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A Simulation-Optimization Model For Optimal Estimation Of The Locations And Chlorine Injection Rates Of The Booster Stations In Water Distribution Networks

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A SIMULATION-OPTIMIZATION MODEL FOR OPTIMAL ESTIMATION OF THE LOCATIONS AND CHLORINE INJECTION RATES OF THE BOOSTER STATIONS IN WATER DISTRIBUTION NETWORKS

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ABSTRACT

The main objective of this study is to present a simulation-optimization model to determine the locations and disinfectant injection dosages of the booster stations for maintaining the disinfectant residual limits in drinking water distribution networks. The proposed model accomplishes this task by utilizing the global exploration feature of the Differential Evolution (DE) optimization algorithm. The objective of the DE based optimization model is to maximize an aggregated objective function value which includes two conflicting objectives. While the first objective aims to maximize the percentage of water within the specified residual limits, the second one deals with the minimization of the chlorine injection rates from the identified booster stations. The applicability of the proposed model is evaluated on an existing water distribution network by comparing the trade-off between booster station numbers and their corresponding water quality improvements. Identified results indicate that the proposed model is an effective way for determining the locations and chlorine injection rates of the booster stations.

INTRODUCTION

Disinfection of the water in distribution networks is usually achieved by means of the chlorine injection at the outlet of the treatment plants. However, such an injection process may not be sufficient to maintain the free chlorine residuals within the specified minimum and maximum limits since chlorine decays in space and time. To address this problem, booster disinfection stations are usually used for chlorine injection. Therefore, estimation of the locations and injection rates of the booster stations becomes a challenging optimization problem.

There exists a large body of literature regarding the solution of booster station optimization problems. Among these studies, Bocelli *et al.* [1] formulated the problem of booster chlorination scheduling as a linear programming (LP) problem. In their problem the objective was to minimize the chlorine injection rates from the pre-defined booster stations by maintaining the chlorine residuals limits. They also demonstrated that chlorine concentrations at consumer points are the linear functions of the chlorine injection rates in case of the first-order bulk and wall reaction kinetics. Using this feature, chlorine residuals for a given consumer point and time can be calculated based on a response matrix (RM) approach. As an extension of Bocelli *et al.* [1], Tryby *et al.* [2] determined the both locations and chlorine injection rates of the booster stations by formulating a mixed integer LP (MILP) problem. Propato and Uber [3] formulated the same problem by using a linear least-square (LLS) formulation and solved through quadratic programming (QP). As an extension, Propato and Uber [4] modified the LLS formulation and determined the booster locations by solving the related optimization problem using a mixed-integer QP (MIQP). Note that all the studies given above were performed by considering the deterministic solution approaches. Although these approaches are very effective on finding the global optimum solutions, their efficiency is usually weak in case of the non-first-order bulk and wall reaction kinetics. For such cases, use of the heuristic optimization approaches is usually preferred due to their strong global exploration capabilities. There are several applications of heuristic approaches for solving the booster station optimization problems. If these applications are examined in detail, it is seen that most of the applications considered the genetic algorithm (GA) as the optimization approach [5-10]. Although several different heuristic approaches including immune algorithm (IA) [11], ant colony optimization (ACO) [12], particle swarm optimization (PSO) [13], etc. were also applied to the solution of booster station optimization problems, to the best of our knowledge, there is no application of the differential evolution (DE) algorithm in this field.

The main objective of this study is to propose a linked simulation-optimization model to determine the locations and the chlorine injection dosages of the booster chlorination stations. The proposed model simulates the water quality process of a given network by utilizing the RM approach proposed by Bocelli *et al.* [1]. This RM based simulation model is then linked to an optimization model where heuristic DE optimization algorithm is used. The performance of the proposed simulation-optimization model is evaluated on an existing water distribution network by comparing the trade-off between booster station numbers and water quality improvements. Identified results indicated that the proposed model not only determines the optimum booster configuration, but also provides better results than those obtained by different solution approach in literature.

PROBLEM FORMULATION

The problem of booster station optimization in water distribution networks is formulated as an optimization model. The main objective of this model is to determine the locations and chlorine injection dosages of the booster stations by maintaining the residual limits and obtaining more uniform chlorine distributions throughout the network. This problem can be defined as follows:

Let n_m be the number of consumer points where chlorine residuals are monitored, n_h be the number of monitoring time steps, t be the monitoring starting time, V_j^m be the volumetric water demand within the specified residual limits at node j in monitoring period m, V be the total volume of demand over a hydraulic cycle, Q_j^m be the demand at node j in monitoring period m, Δt be the length of the monitoring time step, c_j^m be the chlorine residual at monitoring node j and time m, $c_j^{\min}$ and $c_j^{\max}$ be the lower and upper limits of the chlorine residuals at monitoring node j, n_b be the number of booster stations, n_k be the number of chlorine injection time steps, u_i^k be the injected chlorine dosage [ML^{-3}] from booster station i at injection period k, and $\tilde{Q}_i$ be the total outflow [L^3T^{-1}] at node i. Using these definitions, the optimization problem can be formulated as follows:

$$z = \max\left(\omega_1 f_1 - \omega_2 f_2\right) \tag{1}$$

$$f_1 = \frac{\sum_{m=t}^{t+n_h-1}\sum_{j=1}^{n_m} V_j^m}{V} \times 100 \tag{2}$$

$$V_j^m = \begin{cases} Q_j^m \Delta t_h & \text{if } \; c_j^{\min} \le c_j^m \le c_j^{\max} \\ 0 & \text{otherwise} \end{cases} \qquad j = 1, 2, 3, \cdots, n_m; \;\; m = t, \cdots, t + n_h - 1 \tag{3}$$

$$f_2 = \sum_{i=1}^{n_b}\sum_{k=1}^{n_k} u_i^k \tilde{Q}_i \tag{4}$$

where f_1 is the objective function which aims to maximize the percentage of water within the specified residual limits, f_2 is the objective function deals with the minimization of the chlorine injection rate, and ω_1 and ω_2 are the weighting coefficients which are used to adjust the importance of these two conflicting objectives. Since natures of the objectives f_1 and f_2 are different, several trial runs have been conducted to adjust their contribution to the final objective function value. According to the results of these trial runs, use of $\omega_1 = 1$ and $\omega_2 = 0.01$ is sufficient for solving the problem.

It should be noted that calculation of Eq. (1) requires of knowing the nodal chlorine residuals given in Eq. (3). Thus, it is necessary to calculate the values of c_j^m for the each cycle of optimization. In literature, this task is usually performed by modeling the given network on EPANET model and directly linking this model to the optimization approaches to calculate the c_j^m for the generated chlorination plan. Although this is a widely applicable approach, executing EPANET based simulation model may require long CPU times especially for the large networks and/or long simulation times. Therefore, the RM approach proposed by Bocelli *et al.* [1] is considered for calculating the chlorine residuals. According to Bocelli *et al.* [1], value of c_j^m at node *j* and time period *m* can be calculated as follows:

$$c_j^m = \sum_{i=1}^{n_b}\sum_{k=1}^{n_k} \alpha_{ij}^{km} u_i^k \qquad j = 1, 2, 3, \cdots, n_m; \;\; m = t, \cdots, t + n_h - 1 \tag{5}$$

where α_{ij}^{km} represents the composite response coefficient which is calculated by using $\alpha_{ij}^{km} = \partial c_j^m / \partial u_i^k$. Note that values of α_{ij}^{km} are calculated based on the results of EPANET model which is executed for the unit chlorine injections from the booster locations.

OPTIMIZATION MODEL

The problem of booster station optimization is solved by using a DE based optimization model. DE, proposed by Storn and Price [14], is a population-based heuristic optimization algorithm. Like other heuristic algorithms, DE can solve the optimization problems with non-differentiable, non-continuous or noisy solution spaces. It can consider either continuous or discrete decision variables and usually finds global optimum or near global optimum solutions no matter where the solution starts. Note that DE and GA have similar operation and calculation structures that both of them use crossover, mutation, and selection operations for evolving the given population. Although these similarities, they have some differences that while DE can solve the optimization problems only using the real coded decision variables, GA can consider both real and binary coded ones. Furthermore, all the candidate solutions in DE are subjected to genetic evolution while same process is based on the some probabilities in GA. The basic computational steps of DE can be described as follows [15]:

- Randomly initialize all agents $\mathbf{x}$ (e.g. candidate solutions) in the population (*NP* being the population number).
- Repeat the following until a termination criterion is met:
  - For each agent $\mathbf{x}$ in the population do:
    - Randomly select three distinct solutions $\mathbf{a}$, $\mathbf{b}$, and $\mathbf{c}$ from the population
    - Pick a random index $R \in \{1,2,3,\cdots,n\}$ (n being the dimension of the problem).
    - Compute the agent's potentially new position $\mathbf{y} = [y_1, y_2, y_3, \cdots y_n]$ as follows:
      - For each *i*, pick a uniformly distributed random number $r_i = U(0,1)$
      - If $r_i < CR$ ($CR \in [0,1]$ is the crossover rate) or $i = R$ then set $y_i = a_i + F(b_i - c_i)$ ($F \in [0,2]$ is the differential weight) otherwise set $y_i = x_i$
      - In essence, the new position is outcome of binary crossover of agent $\mathbf{x}$ with intermediate agent $\mathbf{z} = \mathbf{a} + F(\mathbf{b} - \mathbf{c})$
    - If $f(\mathbf{y}) < f(\mathbf{x})$ then replace the agent in the population with the improved candidate solution, that is, replace $\mathbf{x}$ with $\mathbf{y}$ in the population.
- Pick the agent from the population that has the highest fitness or lowest cost and return it as the best found candidate solution.

NUMERICAL APPLICATION

The applicability of the proposed simulation-optimization model is evaluated on an existing water distribution network of the Cherry Hill-Brushy Plains of the South Central Connecticut Regional Water Authority. The layout of the network is given in Fig. 1. The network includes a pumping station and tank at the 1st and 26th junctions, respectively. There are 34 consumer nodes in the network and these nodes are connected to each other using 47 links with a total length of 11.26 km. Fig. 1 also shows 6 hypothetical nodes (Junctions A to F) which were considered as the potential booster locations in the previously published studies [1, 3-5, 8, 16-17]. Pumping station pumps water to the consumer nodes in the first and the third 6 hour time periods of a day and for the remaining times the consumer nodes are fed from the storage tank.

As indicated in the previous section, the nodal chlorine residuals in the consumer nodes are determined through RM approach. In order to use this approach, composite response coefficients of α_{ij}^{km} should be determined before executing the optimization model. With this purpose, a number of EPANET runs are conducted for the unit chlorine injections from the potential booster locations. Since there are 42 potential booster locations (e.g. 34 for consumer nodes + 1 for storage tank + 1 for pumping station + 6 for hypothetical nodes A to F) and 1 chlorine injection time period $(\text{e.g. } n_k = 1)$, the EPANET model is executed 42 times to determine the response coefficients. For these solutions, a simulation time of 288 hours is considered and the resulting concentrations in the last 24 hours are selected to calculate the response coefficients. Note that EPANET model is executed by taking the bulk and wall reaction coefficients as 0.50 d^{-1} and 0, respectively.

After building the RM for the considered network, the proposed model is executed for different number of booster stations. For these solutions, lower and upper residual limits are selected as $c_j^{\min} = 0.20$ mg/L and $c_j^{\max} = 4.00$ mg/L $(j = 1, 2, 3, \cdots, 34)$. The related DE solution parameters are selected as $NP = 20$, $F = 0.80$, and $CR = 0.80$ and search process is terminated after 10,000 generations. Fig. 2 shows the convergence plots in terms of the total chlorine injection rates for the solutions with 1 to 6 booster stations. As can be seen, when the number of booster stations increases, the final values of the chlorine injection rates decreases, which is an expected behavior. For different booster station numbers, Table 1 compares the model results with those obtained by the results of Propato and Uber [4] in terms of the identified booster locations and their corresponding chlorine dosages. Note that Propato and Uber [4] considered the locations of the booster stations as integer decision variables and solved the optimization problem through a branch-and-bound solution approach together with a MIQP based optimization model.

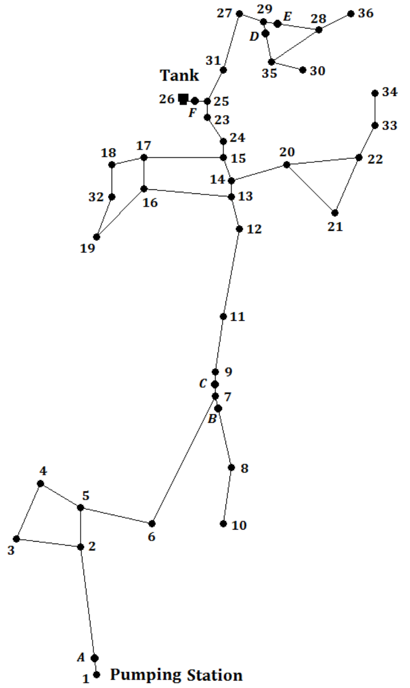

Figure 1. Layout of the Cherry Hill-Brushy Plains network

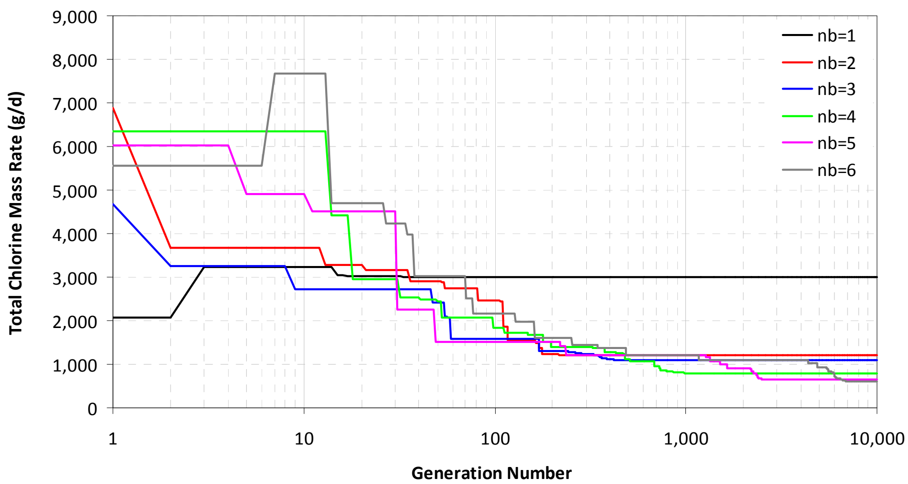

Figure 2. The final convergence plots in terms of the chlorine injection rates (g/day)

Table 1. Comparison of the locations and the injected chlorine concentrations of the identified booster stations

n_b	Injected Chlorine Dosages (mg/L) < Locations of the Identified Booster Stations >											
	Propato and Uber (2004b)						Present Study					
1	1.835 < A >	-	-	-	-	-	1.780 < 2 >	-	-	-	-	-
2	0.531	0.358	-	-	-	-	0.517	0.349	-	-	-	-

	< 1 >	< 26 >					< 2 >	< 26 >				
3	0.489 < 1 >	0.727 < 26 >	0.408 < 29 >	-	-	-	0.433 < 2 >	0.372 < 26 >	0.054 < 29 >	-	-	-
4	0.360 < 1 >	0.703 < 26 >	0.430 < 29 >	0.436 < 33 >	-	-	0.351 < 2 >	0.209 < 26 >	0.143 < 29 >	0.077 < 33 >	-	-
5	0.360 < 1 >	0.709 < 26 >	0.434 < 33 >	0.432 < 35 >	0.682 < E >	-	0.284 < 2 >	0.052 < 8 >	0.220 < 22 >	0.160 < 26 >	0.197 < 29 >	-
6	0.299 < 1 >	0.066 < 8 >	0.191 < 26 >	0.119 < 33 >	0.118 < 35 >	0.187 < E >	0.256 < 2 >	0.066 < 8 >	0.661 < 22 >	0.163 < 26 >	0.207 < 29 >	0.019 < 32 >

As can be seen from the model results given in Table 1, for $n_b = 1$, the booster station is located to the junction A in MIQP model whereas located to the 2nd junction in the proposed model. This result does not produce an important difference in the chlorine distributions in the network since the 2nd junction is located just downstream of the junction A. For $n_b = 2$, both the proposed model and MIQP model found the same locations (e.g. storage tank at the 26th junction) for the second booster station. For the other solutions, the proposed model determined the same or very close locations with those obtained by MIQP model. When the injected chlorine dosages are compared, it can be seen that there are some differences in the calculated values. However, these differences are not significant for the most cases.

For different station numbers, comparison of the identified results in terms of the final chlorine injection rates and the water quality responses are given in Table 2. As can be seen, for each solution the final chlorine injection rates by the proposed model are lower than those obtained by MIQP model by Propato and Uber [4]. When the water quality responses of two studies are compared, it can be seen that both proposed and MIQP models found the minimum chlorine residuals of 0.20 mg/L for all the solutions. On the other hand, maximum chlorine residual values obtained by the proposed model are greater than the ones obtained using the MIQP method. But, these differences are not significant and the maximum chlorine residuals are still in the range of permissible residual limits. For each solution, average chlorine residuals at all the consumer nodes are given in Fig. 3. It is clearly seen that although average residual values are in the range of 0.20 to 4.00 mg/L for all the solutions, more uniform residual distributions are obtained especially for higher booster station numbers.

Table 2. Comparison of the calculated chlorine injection rates and the water quality responses for each solution

n_b	**Propato and Uber (2004b)**				**Present Study**			
	Chlorine Residuals (mg/L)			**Chlorine Injection Rates (g/day)**	**Chlorine Residuals (mg/L)**			**Chlorine Injection Rates (g/day)**
	Mean	**Minimum**	**Maximum**		**Mean**	**Minimum**	**Maximum**	
1	1.06	0.20	3.29	3,116	1.07	0.20	3.52	3,010
2	0.45	0.20	0.55	1,260	0.45	0.20	1.02	1,213
3	0.42	0.20	0.63	1,155	0.41	0.20	0.86	1,094
4	0.31	0.20	0.46	835	0.31	0.20	0.69	799
5	0.31	0.20	0.38	830	0.27	0.20	0.56	645
6	0.27	0.20	0.32	703	0.29	0.20	0.89	614

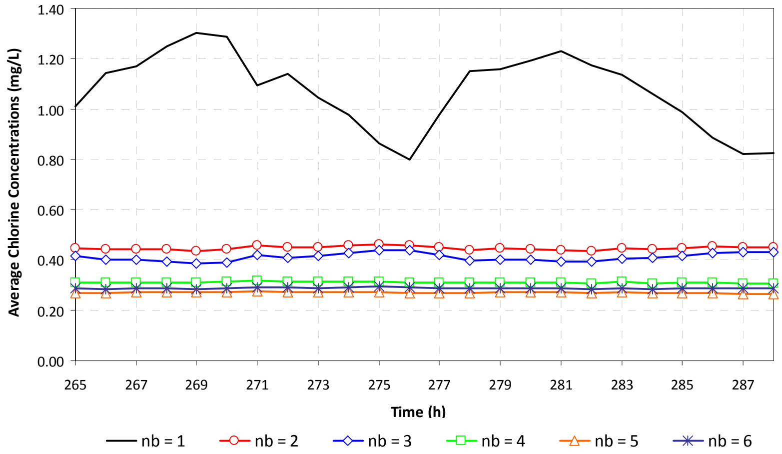

Figure 3. Average chlorine residuals at all consumer nodes

CONCLUSIONS

In this study, a simulation-optimization model is proposed for solving the booster station optimization problems in water distribution networks. The proposed model simulates the water quality process in the network by utilizing the RM approach. This RM based simulation model is then integrated to an optimization model where DE optimization algorithm is used. The main objective of the DE based optimization model is to determine the locations as well as the chlorine injection dosages of the booster stations by maintaining the chlorine residual limits for all the consumer nodes and measurement times. This task is achieved by maximizing an objective function including two different objectives. The performance of the proposed model is evaluated on an existing water distribution network for different booster station numbers. Identified results indicated the proposed model does not only efficiently determine the locations and chlorine injection dosages of the booster stations, but also provides slightly better results than those obtained by using a different solution approach given in literature.

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