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Using shuffled complex evolution to calibrate water distribution network model

Md. Atiquzzaman and Shie-Yui Liong

Department of Civil Engineering
National University of Singapore, Singapore 117576.

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Abstract

Calibration of water distribution network model is of paramount importance for the optimal management of water delivery systems. This includes the determination of network parameters such as pipe roughness coefficients and nodal demands. The parameters are not often exactly known and very much sensitive to the age of the pipe. The calibration is usually accomplished by mimicking the model results to the field conditions. However, it becomes tedious if this is performed manually. In this paper, a population based meta-heuristic evolutionary algorithm, Shuffled Complex Evolution (SCE), is applied to determine the network parameters. Two example problems have been analyzed to demonstrate the robustness of the model. The model results show that SCE is capable in reaching the optimal solution in an effective manner.

Keywords: Water distribution network, Shuffled complex evolution, optimization, nodal demands.

1. Introduction

Water distribution network model is applied to the design of new network and rehabilitation or expansion of the existing network. The applicability of the model is dependent upon how closely the model approximates the actual field results. The ability of approximation in turn relies on the accuracy of the input network parameters. It is, however, difficult to estimate the necessary input parameters, especially the pipe roughness coefficients and nodal demands, due to economic constraint. These parameters are estimated via model calibration. Model calibration can be categorized into two steps consisting of: (1) comparison of pipe flows, nodal pressures, and tank water levels, predicted by the model with those observed in the field for known operating conditions; and (2) adjustment of network input data to decrease the differences between the predicted and observed values (Walski, 1983; Bhave, 1988). This process can be performed manually as well as automatically.

Manual approach uses trial and error method. Values of the parameters are initially assumed based on field measurements for conducting simulation and comparing the predicted and field results. If the predicted results do not agree the actual results, the user then adjusts the parameter values to obtain a better fit. The process is repeated until a satisfactory match is obtained. However, this manual approach is tedious and time consuming, particularly when the number of calibration parameters is very large.

Automatic calibration methods remove the shortcomings of manual calibration and ease the evaluation (decision-making) process to a great extent. This method begins with a population of solutions from the feasible space and successively adjusts the pipe roughness coefficients and nodal demands in an iterative manner. Automatic calibration method is a powerful tool which saves enormous time and improves model performance simultaneously. During the last few decades, many traditional and meta-heuristic evolutionary optimization algorithms have been adapted for determining the optimal network parameters. The traditional methods like linear programming, non-linear programming and dynamic programming are not capable of obtaining the global solution every time and fall trapped in local optima. Moreover, they need high computational effort even to get a feasible solution (Dandy et al., 1996). With the advances in soft computing technology, researchers focus on probabilistic approach such as genetic algorithm (Lingireddy and Ormsbee, 1998) for solving the problems, which have non-convex and multimodal objective function.

In this paper, an attempt is made to apply an optimization method, namely, Shuffled Complex Evolution (Duan et al., 1992) in conjunction with EPANET (Rossman, 1994) hydraulic network simulation tool that can handle both steady state and extended period simulation for the determination of optimal network parameters. Two examples have been solved to demonstrate the efficiency of the proposed algorithm in terms of prediction accuracy and computational overhead.

2. Overview of Shuffled Complex Evolution (SCE)

SCE is a global optimization tool developed at the University of Arizona (Duan et al., 1992).This technique is based on four concepts: (1) combination of probabilistic and deterministic approaches – using probability to determine survivability; (2) shuffling of complexes and information sharing; (3) systematic evolution – to improve the solution globally; and (4) competitive complex evolution – to guarantee the competitiveness of the fittest. For Detailed discussion the readers are referred to (Duan et al., 1992; Duan et al., 1993 and Duan et al., 1994).

The method starts searching with a population of points sampled randomly from the feasible space. The populations of points are partitioned into several complexes after sorting in order of increasing function value. Each complex is evolved in different direction based on the Nelder and Mead Simplex Method (NMSM) (Nelder and Mead, 1965). The NMSM performs reflection and inside contraction step to get a better fit point. The NMSM can be briefly described as follows: (a) based on a triangular probability distribution, some points are selected from the complex to construct a sub-complex; (b) the centroid of the sub-complex is computed excluding the worst point; (c) a new point is generated by reflecting the worst point through the centroid of the sub-complex within the feasible space. If this point is better than the worst point, substitute the worst point. Otherwise, a contraction point is computed which is at the halfway between the centroid and the worst point; (d) if the contraction point is better than the worst point, replace the worst point. Otherwise, a random point is generated within the feasible domain and the worst point is replaced by this point; and (e) the steps (b) to (d) are repeated α times, where $\alpha \geq 1$ and steps (a) to (d) are repeated β times, where $\beta \geq 1$. Figure 1 depicts the NMSM procedure to generate an offspring. The points in the complexes are combined into a sample population. At the periodic stages in the evolution, the entire population is shuffled and points are reassigned to complexes to ensure information sharing. As the search engine advances, the entire population tends to converge toward the global optima.

3. Previous research

Several studies (Ormsbee, 1989; Lingireddy and Ormsbee, 1998; Liggett and Chen, 1994; Vitkovsky et al., 2000) have been carried out to make the calibration scheme automated for the determination of the network parameters. Ormsbee and Lingireddy (1997) illustrated seven steps involved in model calibration such as: (i) identification of the intended use of the model; (ii) determination of initial parameters; (iii) collection of calibration data; (iv) evaluation of results; (v) macro-level calibration; (vi) sensitivity analysis; and (vii) micro-level calibration. The micro-level calibration is subdivided into steady state and extended period calibration. Steady state calibration involves the adjustment of parameters to match pressure and flow rate for static loading condition. However, the extended period calibration involves the adjustment of parameters to match pressure, flow and tank water level for dynamic loading conditions. Ormsbee (1989) and Lingireddy and Ormsbee (2002) proposed to use the nodal pressure, pipe flow and tank water level for the calibration of water network model.

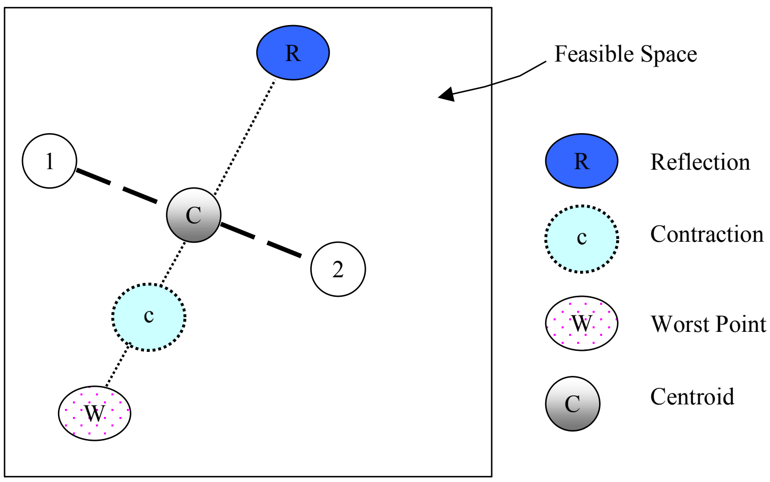

Fig. 1. Nelder and Mead local search technique to the evolution of a sub-complex

Liggett and Chen (1994) introduced inverse transient method (ITM) for the determination of friction factors. This method is further improved by Simpson and Vitkovsky (1997). The ITM offers much potential in comparison to steady state calibration techniques. Vitkovsky el al. (2000), again, enhanced the method using genetic algorithms under the transient condition in water distribution systems. Lingireddy and Ormsbee (2002) successfully applied GA in conjunction with KYPIPE (Wood, 1995) to adjust the pipe roughness and demand factors. Instead of using hydraulic network solver, Artificial Neural Network (ANN) was introduced by Lingireddy and Ormsbee (1998) in the calibration scheme in order to reduce the running time of the model. However, they needed initial training data set to train the ANN before using as a simulation tool. Finally, the trained neural network with GA obtained reasonable agreement between the observed and modeled results.

4. Proposed model

Model calibration deals with the adjustment of the hydraulic network parameters until the results match the actual measured field data. The basic idea behind the calibration of network model is to use an optimization algorithm to generate the decision variables and a simulation model to analyze the network. In this study, SCE is linked with EPANET network solver for the estimation of pipe roughness factors. It should be mentioned that Liong and Atiquzzaman (2004) also used similar model in the optimal design of pipe sizes of new water distribution systems. SCE generates pipe roughness coefficients randomly within a solution space and update the input file of EPANET. These roughness values may be the values used in Colebrook-White formulation, or Hazen-Williams C-factors. Individual pipe may have the roughness value or groups of pipes can be pre-selected to have a common roughness value based on the age, material and location. EPANET (hydraulic simulation program) then evaluates the hydraulics (nodal pressure) of the solution for both steady state as well as extended period simulation. The results from simulation model are passed back to the optimization routine, where the algorithm computes the objective function, evaluates the constraints and updates the decision variables accordingly. The new decision variables are then transferred to the simulation tool again and the process is repeated until an acceptable solution is obtained. The overall process is shown in Fig. 2.

The mathematical formulation includes the minimization of root-mean-square error (*RMSE*) between the observed and predicted pressure heads.
The function is:

$$RMSE = \left[\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(AP_{it} - SP_{it})^2\right]^{1/2} \tag{1}$$

Here, AP_{it} and SP_{it} = actual and simulated nodal pressures at node i and at time t.

Beside the objective function, several implicit and explicit bound constraints are involved in the formulation. For each trial solution, EPANET handles the implicit bound constraints (conservation of mass and energy) and simultaneously evaluates the hydraulic performance. Explicit bound constraint, however, includes the boundary of the pipe roughness. The optimization tool controls this constraint and searches the optimum value of pipe roughness for all pipes.

The mathematical formulation can thus be stated as follows:

$$\text{Minimize } RMSE \tag{2}$$

Subjected to:

$G(H,D) = 0$, a conservation of mass and energy equation (3a)

$C_{\min} < C(k) < C_{\max}$, constraints related to design parameters (3b) where, $C(k)$ = decision variables (pipe roughness); C_{min} = lower limit of roughness coefficients; C_{max} = upper limit of pipe roughness.

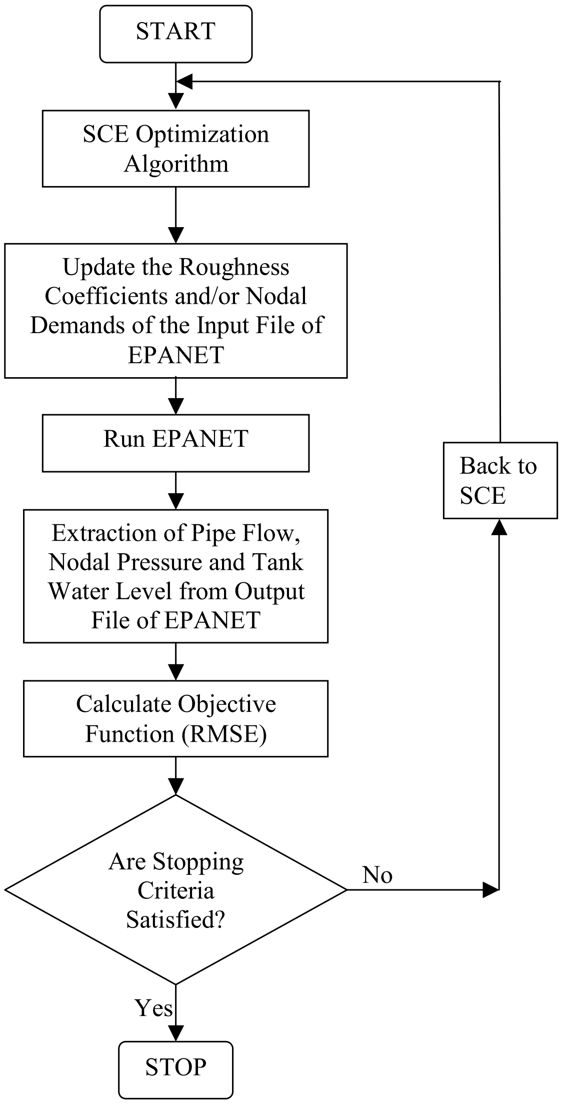

Fig. 2. Flow chart of the calibration problem

5. Case studies

5.1 Case study one: EPANET network

The first test example (Figure 3) has been taken from EPANET manual (Rossman, 1994). This network is chosen to check whether the model is able to get the optimal calibration parameters. The network comprises of 12 pipes, 9 junction nodes, one reservoir, one pump and an elevated water tank. The objective is to determine a set of roughness coefficients for all pipes in the network so that the resulting pressure would closely mimic the field pressure. The actual roughness coefficient (Hazen-Williams C factor) for all pipes is 100. A hydraulic analysis is performed using this roughness parameter for extended period simulation to obtain a set of values of nodal pressure at a particular node 9, which are used later on to reproduce the roughness coefficients of the pipes.

The analysis is preformed using the boundary of lower limit 50 and upper limit 150 for the decision variables and the following SCE parameters are used: the number of complexes = 12, number points in each complex = 25, total number of population = 300 and the maximum number of function evaluation allowed = 15,000. The initial value of roughness is assumed 90 for all pipes. Two stopping criteria are checked at each run which were: (1) if the number of evaluation of the objective function reaches the maximum; or (2) if the objective function value is less than a specified limit (usually 0.001), the model will be terminated. Ten runs are performed using different initial seed value. SCE finds the optimum solution with the expense of shorter period of time. The algorithm requires 7,376 function evaluations and a CPU time of only 2 minutes [PC with Pentium 4 (Processor 1.79 GHz, RAM 512 MB)].The final roughness coefficients are shown in Table 1. Figure 4 depicts the reducing *RMSE* value with the increasing function evaluation number. The simulated and actual pressure head at node 9 over 24 hours are shown in Fig. 5. It could be seen that the model predicts the actual field results with sufficient accuracy.

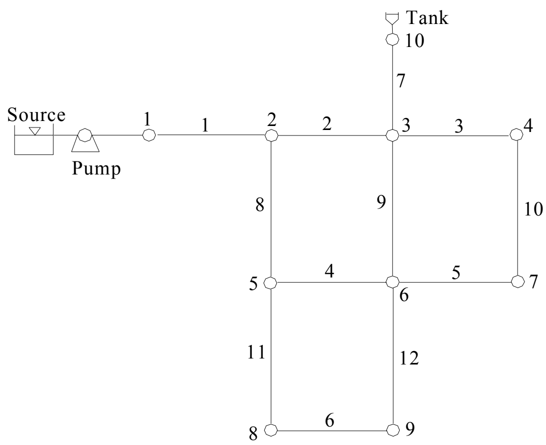

Fig. 3. EPANET Network (Rossman, 1994)

Table 1
Measured roughness coefficients of the pipes

Pipe No	Measured Roughness Coefficients
1	99.739
2	100.577
3	100.659
4	101.409
5	101.875
6	101.472
7	101.435
8	99.116
9	97.534
10	100.617
11	104.196
12	98.784

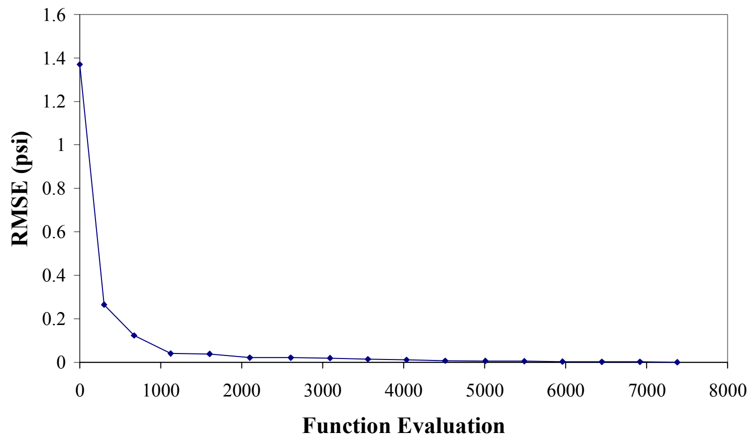

Fig. 4. Evolution of RMSE with Function Evaluation

5.2 Caste study two: Ormsbee and Wood (1986)

The second example (Fig. 6) was presented by Ormsbee and Wood (1986). Table 2 illustrates the network configuration. It consists of 21 pipes and 13 junction nodes, three elevated storage tanks and a pump. The actual pressure heads for nodes 6, 8, 10, and 13 are given in Table 3. Greco and Giudice (1999) solved this network to adjust the roughness coefficients. The pressure head obtained at test nodes by Greco and Giudice (1999) and Ormsbee and Wood (1986) are also shown in Table 3.

The program is run with the parameters of the number of complexes = 4, number points in each complex = 20, number points in each sub-complex = 10, total number of population = 80 and the maximum number of function evaluation allowed = 4,000. The model improves the pressure heads at nodes 6 and 8 (Table 3) which are very much close to the original value. The good match between the actual and simulated pressure heads are obtained only after 1,315 evaluations (average of five runs) of the objective function and which takes 22 sec of the computational time in the same PC.

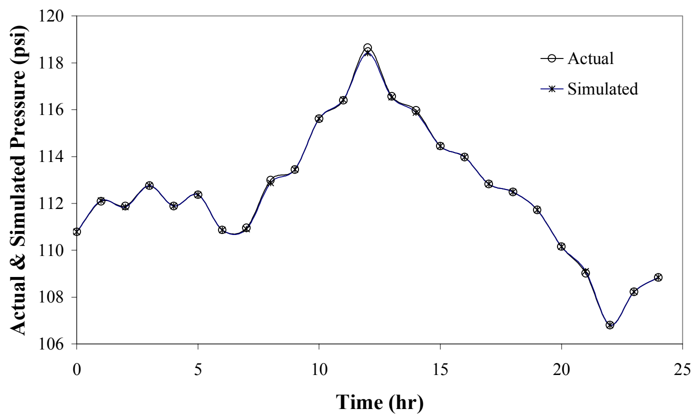

Fig. 5. Variation of actual and simulated pressure at node 9 over time

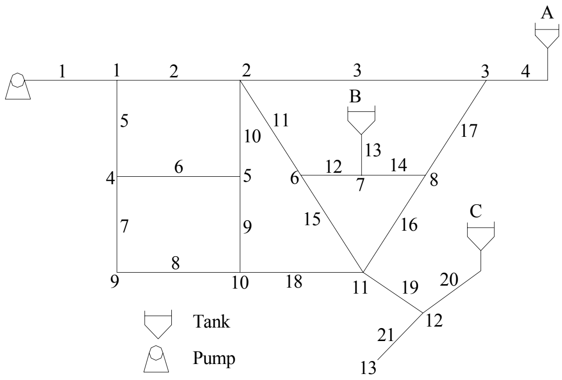

Fig. 6. Ormsbee and Wood (1986) Pipe Network

Table 2
Ormsbee and Wood (1986) pipe network

Pipe Number	Starting Node	Ending Node	Length (m)	Diameter (mm)	Node Number	Demand (L/s)
1	0	1	300	300	2	40
2	1	2	250	250	3	40
3	2	3	450	250	6	80
4	3	0	300	200	8	40
5	1	4	150	250	9	60
6	4	5	250	200	11	100
7	4	9	170	250	13	20
8	9	10	250	250		
9	10	5	170	200		
10	2	5	150	200		
11	2	6	160	200		
12	6	7	140	200		
13	0	7	80	200		
14	7	8	140	200		
15	6	11	300	200		
16	8	11	300	250		
17	8	3	200	250		
18	10	11	200	250		
19	11	12	300	150		
20	0	12	200	150		
21	12	13	175	150		

Table 3
Actual and calibrated nodal pressures

Node	Actual Pressure (m)	Calibrated Pressure (m)		
		Ormsbee and Wood (1986)	Greco and Giudice (1999)	SCE
6	142.00	141.90	141.97	142.08
8	143.00	142.69	142.72	143.00
10	142.00	142.00	142.00	141.92
13	141.50	141.50	141.50	141.50

6. Conclusions

Water distribution network model is calibrated to adjust the network parameters (pipe roughness coefficients and nodal demands) so that the hydraulic performance closely mimics the field condition. However, optimal calibration is not an easy task due to nonlinear objective function and numerous local minima within the solution space. Many conventional techniques do not guarantee optimal solutions. In this study, SCE (Duan, et al., 1994) has been applied in conjunction with widely used hydraulic network solver, EPANET to determine optimal network parameters. Two problems have been solved to demonstrate the capability of SCE. The results show that SCE performs efficiently in reaching the global optimum solution in both the case studies.

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