CHAPTER 5
WATER DISTRIBUTION SYSTEM OPERATION: APPLICATION OF SIMULATED ANNEALING

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5.1 INTRODUCTION

The operation of water distribution systems affects the water quality in these systems. EPA regulations require that water quality be maintained at all points in the system including the point of delivery. Methods to optimize water system operations have been restricted to reducing costs related to pumping and costs related to sizing, construction, and/or maintenance of piping while meeting customer demands, pressure limits, and tank operation restrictions. There have been few attempts to optimize water system operations for both hydraulic and water quality performance and they have been restricted to simplified systems.

A new methodology that formulates the water distribution system problem as a discrete time optimal control problem was developed that linked the method of simulated annealing with EPANET for optimal operation of water distribution systems for both water quality and hydraulic performance. Most optimization techniques require the calculation of derivatives, response functions, or other methods that are limited to specific problems. Simulated annealing allows optimization for a variety of objective functions and can consider many modifications to operational conditions without reprogramming of the optimization procedure. The new methodology was applied to two water systems as examples. The northwest pressure zone in the Austin, Texas application considered pump operation to minimize energy costs, which allowed comparison to published nonlinear optimization methods. The second system was the North Marin Water District, Novato, California system, which considered optimal pump operation for minimizing power costs while meeting hydraulic and water quality constraints. A comparison is made between using a gradient-based method and simulated annealing.

Until 1974, government regulators and water system operators concentrated their efforts on meeting water quality Maximum Contaminant Levels (MCLs) at the water source or water treatment plant. However, with the implementation of the Safe Water Drinking Act in 1974 and amendments in 1986 and 1996, water system operators are being required to meet standards throughout their distribution systems and at the points of delivery. The Surface Water Drinking Rule requires that a detectable level of chlorine be maintained in the system. The Total Coliform Rule requires that total coliform standards be met at the customer's tap. The Lead and Copper rule requires testing at the point of delivery (Clark, 1994b; Clark et al., 1994, 1995; Pontius, 1996).

Water quality can undergo significant changes as it travels through the water distribution system from the point of supply and/or treatment to the point of delivery. For example, chlorine concentration will decrease with time in pipes and tanks through bulk decay and through reaction with the pipe wall. Also, chlorine mass leaves the system at demand nodes or can be added to the system at chlorine booster nodes. Mixing of water from different sources can also affect water quality (Clark et al., 1995).

Pumps are usually operated according to an operating policy, which includes the scheduling of pump operation, which can affect water quality if the system pumps draw water from sources with differing water quality. Pump operation will affect the turnover rate of storage tanks. Chlorine dosage may differ at each pump depending on the water source quality. For example, consider a pump that operates for 6 h divided into 1-h periods. The pump can either be on or off for any period. The number of combinations is $2^6 = 64$. A pump, which operates for 24 h divided into 1-h periods, has $2^{24} = 16{,}777{,}216$ combinations. The 6-h example can be solved by trial and error but the 24-h example is prohibitively large to solve by trial and error. For large combinatorial optimization problems, simulated annealing provides a manageable solution strategy.

These considerations have generated a need for computer models and optimization techniques that consider water quality in the water distribution system as well as system hydraulics.

5.2 GENERAL PROBLEM STATEMENT

Consider a water distribution system with M pipes, K junction nodes, S storage nodes (tanks or reservoirs), and P pumps, which are operated for T time periods. The objective function is the minimization of the total energy cost for pumping:

$$\text{Minimize } Z = \sum_{p=1}^{P} \sum_{t=1}^{T} \frac{\text{UC}_t \, 0.746 \, \text{PP}_{pt}}{\text{EFF}_{pt}} D_{pt} \tag{5.1}$$

where UC_t = unit energy cost of pumping during time period t (\$/kw-hr)
PP_{pt} = power of pump during time period t (hp)
D_{pt} = length of time pump p operates during time period t (hr)
EFF_{pt} = efficiency of pump p during period t.

Conservation of mass and conservation of energy conditions must be met throughout the water distribution system. These conditions make up the system hydraulic constraints. For each link (which can be a pipe or pump) between nodes i and j and node k, the conservation of mass is

$$\sum_i (q_{ik})_t - \sum_j (q_{kj})_t - Q_{kt} = 0 \quad \forall i, j \in M; \qquad k = 1,\ldots,K \quad \text{and} \quad t = 1,\ldots,T \tag{5.2}$$

where q_{ik} = flow in link connecting nodes i and k during time period t and Q_{kt} = flow consumed (+) or supplied (−) at node k during time period t. The conservation of energy for each pipe connecting nodes i and j, in the set of all pipes M is:

$$h_{it} - h_{jt} = f\left(q_{ij}\right)_t \qquad \forall i, j \in M \quad \text{and} \quad t = 1,\ldots,T \tag{5.3}$$

where h_{it} = hydraulic grade line elevation (ground elevation and pressure head) at node i during time t and $f(q_{ij})_t$ = headloss in link connecting nodes i and j during time t. The total number of hydraulic constraints is $(K + M)T$, and the total number of unknowns is also $(K + M)T$, which are the discharges in M pipes and the hydraulic grade line elevations at K nodes.

In addition to the equality hydraulic constraints there are inequality hydraulic bound constraints. The nodal pressure head bounds are

$$\underline{H}_{kt} \le H_{kt} \le \overline{H}_{kt} \qquad k = 1,\ldots,K \quad \text{and} \quad t = 1,\ldots,T \tag{5.4}$$

where H_{kt} and H_{kt} are, respectively, the lower and upper bounds on the pressure head at node k at time t.

The pump operation problem is an extended period simulation. The height of water stored at a tank for the current time period t, y_{st}, is a function of the height of water stored from the previous time period and the flow entering or leaving the tank during the period Δt and can be expressed as

$$y_{st} \le y_{s(t-1)} + \frac{q_{s(t-1)}}{A_s} \Delta t \tag{5.5}$$

where A_s = cross sectional area of tank s and q_s = flow entering or leaving the tank during periods t and $t - 1$. The inequality bound constraints on the height of water in the storage tanks are

$$\underline{y}_{st} \le y_{st} \le \overline{y}_{st} \qquad s = 1,\ldots,S \quad \text{and} \quad t = 1,\ldots,T \tag{5.6}$$

where $\underline{y}_{st}$ and $\overline{y}_{st}$ are, respectively, the lower and upper bound tank water levels.

The water quality constraint is the conservation of mass of the chemical in each pipe m connecting nodes i and j in the set of all pipes M and is

$$\frac{\partial(C_{ij})_t}{\partial t} = -\frac{(q_{ij})_t}{A_{ij}}\frac{\partial(C_{ij})_j}{\partial x_{ij}} + \theta(C_{ij})_t \qquad \forall i, j \in M \quad \text{and} \quad t = 1,\ldots,T \tag{5.7}$$

where $(C_{ij})_t$ = concentration of chemical in pipe m connecting nodes i and j as a function of distance and time (mass/ft^3)
x_{ij} = distance along pipe (ft)
A_{ij} = cross-sectional area of pipe connecting nodes i and j
$\theta(C_{ij})_t$ = rate of reaction of chemical within pipe connecting nodes i and j at time t (mass/ft^3/day).

The bounds on chemical concentrations are

$$\underline{C}_{nt} \le C_{nt} \le \overline{C}_{nt} \qquad n = 1,\ldots,N \quad \text{and} \quad t = 1,\ldots,T \tag{5.8}$$

where $\underline{C}_{nt}$ and $\overline{C}_{nt}$ are, respectively, the lower and upper bounds of the chemical concentration.

The above formulation results in a large-scale nonlinear programming problem with decision variables $(q_{ij})_t$, H_{kt}, y_{st}, D_{pt}, and $(C_{ij})_t$. In the proposed solution methodology, the decision variables are partitioned into two sets: control (independent) and state (dependent) variables. The operation of a pump during a time period (on or off) is the control variable. The problem is formulated above as a discrete-time optimal control problem.

5.3 SOLUTION METHODOLOGY

5.3.1 Previous Models for Water Distribution System Optimization

Ormsbee and Lansey (1994) reviewed methods used to optimize the operation of water supply pumping systems to minimize operation costs. Ostfeld and Shamir (1993) developed a water quality optimization model that optimized pumping costs and water quality using steady-state and dynamic conditions using GAMS/MINOS [general algebraic modeling system (Brooke et al., 1988); mathematical in-core nonlinear optimization systems (Murtagh and Saunders, 1982)]. Ormsbee (1991) suggested that on–off operation of pumps poses a difficulty for optimization techniques that require continuous functions. Computer-based water quality models exhibit the same difficulties. Most modeling methods include numerical methods rather than continuous functions. Linear superposition was used by Boccelli et al. (1998) for the optimal scheduling of booster disinfection stations by developing system-dependent discretized impulse response coefficients using EPANET and linking with the LP solver MINOS (Murtagh and Saunders, 1987).

Dynamic programming has been used for the optimal scheduling of pumps in a water distribution system by Coulbeck and Orr (1982) and Coulbeck et al. (1987). The method is sensitive to the number of reservoir states and the number of pumps. In general, the increase in number of discretizations and state variables increases the size of the problem dramatically, which is known as the curse of dimensionality (Mays and Tung, 1992). This has restricted the application of this method to small systems.

The nonlinear programming approach by Brion and Mays (1991) evaluates gradients using finite differences or a mathematical approach to provide derivatives required by GRG2, which solves nonlinear optimization problems by using the generalized reduced gradient method (Lasdon et al.,

1978). The method has been used for scheduling pump operations to minimize energy and improve water quality by Sakarya (1998) and Sakarya and Mays (2000), who considered three objective functions: (1) the minimization of the deviations of actual concentrations from a desired concentration, (2) minimization of total pump duration times, and (3) the minimization of total energy while meeting water quality constraints.

5.3.2 The Method of Simulated Annealing

Simulated annealing is a combinatorial optimization method that uses the Metropolis algorithm to evaluate the acceptability of alternate arrangements and slowly converge to an optimum solution. The method does not require derivatives and has the flexibility to consider many different objective functions and constraints. Simulated annealing uses concepts from statistical thermodynamics and applies them to combinatorial optimization problems. Kirkpatrick et al. (1983) explain how the Metropolis algorithm was developed to provide the simulation of a system of atoms at a high temperature that slowly cools to its ground energy state. If an atom is given a small random change there will be a change in system energy ΔE. If $\Delta E \leq 0$, the new configuration is accepted. If $\Delta E > 0$, then the decision to change the system configuration is treated probabilistically. The probability that the new system is accepted is calculated by:

$$P(\Delta E) = \exp(-\Delta E / k_B T) \tag{5.9}$$

A random number evenly distributed between 0 and 1 is chosen. If the number is smaller than $P(\Delta E)$ then the new configuration is accepted; otherwise it is discarded and the old configuration is used to generate the next arrangement. The Metropolis algorithm simulates the random movement of atoms in a water bath at temperature T. By using Eq. (5.9), the system becomes a Boltzmann distribution.

Entropy is a measure of the variation of energy at a given temperature. At higher temperatures there is significant energy variation, which reduces dramatically as the temperatures are lowered. This implies that the annealing process should not get "stuck" because transitions out of an energy state are always possible. Also, the process is a form of *adaptive divide-and-conquer.* Gross features of the eventual solution appear at the higher temperatures with fine details developing at low temperatures (Kirkpatrick et al., 1983).

The requirements for applying simulated annealing to an engineering problem are: (1) a concise representation of the configuration of the decision variables, (2) a scalar cost function, (3) a procedure for generating rearrangements of the system, (4) a control parameter (T) and an annealing schedule, and (5) a criterion for termination. (Dougherty and Marryott, 1991).

5.3.3 Configuration of Decision Variables

The decision variables consist of the operational schedule of each pump during discrete time periods. For this application, the 24-h day was divided into 1-h periods. The program finds the optimum pump schedule where each of the pumps is either on or off during each of the time periods. A configuration is a given schedule of pump operation, which determines in which 1-h period each pump is operating. EPANET is then run using that pump configuration. The program results are used to rate the performance of the simulation. The decision on whether to retain or change the pump operation configuration is based on the Metropolis algorithm as shown in Fig. 5.1, a pseudocode description of the adaptation of the simulated annealing algorithm to pump operation optimization.

5.3.4 Development of Cost Function

The cost function $g(C_i)$ for a given configuration C_i is used in place of energy of a system of atoms. The temperature T can be considered a control parameter, which has the same units as the cost function. The cost function should include the cost of pumping and penalties for violations of the storage tank

```
INITIALIZE;
T = T0;
C = Ck0;
g = g(Ck0);
DO WHILE (stopping criterion not satisfied);
  DO WHILE (equilibrium not satisfied);
    PERTURB:
    Ck+1 = rearrangement of Ck;
    Δg = g(Ck+1)−g(Ck);
    IF Δg ≤ 0 THEN
      ACCEPT
      C = Ck|1;
    ELSE
      IF random(0,1) < exp (−Δg/T)THEN
        ACCEPT:
        C = Ck+1;
      ENDIF
    ENDIF
  ENDDO
  T = α T
ENDDO
```

T = pseudotemperature
C_k = pump operation schedule configuration
g = cost of pump operation schedule configuration C_k including pseudocosts for constraint violations

FIGURE 5.1 Pseudocode description of the simulated annealing algorithm. [*After Dougherty and Marryott (1991)*).]

level, pressure, and water quality bounds. The pumping cost is calculated for each period for each pump running and is a function of the pump flow rate, head, efficiency, and electricity rate during that period. The cost of violations of the pressure and water quality bounds is calculated using penalty functions. By adjusting the penalty functions, the optimization problem can be adjusted to bias one constraint over another constraint.

The cost of pumping is added to the pseudocost penalty functions:

$$\mathrm{COST}_{\mathrm{pumps}} = K \sum_{ij} \frac{Q_{ij}\,\mathrm{TDH}_{ij}\,P_j\,t_j}{\eta_{ij}} \tag{5.10}$$

where K = unit conversion factor
Q_{ij} = flow from pump i during period j
TDH_{ij} = the operating point total dynamic head for pump I during period j
P_j = power rate per kilowatt hour during period j
t_j = length of time that pump operates during period j
η_{ij} = wire to water efficiency of pump i during period j.

Storage tanks have a minimum level to provide emergency fire flow storage. If the tanks are depleted below this level then fire protection is compromised. A penalty term τ_1 has been developed to account for this constraint which is based on the constraint penalty terms developed by Brion (1990) given by:

$$\tau_1 = \sum_j \beta_s \,(\min\,[0, E_{sj} - E_{\min,s}])^2 \tag{5.11}$$

where τ_1 = penalty for violations of the tank low water level bound
E_{sj} = water level for tank s during period j
$E_{\min,s}$ = lower bound or the minimum level in tank s
β_s = penalty term for tank low-level constraint for tanks

Cohen (1982) has stated "optimization of a network over a limited horizon of, say, 24 hours has no meaning without the requirement of some periodicity in operation; a simple way to do that is to constrain the final states to be the same as the initial ones." A constraint τ_2 is developed to generate a cost if the tank levels do not return to their starting elevation.

$$\tau_2 = \sum_s \beta_{s2} \,(\min\,[0, 1 - / E_{s,1} - E_{sj} /])^2 \tag{5.12}$$

where $E_{s,1}$ = water level for tank s at beginning of the simulation, during period 1
$E_{s,j}$ = water level for tank s at the end of the simulation, during the final period j
β_{s2} = penalty term for beginning and ending tank level constraint for tank s

For a 24-h simulation the concept of returning tanks to their starting level is somewhat addressed by using a starting configuration where the pumps supply a volume of water equal to the sum of the nodal demands. Providing a total volume of pumped water equal to the total volume of the system demands will return the tanks exactly to their original level if there is only one tank. Even if pumping equals demand exactly, the tanks may not return to their original level if there are several tanks unless the tanks all start full; because one tank may supply water to another tank during the simulation, the total volume stored will be the same but shifted from one tank to another.

The Cohen condition may be unnecessarily restrictive. The second example involved modifying pump operation for a 24-h period that was repeated for 12 days to allow the water quality variations to overcome the initial conditions. It was observed that the tanks exhibited periodic behavior and adjusted themselves until the pumps were supplying a quantity equal to the demands (see Fig. 5.2). If the pumps operated for longer periods, the tanks remained closer to full and the pump heads moved to the left of the system curve reducing the flow. If the pumps operated for shorter periods, the tank levels lowered until the flows increased to meet the demands. By running the simulations over several days, the pump operation can be scheduled to optimize efficiency and perhaps reduce cost.

A water distribution system needs to deliver water to its customers at sufficient pressure to service the water system customers but at a pressure that will not damage water systems or customer's facilities. The Uniform Plumbing Code sets the normal pressure range as 15 psi to 80 psi (IAPMO, 1994), although a city may have a range in a pressure zone from 40 to 80 psi with a 20 psi residual during a fire flow (Malcolm Pirnie, 1996). The system operation needs to operate between two extreme pressures, $p_{\min}$ and $p_{\max}$.

The constraints and penalty functions for pressure bounds at each node are:

$$\tau_3 = \sum_{kj} \gamma_1 \,(\min\,[0, P_{kj} - P_{\min}]^2 \tag{5.13}$$

$$\tau_4 = \sum_{kj} \gamma_2 \,(\min\,[0, P_{\max} - P_{kj}]^2 \tag{5.14}$$

where $p_{\min}$ = minimum system pressure bound
$p_{\max}$ = maximum system pressure bound
p_{kj} = pressure at node k during time period j
γ_1, γ_2 = penalty terms for minimum and maximum pressure violations

The EPANET (Rossman, 1993) program solves distribution systems hydraulically and then routes chemicals or contaminants through the water system during the time period. EPANET can also consider chemical reactions and calculate the decay of chlorine with time. The combination of hydraulic solver and water quality calculations allows the program to predict the chlorine residual at

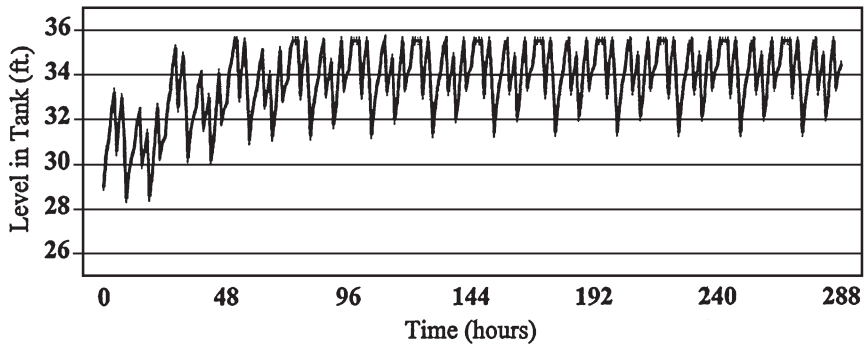

FIGURE 5.2 Periodic behavior.

any node in the system at any time period. A penalty term will be used to consider upper and lower limit bounds on free chlorine to adjust the cost function for chlorine violations.

The penalty terms for minimum and maximum free chlorine concentration are:

$$\tau_5 = \sum_{kj} \gamma_3 \,(\min\,[0, c_{kj} - c_{\min}])^n \tag{5.15}$$

$$\tau_6 = \sum_{kj} \gamma_4 \,(\min\,[0, c_{\max} - c_{kj}])^n \tag{5.16}$$

where $c_{\min}$ = minimum free chlorine concentration
$c_{\max}$ = maximum free chlorine concentration
c_{kj} = chlorine residual concentration at node k during time period j
γ_3 = penalty term for minimum chlorine residual pressure bound violations
γ_4 = penalty term for maximum chlorine residual pressure bound violations

The value of n will usually be 2. In cases where the lower concentration bound is more important, a value of $n < 1$ will place a higher penalty on minimum free chlorine violations. There will also be a term for the amount of chlorine used. The goal will be to meet the chlorine residual bounds while using the smallest amount of chlorine. Not only will the operational cost be decreased but also the creation of Total Trihalomethane (TTHM) will also be reduced.

5.4 DEVELOPMENT OF SOFTWARE

Version 1.1e of EPANET (5/1/96) authored by Dr. Lewis A. Rossman, Risk Reduction Engineering Laboratory of the Office of Research and Development, U.S.E.P.A., Cincinnati, Ohio, was used as the basis of the annealing computer program. The program source files, in the C language, were provided by Dr. Rossman. The basic strategy was to use EPANET as the simulator and to develop around EPANET new functions that calculate penalties or costs, generate pump operation configurations, and evaluate the acceptance of potential configurations using the Metropolis algorithm. The EPANET program was developed for a single simulation as described by the flowchart in Fig. 5.3. In order to carry out the numerous simulations required for annealing, several modifications were required. New functions were written in the C programming language to carry out penalty calculations, generate pump operation configurations, modify the temperature according to the annealing schedule, and analyze each result using the Metropolis algorithm. Pump scheduling is determined by dividing the 24-h day into 1- or 2-h periods. The pump schedule is repeated if the simulation is carried out for several days. The schedule specifies the on–off condition for each pump for each period. The starting pump operation configuration is completely arbitrary. Each pump operation schedule

after the beginning schedule is determined using a random number generator that chooses the pump and period for change. The change is to turn the chosen pump on during the chosen period if it was off or vice versa. This new pump schedule becomes the new data set for EPANET and the program output is checked for energy costs and penalty functions to determine the value of the objective function. The code also detected special "flags" generated by the EPANET program to identify nonfeasible data sets caused by violations of conservation of mass and energy [Eqs. (5.2) and (5.3)]. Special routines were developed to collect information useful in understanding the progress of the annealing method and to develop the current value of the objective function.

Figure 5.4 is a flowchart that shows the operation of the annealing program. The chart shows that the number of loops and iterations per loop are set before the process begins. Each loop carries out a number of iterations at a given temperature. If a pump configuration is held for 50 times it is considered the optimal configuration. If the program finishes normally, the final pump configuration is considered optimal. Frustration between constraints in a water distribution system provides many good configurations to recommend to the system operators. There may be pump configurations that provide better solutions than the final solution. A routine was added, to save the 20 best configurations for examination by the user.

5.5 APPLICATIONS

5.5.1 The Austin Data Set

Brion (1990) and Brion and Mays (1991) applied their model to the City of Austin Northwest B Pressure Zone which consisted of three pumps, 126 pipes of approximately 38.5 miles in total length, 98 junction nodes of which 5 were pressure "watch points," and one storage tank (Fig. 5.5). The 24-h simulation was broken down into twelve 2-h time periods. The system served about 31,000 residents located in about 32,000 acres.

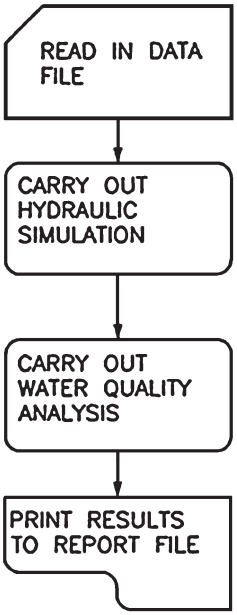

FIGURE 5.3 EPANET flowchart.

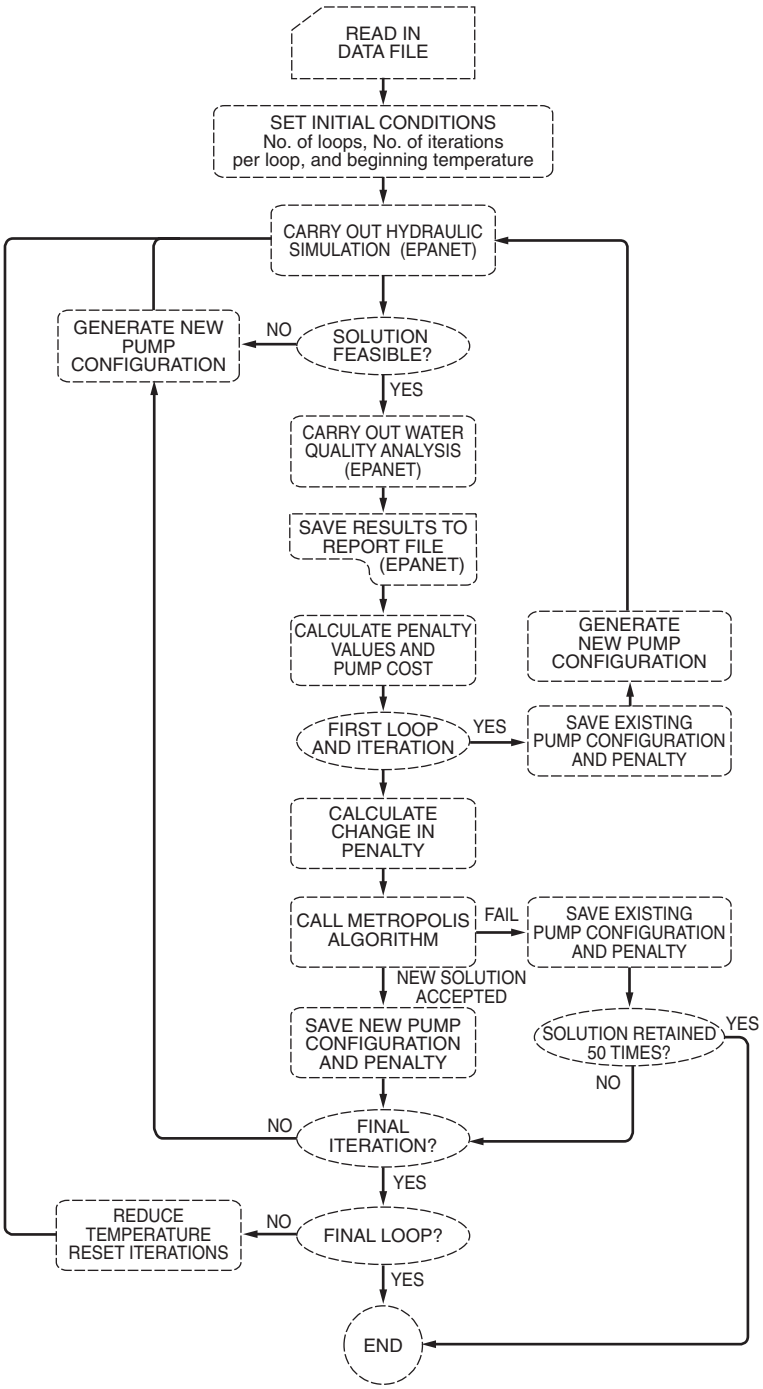

FIGURE 5.4 Simulated annealing flowchart.

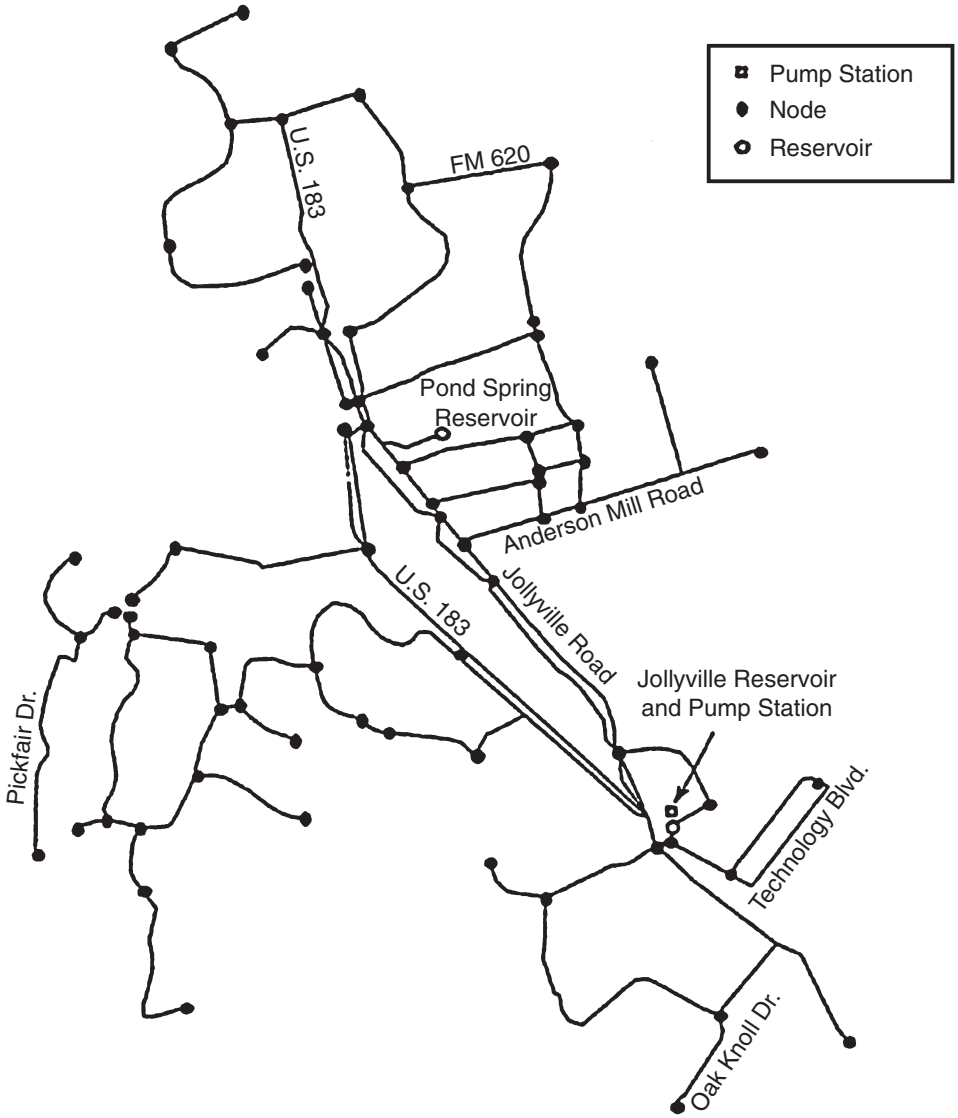

FIGURE 5.5 Water distribution system for City of Austin, Northwest B Pressure Zone. (*Brion and Mays, 1991.*)

The pipes, junctions, pumps, tanks, and diurnal flow distribution can be found in Goldman (1998) or Brion (1990). Brion and Mays (1991) collected information on the actual pumping times used on September 29, 1988 which resulted in a pumping cost of $231 during the day. Using NLP with an augmented Lagrangian description of the pressure and tank constraints and linking the GRG2 program with KYPIPE the cost was reduced to $219, a savings of 5.2 percent. The resulting pump operation schedule is shown in Fig. 5.6.

Simulated annealing was applied to the same data set. Four loops of 200 iterations were performed. The computer time on the Arizona State University Research UNIX cluster was 19 min 38 s. The cost function was the sum of the cost of pumping and constraint violation penalties. The

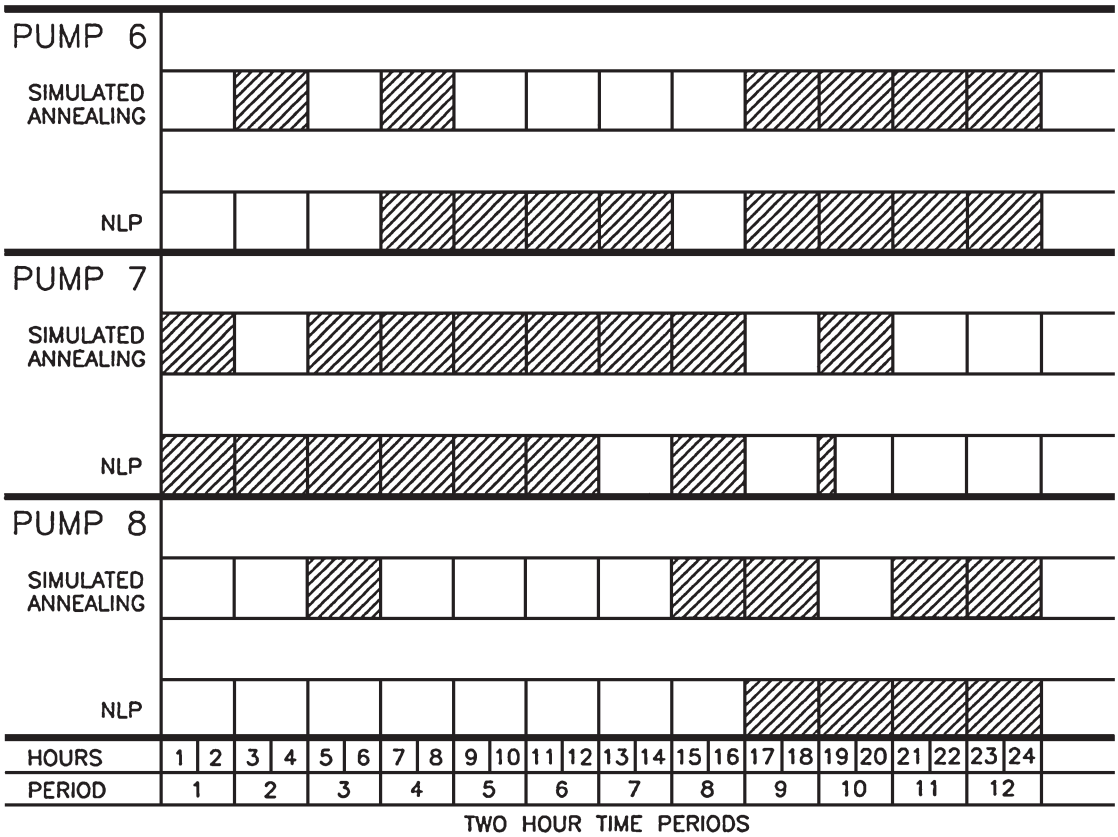

FIGURE 5.6 Austin example—simulated annealing and NLP pump operation schedules.

beginning temperature was 160, which was reduced using the Huang Method (Dougherty and Marryott, 1991).

The series of trial pump configurations was generated starting with the last trial configuration, using a random number generator to choose a pump and a period, and switching the operation. If the chosen pump was operating during the chosen period in the previous trial it is turned off. If it was off during the chosen period it is changed to operating. The stopping condition was having a pump schedule withstand 20 challenges from new pump schedules. Because of the high level of frustration with many pump schedules having very similar cost, the ending condition was not met.

The best result was $221.38, which occurred in trial 67 of loop 3. This resulted in a savings of 4.1 percent. The annealing method did not isolate one solution because of the high level of frustration. The program found 173 solutions, which met the pressure and tank constraints and resulted in a cost less than $235; 50 pump schedules had a cost less than $230. The feasible solutions were reviewed to find the least costly pump operation schedule that met the pressure and tank constraints. The optimum pumping schedule found using simulated annealing and NLP is shown in Fig. 5.6.

A review of Fig. 5.6 shows the NLP solution had a 15-min sliver of operation occurring for pump 7 during the period between hours 18 and 20, which is undesirable for operating pumps and most likely would need to be adjusted by the operator. Short period results can be expected from the NLP method, which is optimizing the duration of pump operation for a 2-h time period. Simulated annealing resulted in a minimum 2-h pumping period because it is a combinatorial optimization method where the pump has to be on or off during the entire period; thus the minimum operating time is 2 h.

The tank trajectory for the simulated annealing optimization pump schedule is shown in Fig. 5.7. The minimum height in the tank was 1 ft. A penalty term was used to return the tank level to the original tank level, within a tolerance of 1 ft.

5.5.2 North Marin Example

This example is a water quality optimization problem that was solved simultaneously by simulated annealing as part of this research project and by the mathematical programming approach using the GRG2 optimizing code linked with EPANET as part of the research project carried out by Sakarya (1998). The water distribution system is taken from example 3 of the EPANET users' manual (Rossman, 1993). It consists of the piping system for the North Marin Water District—Navato, California (Fig. 5.8), which was the location of the sampling and modeling study carried out as part of a recent AWWA Research Project (Vasconcelos et al., 1996).

The goal of the optimization is to find the optimal operation of two pumps with differing capacity characteristics pumping from two different sources of water. Dr. Sakarya's original code minimized the operating time of the two pumps considering pressure and water quality constraints without considering pumping cost. Her code was modified to consider pumping cost by assuming a constant efficiency.

Two systems were studied. In the first system, both sources had free chlorine concentrations of 0.5 mg/L and the minimum free chlorine concentration at any demand node was taken as 0.05 mg/L. Pressures at demand nodes were to be kept between 20 and 100 psi. Global bulk decay was taken as 0.1/day and global wall decay was taken as 1.0 ft/day. The second system had two different chlorine residuals. The free chlorine for the larger pump was 0.4 mg/L and the smaller pump was 0.2 mg/L. The minimum free chlorine concentration was taken as 0.05 mg/L.

It takes many days for initial chemical concentrations to be overcome and repeatable steady-state behavior to be observed. This periodic behavior was discussed previously and was reported for water quality by Boccelli et al. (1998). Figure 5.9 shows the periodic behavior of the chlorine concentration in Tank 1 of this example. To reach steady-state conditions, each iteration was run for 288 h. This resulted in an average of 10 s for each iteration. The results for the last 24 h were used to calculate pumping cost and constraint violation penalties.

The piping system consisted of 125 pipes, 102 nodes, three tanks, and two pumps as described in Goldman (1998) and Rossman (1993). Twenty-four 1-h periods were considered with the pumping schedule repeated every 24 h. The two optimization techniques, simulated annealing and NLP using reduced gradients with Lagrangian multipliers for constraints and GRG2, obtained similar results. For the case where the source chlorine concentration for both sources was 0.5 mg/L, there were no pressure or chlorine violations and the minimum cost found by NLP was $399.95 per day versus $429.53 for simulated annealing. For the case where water qualities for the two sources were 0.2 and

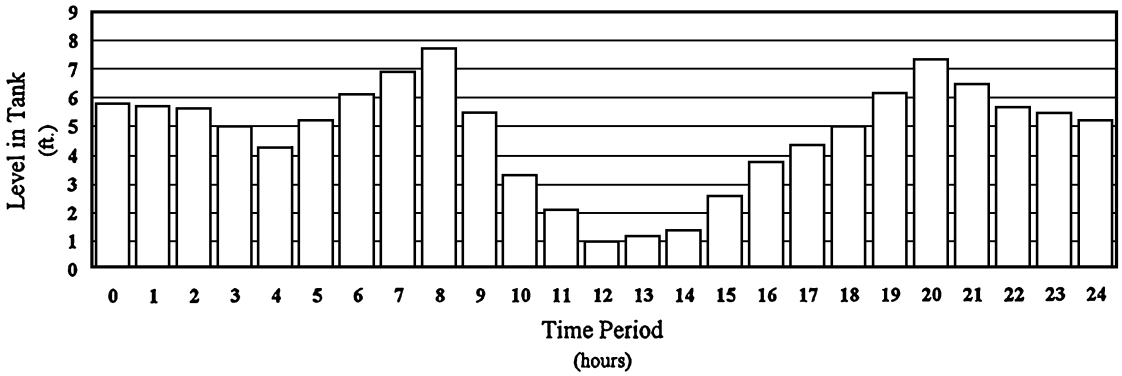

FIGURE 5.7 Austin example tank levels—simulated annealing.

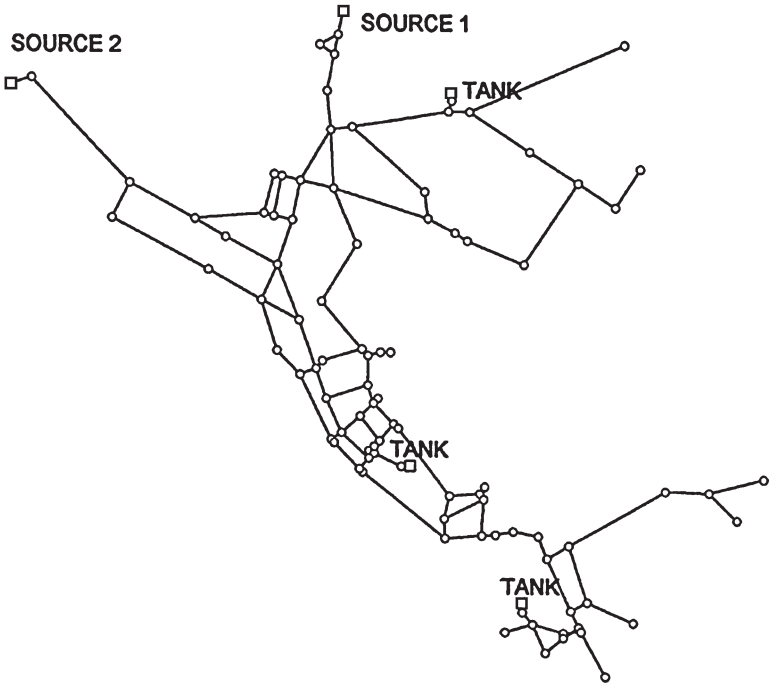

FIGURE 5.8 Water distribution system for North Marin Water District—Navato, California. (*Rossman, 1993 and Vasconcelos et al., 1996.*)

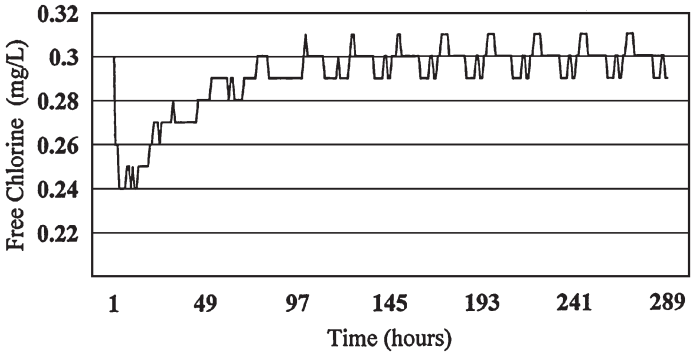

FIGURE 5.9 North Marin example, chlorine concentration: Tank 1.

0.4 mg/L the NLP cost was $408.39 versus $407.66 for simulated annealing. There were no pressure violations but the total chlorine violations measured in total chlorine excursions for all nodes for 24 h in μg/L, was 69.76 for NLP versus 5.89 for simulated annealing.

There were distinct differences in time to arrive at a solution. Dr. Sakarya used a PC with a Pentium processor and the simulated annealing was run on the ASU UNIX computer cluster which consists of five IBM computers including two RS/6000 Model 390 interactive servers and three RS/6000 Model 590 mathematical computational processing. The ASU machines run the IBM AIX operating system, which is IBM's version of UNIX. In both instances the time to run a 12-day long

EPANET simulation was about 10 s. The NLP optimization required about one-third the iterations of the simulated annealing optimization although there was no attempt to streamline the simulated annealing and it turned out that the best solutions occurred before the final loop started. It is believed that even with some improvement in efficiency the simulated annealing would require at least twice the iterations that NLP requires.

Simulated annealing has been shown to be more flexible and adaptable than NLP optimization. The requirement that many parts of the distribution system such as node quality, pressures, tank levels, and pump operation require derivatives with respect to pump operation time during each period restricts the flexibility of the method to accept changes to the system or consider a variable pump efficiency. On the other hand, simulated annealing can accept changes to the distribution system because it is only concerned with cost calculation and deriving a Markov chain of operation schedules.

The NLP method's efficiency in finding optimum solutions appears to be very sensitive to the Lagrangian coefficients used in the outer loop of the optimization. Also, the significant differences in the pump capacities result in much more rapid changes in energy cost, pressures, and water quality to changes in the operation of the larger pump. This resulted in the preferred changes in the larger pump, which reduced its operating time until any more restrictions would have resulted in an unbalanced solution. If a smaller pump was included in the pump operation schedule, it was rarely changed by NLP because such changes were likely to result in violations of conservation of mass and energy and infeasible solutions from the EPANET simulator.

A fundamental tenet in using NLP optimization linked to simulators such as EPANET is the implicit function theorem (Brion, 1991) which states that if D_t is the set of pump durations during periods t (the control variable) then $H(D_t)$ the node pressure matrix, and $E(D_t)$ the tank level matrix (the dependant or state values) exist in the neighborhood of D^*, the set of optimum pump operations. This implies that the solutions exist in the neighborhood. However, in running the simulated annealing routines many unbalanced infeasible solutions existed in the vicinity of the optimum solution. This becomes important if continuity is assumed in the vicinity of the NLP optimums. This problem does not reveal itself in NLP that includes water quality because the water quality portion of EPANET does not include the solving of equations that could be unbalanced. Dr. Sakarya was aware of the continuity problem and her optimum solutions are continuous. However, optimizations that use NLP and do not include water quality could be affected by this problem.

Another important issue is global versus local optimum and the concept of frustration. A total of 36 pump operation configurations were found by simulated annealing that have total water quality violations less than 5.89 μg/L and energy costs less than $420 per day, where the water quality violations are the sum of the violations at all demand nodes for the last day of the simulation. There are many "nearly equal" optimal pump operation schedules that have nearly the same penalty values. This is most likely the reason that simulated annealing found optimum solutions in the next to the last loop.

The actual pump operation schedules developed by the two optimization techniques are shown in Fig. 5.10 for the case where both sources had 0.5 mg/L chlorine concentration.

As previously mentioned, the NLP solution where the sources had identical 0.5 mg/L concentrations resulted in a cost of $399.95 versus $429.53 which appears to be a preferred solution. However, a review of Fig. 5.10 reveals a problem with the NLP optimization. NLP is optimizing the amount of pumping time for a given period. This can result in several periods where the pumps operate only part of the time. This occurs during periods 2,3,8,10,12, and 14. In order to operate pumps more continuously there would need to be some adjustment of the pumping schedule shown in Fig. 5.10, which could affect the ultimate cost of pumping.

5.6 SUMMARY AND CONCLUSIONS

Simulated annealing has been successfully linked with EPANET to optimize the operation of a water distribution system for hydraulic behavior and water quality.

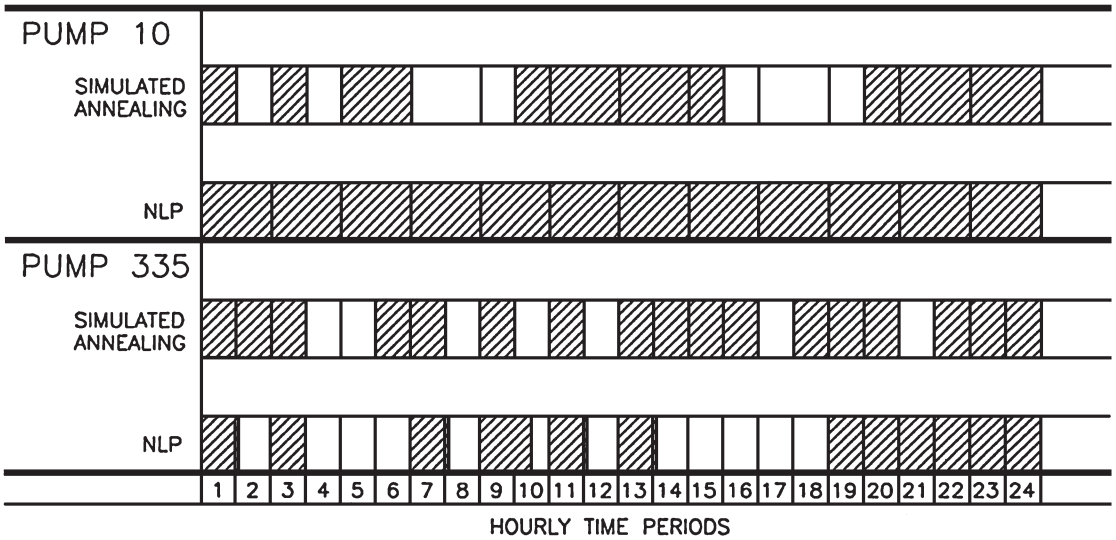

FIGURE 5.10 Simulated annealing and NLP pump operation schedules for system 1 with 0.5 mg/L free chlorine at both sources and minimum free chlorine at nodes as 0.05 mg/L.

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