithms in terms of efficiency. This computational analysis approach has been used for each case study investigated in this paper.

Case study 2: Hanoi Problem (34 decision variables)

The Hanoi Problem (HP) (Fujiwara and Khang 1990) has frequently been used as a benchmark WDS case study to test the performance of various optimization algorithms. The layout of the HP is given in Figure 4. The details of the HP, the available pipe diameters and the cost of these diameters are given by Fujiwara and Khang (1990).

The decomposition results for the HP network in the first stage of the proposed BLP-DE method are given in Figure 5. As shown in Figure 5, two trees were identified for the HP network including T_1={11, 12, 13, [10], [11], [12]} and T_2={21, 22, [21], [22]}, where 11, 12, 13, 21 and 22 are nodes, and [10], [11], [12], [21] and [22] are links. $r(T_1)$=10 and $r(T_2)$=20 are root nodes of the T_1 and T_2 respectively as $T_1 \cap C$=10 and $T_2 \cap C$ =20 (C is the core of the HP network as shown in Figure 5).

For the HP case study, the head provided by the reservoir is 100 meters and the minimum head requirement for each node is 30 meters (Fujiwara and Khang 1990). In this study, a series of H_R ($H_R \in [30,100]$) with an increment of 0.1 meter was used for $r(T_1)$ and $r(T_2)$ to enable the BLP optimization of T_1 and T_2 in the second stage, thereby generating a solution choice table for each of the trees. The values of H_R^* and the optimal solution costs from the solution choice table for each tree are presented in Figure 6.

As shown in Figure 6, 18 different optimal solutions were found for each of both T_1 and T_2 of the HP network, although 700 BLP runs with a range of heads between 30 and 100 meters at the root nodes (0.1 meter interval) were performed for each tree. This indicates that a larger interval (of say 0.5 meter or 1 meter) may be enough to obtain these 18 optimal solutions for each tree. However, due to the extreme efficiency for the BLP applied to the tree optimization, a relatively small interval (0.1 meter) was used in this study to improve the likelihood of including all possible optimal solutions. These optimal solutions are used to form solution choice tables for the trees, which are used for the DE optimization in the third stage of the proposed method.

In the third stage, a DE with N=80, F=0.7, Cr=0.8, and $NMAE$=40,000 was applied to the core of the HP network. The number of decision variables to be considered is 29 since five pipes of the 34 pipes in the HP network are consigned to the two trees. Based on the heads at the root nodes, the DE algorithm chooses the optimal solutions for the trees from their corresponding solution choice tables while also exploring the search space of the core. As such, the optimal solutions for the tree are used in conjunction with solutions from the core to yield optimal solutions for the whole HP network.

Table 3 provides the final results of the proposed BLP-DE approach applied to the HP case study. The other previously published results for the HP case study are also included in Table 3 to enable the performance comparison.

The current best known solution for the HP case study, with a cost of \$6.081 million, was first found by Reca and Martínez (2006) and they presented the pipe diameters for this current best known solution. As shown in Table 3, the proposed BLP-DE performs the best in terms of the percentage of the current best solution found for the HP case study. This is reflected by the fact that the proposed BLP-DE found the current best solution for the HP case study 98% of the time over 100 runs using different starting random number seeds, which is higher than all the other algorithms given in Table 3.

As displayed in Table 3, the proposed BLP-DE used an average number of 33,148 equivalent full network evaluations to find the optimal solutions, which is fewer than all the other algorithms shown in Table 3. This indicates that the proposed BLP-DE is able to find optimal solutions more quickly than other algorithms.

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Case study 3: Real-world network case study (96 decision variables)

The real-world network case study (denoted as RN case study) was taken from a small town in the south of China. This is a completely new case study and has not been previously studied. The RN network has 96 pipes, 85 demand nodes and one reservoir with a fixed head of 50 meters. Three demands loading cases have been considered for this network including a peak hour demand loading case and two fire loading cases. The layout of RN case study and the two fire loading positions are shown in Figure 7. The objective of this case study is to determine the least-cost design of this water network, while satisfying a minimum pressure of 15 meters at each demand node for all demand loading cases and 10 meters only at the fire demand loading nodes during the two separate fire loading cases. All the pipes have an identical Hazen-Williams coefficient of 130. A total of 14 commercially available pipe diameters ranging from 150 mm up to 1000 mm are available for selection for each pipe and the cost of each pipe is given by Kadu et al. (2008).

The graph decomposition algorithm was applied to RN case study in the first stage of the proposed method in order to identify the trees and the core. The decomposition results are given in Figure 8. As shown in Figure 8, a total of eight trees are determined and 43 pipes are assigned to these trees.

In the second stage of the proposed method, eight solutions choice tables were generated for the trees. The number of pipes involved in the core of RN case study is 53 since 43 pipes are assigned to trees (96 pipes exist in the full RN case study). Thus, only the 53 pipes rather than the 96 pipes are handled by the DE in the third stage of the proposed method. For the DE applied to the core optimization of the RN case study,

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N=150, *F*=0.4 and *Cr*=0.8 were selected based on a few parameter trials. The maximum number of allowable evaluations was set 75,000 (*NMAE*=75,000).

In order to enable a performance comparison, a standard DE (SDE) was also applied to the original full RN case study (96 pipes). For the SDE, *N*=300, *F*=0.3, *Cr*=0.8 and *NMAE*=600,000 were selected based on a detailed preliminary analysis. Ten runs with different starting random number seeds were performed for the DE applied to the core in the third stage of the proposed method and the SDE applied to the original full network (the proposed method and the SDE used the same random number seeds). It is not necessary to perform multiple runs for the tree optimization in the second stage of the proposed method. This is because that the same solutions are found for the trees using the deterministic BLP method.

The solutions of the proposed BLP-DE method and the SDE algorithm applied to the BN case study are provided in Figure 9. It is clearly shown in Figure 9 that the proposed BLP-DE method significantly outperformed the standard different evolution (SDE) with calibrated parameter values for the RN case study in terms of solution quality and efficiency. In addition, it is observed that the solutions produced by the proposed BLP-DE are less scattered than those generated by the SDE based on ten different runs. This indicates that the performance the proposed BLP-DE approach is less affected by the random number seeds than that of the SDE. The proposed method is therefore able to yield good quality optimal solutions with a higher confidence level.

The results of the proposed BLP-DE and the SDE applied to the RN case study are provided in Table 4. As shown in Table 4, the proposed BLP-DE found a best solution for the RN case study with a cost of \$6.16 million. The best solution found by the SDE

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was \$6.24 million, which is 1.3% higher than the best solution produced by the proposed BLP-DE method. The average cost solution over 10 runs found by the BLP-DE method was \$6.18 million, which is only 0.3% higher than the best solution (\$6.16 million found by the proposed BLP-DE method in this study) while 2.1% lower than that generated by the SDE.

In terms of efficiency, the proposed BLP-DE was approximately 4.5 times more efficient in terms of average numbers of evaluations than the SDE in finding optimal solutions for this case study. This is evidenced by the fact that the average number of equivalent full network evaluations required by the proposed BLP-DE method for convergence was 73,092, which is only 18% of the number of evaluations required by the SDE. The average number of 73,092 was obtained by converting the total computational overhead of the proposed method to the equivalent number of full RN network evaluations. In terms of comparing the execution time in Matlab 7.5, the proposed method required a total of 2.2 hours to find optimal solutions for ten optimization runs, while the SDE needed a total of 12.4 hours to arrive at optimal solutions for ten runs. For the proposed method, the total execution time for the BLP optimization was 0.48 hours, which is 21% of that required by the total execution time of the proposed BLP-DE method. Note that the graph decomposition process is extremely efficient and hence its computational overhead is not included.

CONCLUSIONS

In this paper, a novel coupled binary linear programming and differential evolution (BLP-DE) optimization approach based on network decomposition is proposed for dealing with WDS optimization problems. Three stages are involved in the proposed BLP-DE optimization method. These are (i) the full water network is decomposed into trees and the core using a graph decomposition algorithm; (ii) the trees are individually optimized by BLP and a solution choice table is constituted for each tree and (iii) a DE is employed to optimize the core of the original full network while incorporating the optimal solutions for any tree. Different components of the original full network are, therefore, optimized by different optimization algorithms.

The proposed BLP-DE method has been applied to three case studies and the results compared with those of other algorithms. For the NYTP and HP case studies, the proposed BLP-DE method found the current best known solutions for both of them with a higher success rate and a significantly improved efficiency compared to other algorithms given in Tables 2 and 3. For the relatively larger and more complex case study (RN case study with three demand loading cases: 96 decision variables), the proposed BLP-DE was able to find better quality optimal solutions than a standard differential evolution (SDE) with approximately 4.5 times faster convergence speed. Thus, the proposed method shows substantial promise as a tool for finding good quality solutions for relatively large water networks.

It should be noted that the proposed BLP-DE method is not appropriate to optimize the types of water networks having only loops or only trees. However, it is very common for a water network to have loops and multiple trees in practice and the proposed BLP-DE method has advantages in efficiently finding good quality optimal solutions for this common type of network over other optimization methods as demonstrated in this paper. It has been also found in this study that the computational overhead increases significantly when the number of decision variables in the tree handled by the BLP increases. Thus, the proposed method would need to be further developed when dealing with the water network having very large trees to be optimized by the BLP. Incorporation of the pressure dependent demands within the proposed BLP-DE method would also need to be the focus of a future study.

Other future studies on this research line may include (i) the application of the proposed BLP-DE method to deal with the optimization of complex water networks, which may have pumps, valves and tanks involved, and (ii) the extension of the proposed BLP-DE method to tackle the multi-objective optimization problem for WDSs.

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Figure captions list

Figure 1

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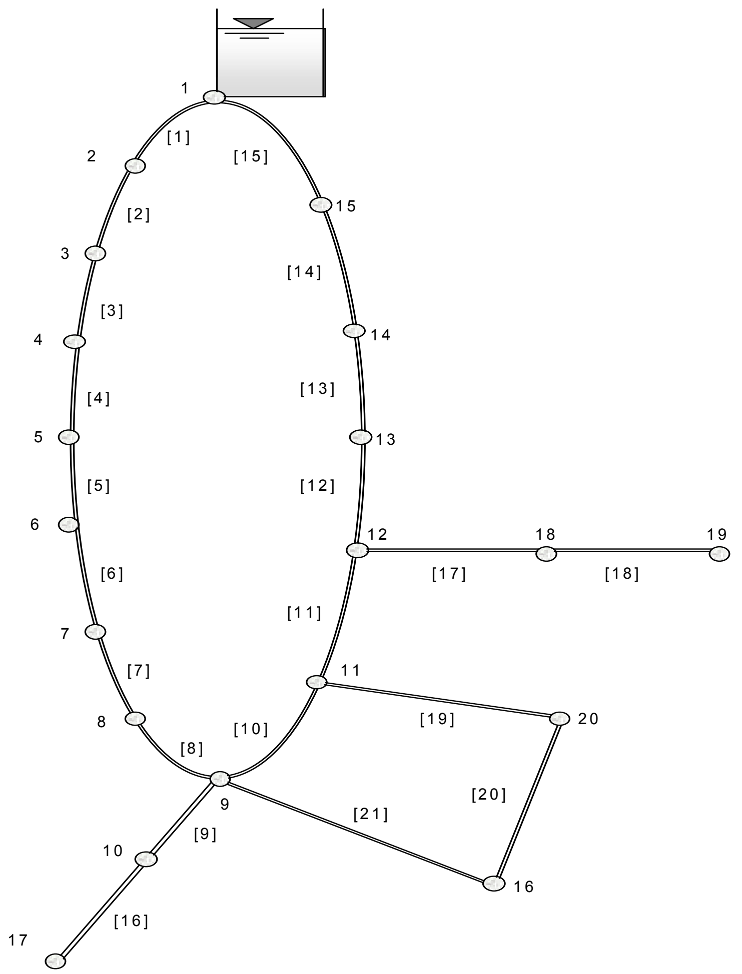

Figure 1 The network layout of the New York Tunnels problem

Figure 2

Journal of Water Resources Planning and Management. Submitted June 4, 2012; March 8, 2013; posted ahead of print March 11, 2013. doi:10.1061/(ASCE)WR.1943-5452.0000367

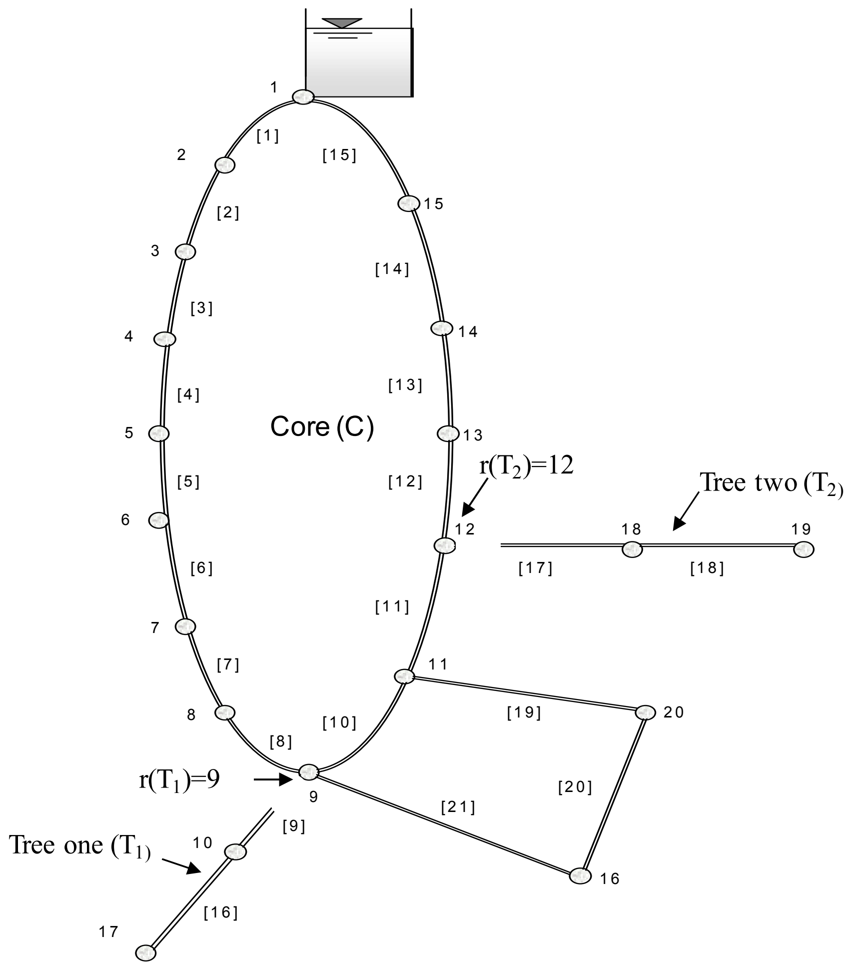

Figure 2 The decomposition results of the New York Tunnels problem

Figure 3

Journal of Water Resources Planning and Management. Submitted June 4, 2012; March 8, 2013; posted ahead of print March 11, 2013. doi:10.1061/(ASCE)WR.1943-5452.0000367

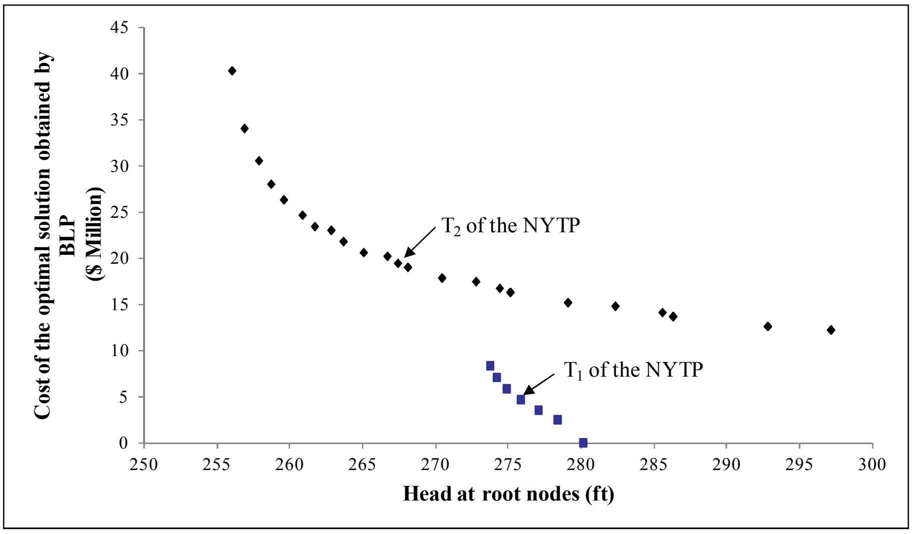

Figure 3 The H_R^* versus the optimal costs in the solution choice tables of two trees for the NYTP case study

Figure 4

Journal of Water Resources Planning and Management. Submitted June 4, 2012; March 8, 2013; posted ahead of print March 11, 2013. doi:10.1061/(ASCE)WR.1943-5452.0000367

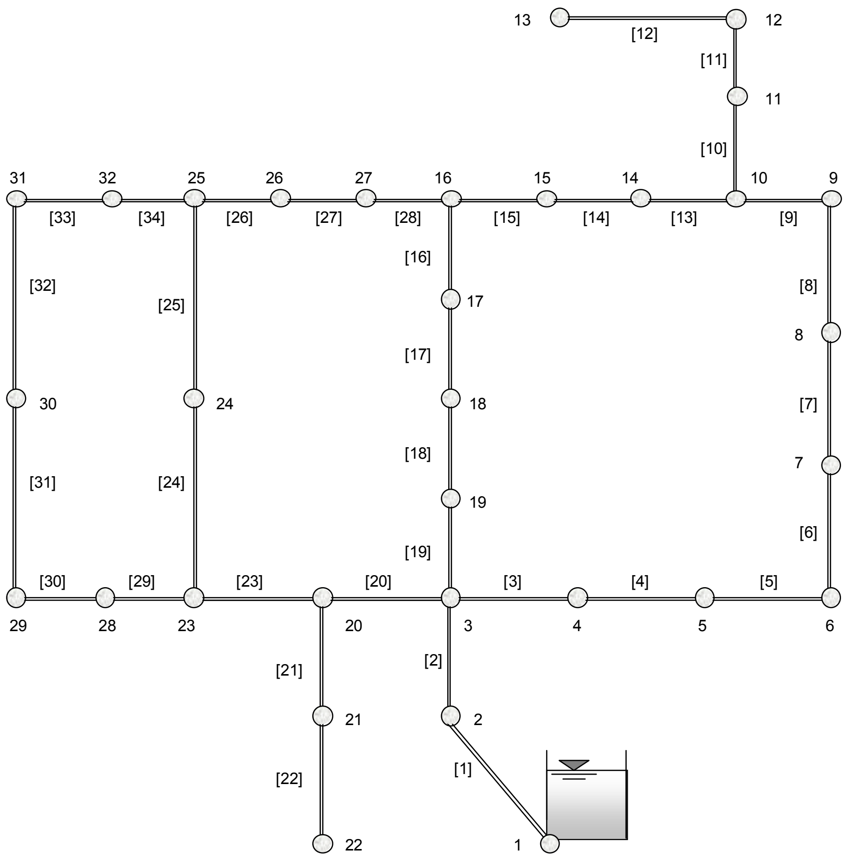

Figure 4 The network layout of the HP case study

Figure 5

Journal of Water Resources Planning and Management. Submitted June 4, 2012; March 8, 2013; posted ahead of print March 11, 2013. doi:10.1061/(ASCE)WR.1943-5452.0000367

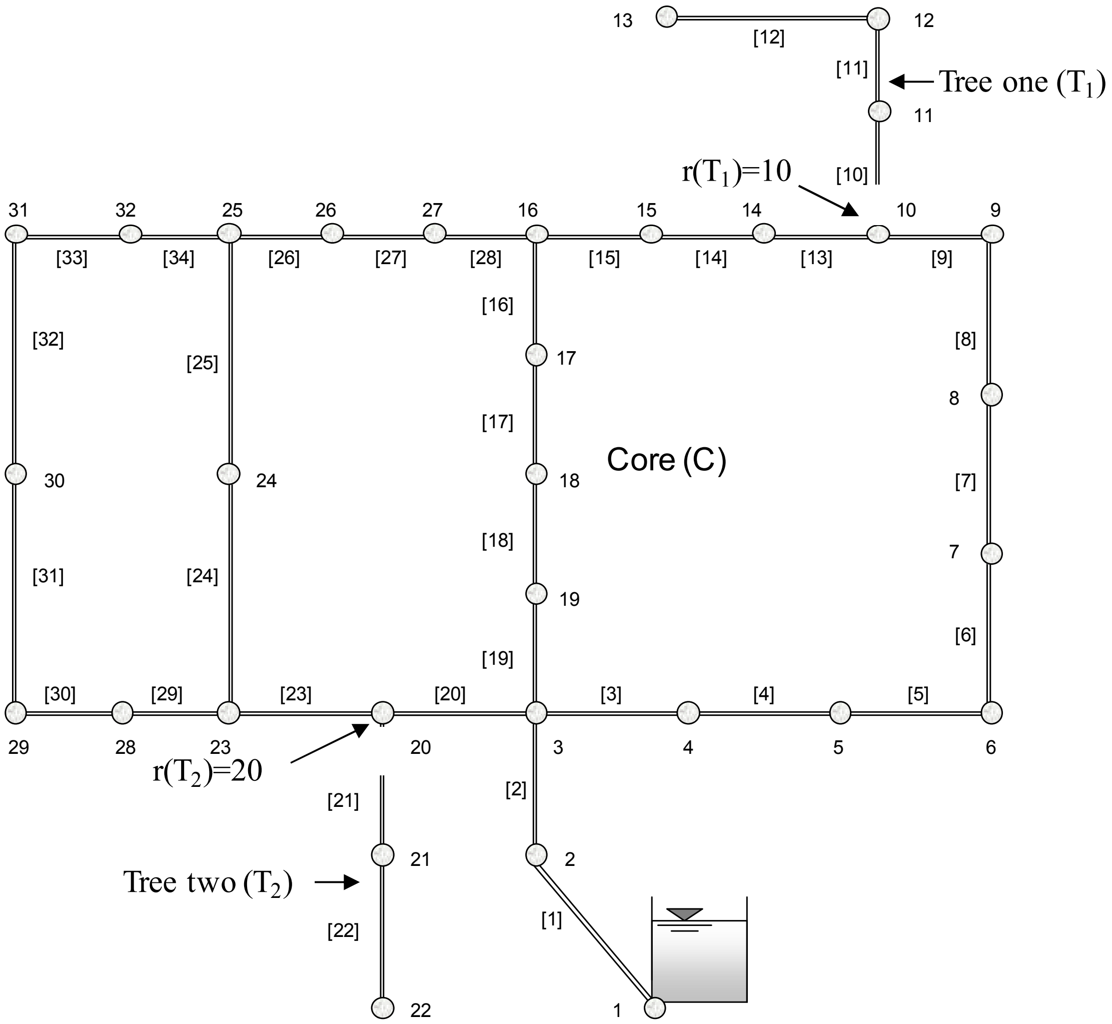

Figure 5 The decomposition results of the HP case study

Figure 6

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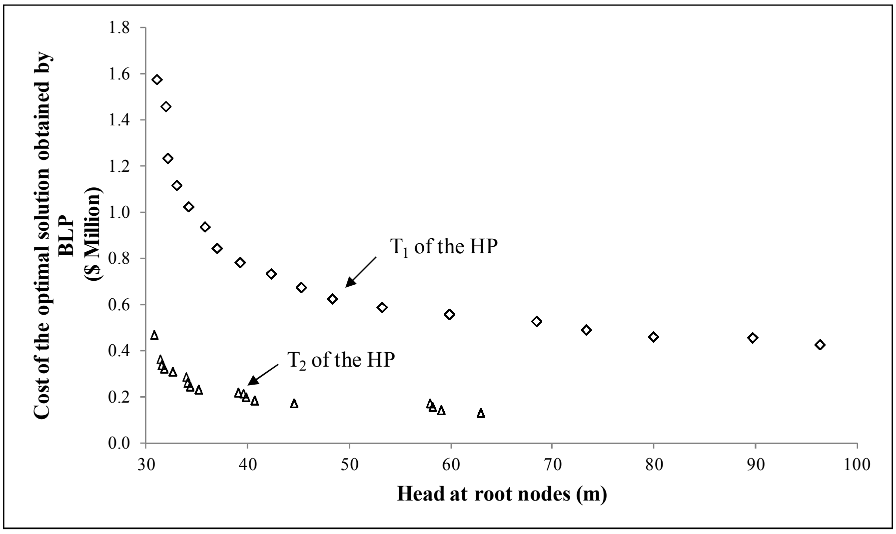

Figure 6 The H_R^* versus the optimal costs in the solution choice tables of two trees for the HP case study

Figure 7

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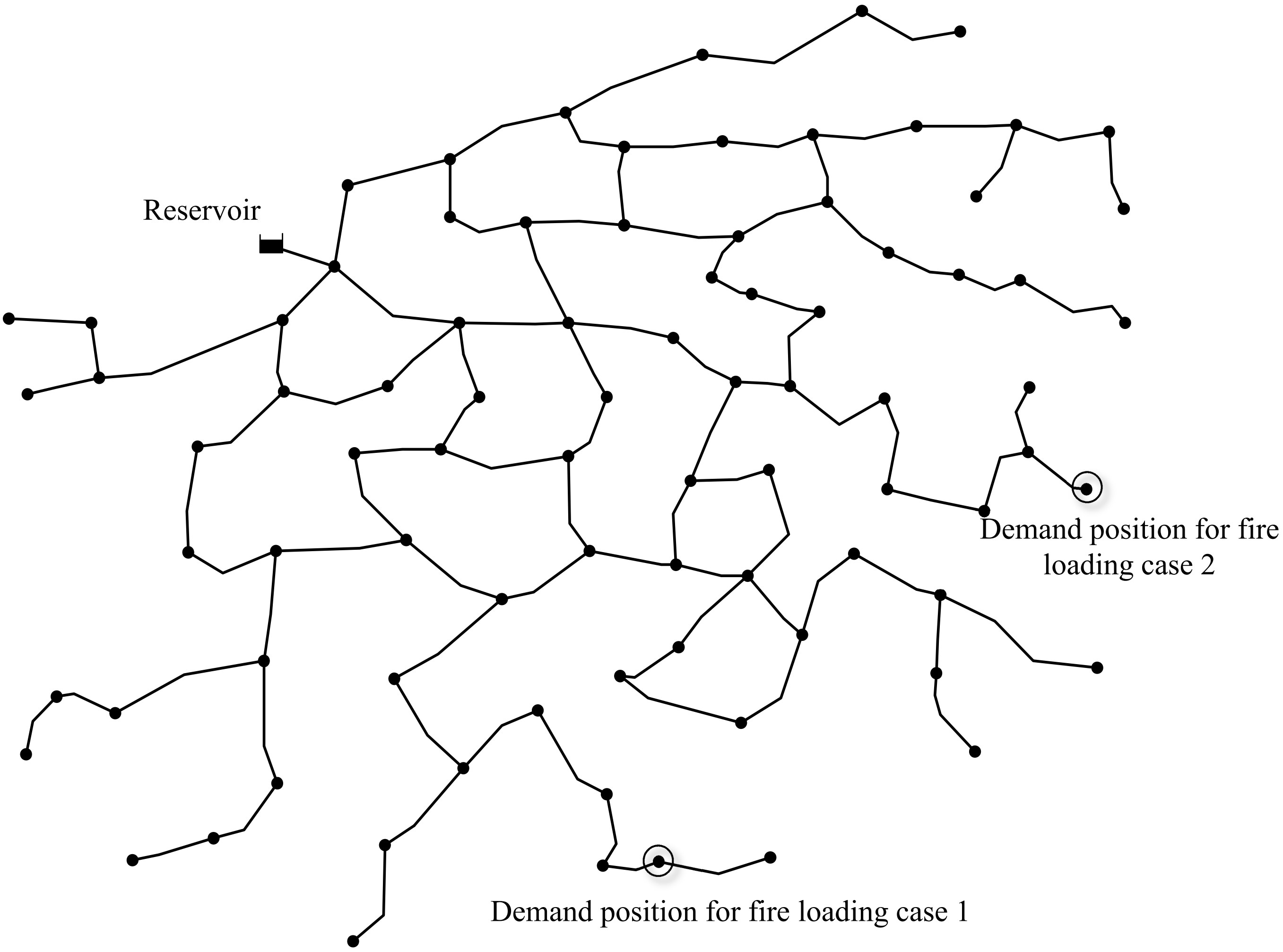

Figure 7 The network layout of the RN case study

Figure 8

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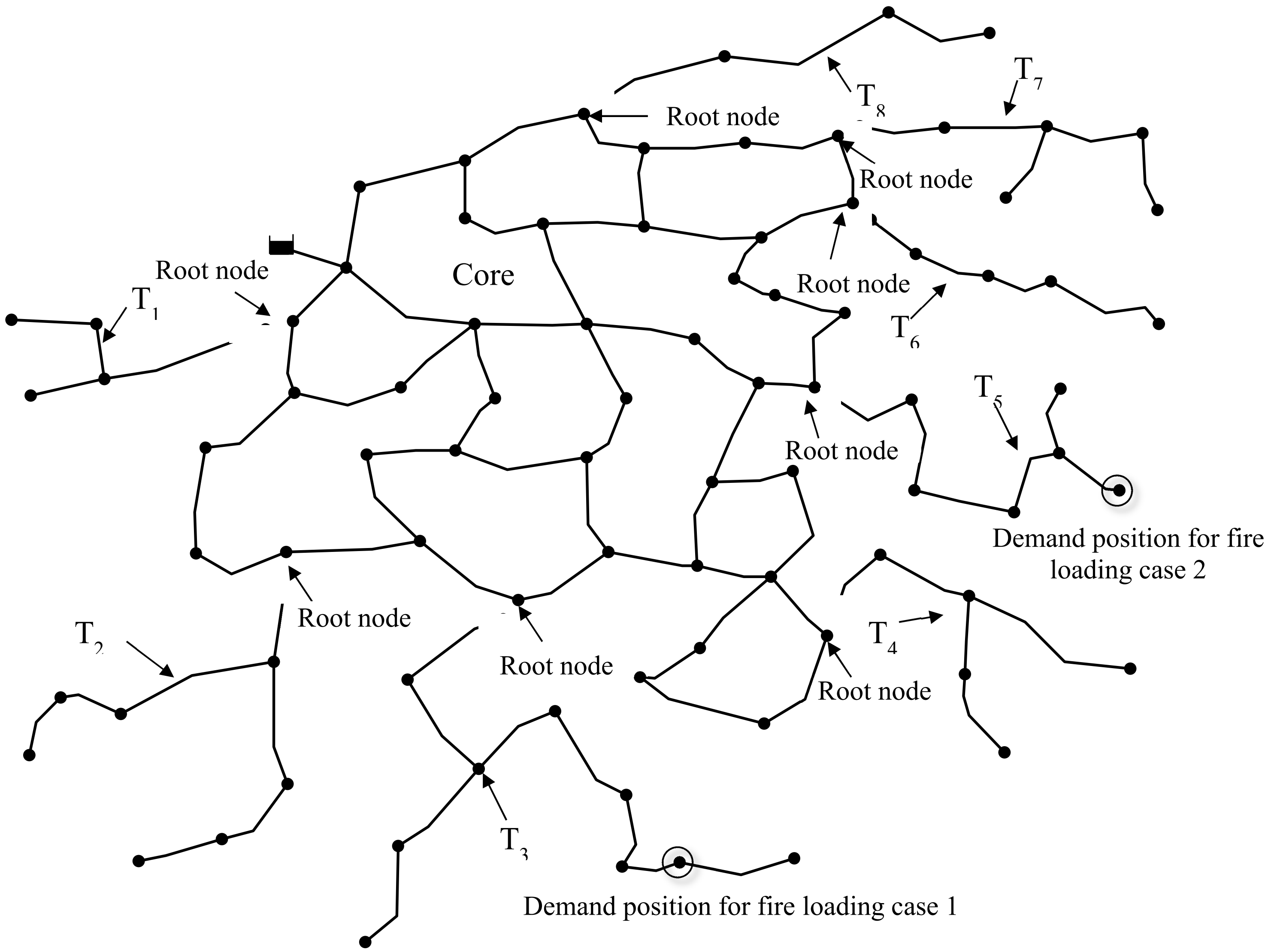

Figure 8 The decomposition results of the RN case study

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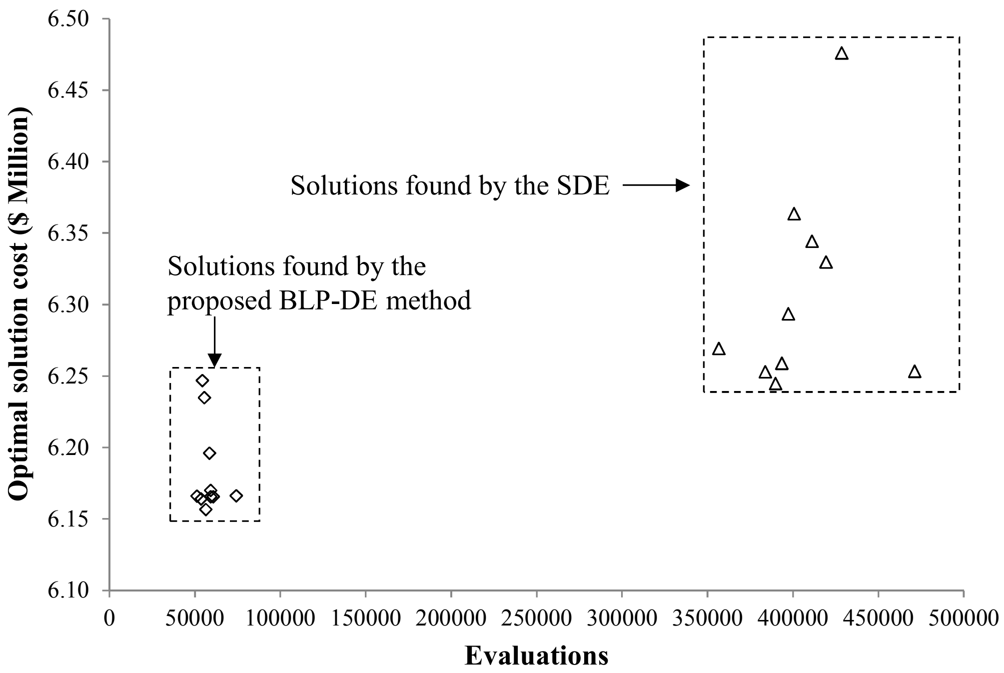

Figure 9 Solution distributions of two algorithms applied to the RN case study (10 runs for each)

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Table 1 Optimal solutions for T_1 of the NYTP

H_R at $R(T_1)$ (ft)	Cost of Optimal solutions from BLP ($)	Duplicate pipe diameters[1] (inches)	Minimum pressure head excess (H_e) (ft)[1]	$H_R^* = H_R - H_e$ (ft)
272.8	Infeasible solution	-	-	-
273.8	8,337,060	(0, 96)	0.09	273.71
274.8	7,0648,50	(0, 84)	0.64	274.16
275.8	5,835,646	(0, 72)	0.96	274.84
276.8	4,654,834	(0, 60)	1.00	275.80
277.8	3,529,683	(0, 48)	0.77	277.03
278.8	2,470,653	(0, 36)	0.47	278.33
279.8	2,470,653	(0, 36)	1.47	278.33
280.8[2]	0	(0, 0)	0.71	280.09

[1]The first diameter is for link 9 and the second diameter is for link 16 in Figure 1. [2]The solution is zero in cost as no pipe needs to be duplicated when the H_R is greater than 280.8 ft and hence these solutions are not given in Table 1.

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Table 2 Summary of the results of the proposed method and other EAs applied to the NYTP case study

(1) Algorithm[10]	(2) No. of runs	(3) Best solution ($M)	(4) Percent of trials with best solution found	(5) Average cost ($M)	(6) Average evaluations to find first occurrence of the best solution	(7) Maximum allowable evaluations
BLP-DE[1]	100	38.64	100%	38.64	3,486[9]	7,500
NLP-DE[2]	100	38.64	99%	38.64	8,277	20,000
GHEST[3]	60	38.64	92%	38.64	11,464	-
HD-DDS[4]	50	38.64	86%	38.64	47,000	50,000
Suribabu DE[5]	300	38.64	71%	NA	5,492	10,000
Scatter Search[6]	100	38.64	65%	NA	57,583	-
MMAS[7]	20	38.64	60%	38.84	30,700	50,000
PSO variant[8]	2000	38.64	30%	38.83	-	80,000

[1]Results from this study. [2]Zheng et al. (2011b). [3]Bolognesi et al. (2010). [4]Tolson et al. (2009). [5]Suribabu (2010). [6]Lin et al. (2007). [7]Zecchin et al. (2007). [8]Montalvo et al. (2008). [9]The total computational overhead required by proposed BLP-DE method has been converted to the equivalent number of full NYTP evaluations. [10]Results are ranked based on column (4).

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Table 3 Summary of the results of the proposed BLP-DE method and other EAs applied to the HP case study

(1) Algorithm[11]	(2) No. of runs	(3) Best solution ($M)	(4) Percent of trials with best solution found	(5) Average cost ($M)	(6) Average evaluations to find first occurrence of the best solution	(7) Maximum allowable evaluations
BLP-DE[1]	100	6.081	98%	6.085	33,148[10]	40,000
NLP-DE[2]	100	6.081	97%	6.082	34,609	80,000
Suribabu DE[3]	300	6.081	80%	NA	48,724	100,000
Scatter Search[4]	100	6.081	64%	NA	43,149	-
GHEST[5]	60	6.081	38%	6.175	50,134	-
GENOME[6]	10	6.081	10%	6.248	NA	150,000
HD-DDS[7]	50	6.081	8%	6.252	100,000	100,000
PSO variant[8]	2000	6.081	5%	6.310	NA	500,000
MMAS[9]	20	6.134	0%	6.386	85,600	100,000

[1]Results from this study. [2]Zheng et al. (2011b). [3]Suribabu (2010). [4]Lin et al. (2007). [5]Bolognesi et al. (2010). [6]Reca and Martínez (2006). [7]Tolson et al. (2009). [8]Montalvo et al. (2008). [9]Zecchin et al. (2007). [10]The total computational overhead required by proposed BLP-DE method has been converted to the equivalent number of full HP evaluations. [11]Results are ranked based on column (4).

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Table 4 Summary of the results of the proposed BLP-DE method and the SDE applied to the RN case study

Algorithm	No. of runs	Best solution ($M)	Percent of trials with best solution found	Average cost ($M)	Average evaluations to find first occurrence of the best solution	Maximum allowable evaluations	Total execution time (hours) for 10 runs to find optimal solutions on Matlab 7.5[3]
BLP-DE[1]	10	6.16	10	6.18	73,092[2]	75,000	2.2
SDE[1]	10	6.24	0	6.31	405,330	600,000	12.4

[1]Results from this study. [2]The total computational overhead required by proposed BLP-DE method has been converted to the equivalent number of full RN evaluations. [3]The computer configuration is a 3.0 GHz Pentium PC (Inter R).