# IMPLICIT CALIBRATION OF WATER DISTRIBUTION NETWORKS USING SCE-UA

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This paper introduces an implicit water distribution network calibration technique using a relatively new optimization concept known as Shuffled Complex Evolution-University of Arizona (SCE-UA). The aim is to create a descriptive network that predicts the behavior of the system under various loading conditions to achieve convergence between both real and model networks based on observed data recorded from telemeters attached to the water network. The adjustable model parameters are the different nodal demands and pressure at source nodes while pipes roughness is assumed well estimated parameters. The optimization algorithm which incorporates a network simulation model is used to calibrate the network through a specified time interval presenting several demand patterns. To investigate the performance and accuracy of this technique, the developed algorithm is applied to a certain block of Fukuoka City water supply network. Results show that the proposed model is capable to minimize the objective function and finds several good optimal solutions.

## INTRODUCTION

The accuracy of water distribution network models depends on how well it is calibrated. When simulating the water distribution system by a computer model to obtain the different pipe flows and node pressures, data associated with the different components of the system should be provided. The essential data that should be provided are elevation, demand and demand pattern of junctions; diameter, length and roughness coefficient of pipes and elevation of water levels in the different reservoirs. In case of presence of pumps and valves, additional data should be available like the type of valves and its characteristics and the head-discharge curves of the used pumps.

Among all previous properties, the variables that possess the highest degree of uncertainty are the roughness coefficient of pipes, the different nodal demands and in a lesser degree the unmeasured hydraulic pressure in some source nodes. To overcome the difficulty in determining those quantities, a model calibration should be done. The step of network model calibration is essential and always be done before the analysis step.

Calibration is the process of minimizing the error obtained between the model results and observations field data by adjusting the different nodal demands and the roughness of pipes. Regarding the problem of estimating pipe-roughness coefficient values, an accurate estimate of these values could be obtained using average empirical values in the literature or from field measurements; therefore, following any of these two methods will reduce the uncertainty in determining these quantities [1].

The American Water Works Association Research Committee on water distribution systems states that "The major source of error in simulation of contemporary performance will be in the assumed loading distribution and their variations" [2]. An initial accurate estimate of the average nodal demands in any water distribution network could be done by a categorized and classification method of land use, type and number of dwellings, meter route and individual meter billing records [1]. As nodal demand varies with time, it should multiply by an adjustment hourly factor equal to the consumption of this hour divided by the average daily consumption [1]. Recently, some demand forecast models had considered such factors as daily weather conditions, weather forecasts, seasons of the year and past trends in water use [1 & 3].

Water supply network calibration could be done through several approaches; the first approach is based on iterative procedures [4 & 5] in which the unknown parameters are updated at each trial. This approach is limited for calibrating small networks and the main drawback of the iterative models that the convergence rate is rather slow [5].

The second approach named as explicit models is based on solving numerically a group of steady-state, mass-balance, and energy equations [6 & 7]. In this approach the number of unknown calibration parameters should not exceed the total number of available measurements and if this condition is not satisfied the only way to make this approach applicable is to reduce the number of unknown parameters by grouping [6].

The third approach known as implicit models is presented by introducing an objective function which presents the error calculated between observed values and the output values obtained from the hydraulic model. To minimize this objective function usually an optimization tool is applied [8 & 9]. The basic advantage of this approach over the previous mentioned two approaches is that multiple loading conditions could be considered. In addition, individual network components as well as various operational constraints can be incorporated directly into the overall calibration process [8].

However, review of the literature shows that the available techniques used in the calibration of the hydraulic network are very sensitive to the initial given values to the nodal demand and could not detect the real values of water demands in all the network nodes due to the compensating errors [9].

In this paper we test the capacity of a relatively new approach known as Shuffled Complex Evolution (SCE) developed in the University of Arizona [10] for the calibration of water distribution networks. SCE has been successfully used in the area of surface and subsurface hydrology for the calibration of conceptual rainfall-runoff models and the identification of aquifer formation parameters [10], this algorithm has never been used in the calibration of water supply network. The implicit model proposed in this study used SCE as an evolutionary optimization technique with a general hydraulic network solver. The model uses continuous sensor information on pipe discharges, hydraulic pressures and valve openings from some measurement points in the network to adjust the different nodal demands and source nodes pressure while pipes roughness is assumed well estimated parameters. To demonstrate the accuracy of the method, it is applied to Block No. 12 of the water supply network in Fukuoka City.

## FORMULATION OF THE MODEL

For a network has $n_p$ pipes, $n_n$ junction nodes, $n_f$ fixed source grade nodes (constant water level), $n_c$ independent closed loops, $n_g$ number of observed nodes pressure and $n_m$ number of observed pipes flow, the following mathematical statement of the network calibration is used as an objective function to be minimized using SCE Algorithm

$$\sum_{k=1}^{k_{\max}} \left[ \begin{array}{l} \sum_{i=1}^{n_g} \left| WP_{ki} \left( P_{ki} - \bar{P}_{ki} \right) \right| \\ + \sum_{j=1}^{n_m} \left| WF_{kj} \left( F_{kj} - \bar{F}_{kj} \right) \right| \end{array} \right] \to \min \tag{1}$$

where $P_{ki}$ and $\bar{P}_{ki}$ are the calculated and the observed pressure at node $i$ which is a set of the number of observed nodes $n_g$; $F_{kj}$ and $\bar{F}_{kj}$ are the calculated and the observed flow at pipe $j$ which is a set of the number of observed pipes $n_m$; according to unit difference between the pressure and the flow, we used $WP_{ki}$ and $WF_{kj}$ which are scaling factors to make an agreement between both terms in Eq. (1) and increase the efficiency of the optimization algorithm. The objective function represented by Eq. (1) measure the absolute deviation of the error summation over several loading conditions $k_{max}$ which doesn't require that the observed points location are same for the different loading conditions. The foregoing function is to be minimized under the following constraints.

For each node of the network $n_n$, the mass continuity equation should be satisfied.

$$\sum_j \left( Q_{in} - Q_{out} \right) = C_j \tag{2}$$

where $C_j$ is the consumption or demand at junction $j$, positive for outflow and negative for inflow, $Q_{in}$ and $Q_{out}$ are the flow entering and leaving the node $j$, respectively. The sum of the head losses and gains around a closed loop must be equal to zero since $\Delta H = 0$.

$$\sum_i h = \Delta H \; ; \quad i = 1, 2, \ldots, n_c + n_f - 1 \tag{3}$$

The minimum and maximum nodal demand flow for each node in the network is given in the form.

$$q_j^{max} \geq q_j \geq q_j^{min} \; ; \quad j = 1, \ldots, n_n \tag{4}$$

The minimum and maximum pressure head at the different fixed grade nodes is given in the form.

$$H_j^{max} \geq H_j \geq H_j^{min} \; ; \quad j = 1, \ldots, n_f \tag{5}$$

The hydraulic analysis of the network is performed using the Hazen-Williams empirical equation which is often applied in pipe network analysis.

$$H_i - H_j = r_{ij}^{-1/\alpha} \left|Q_{ij}\right|^{1/\alpha - 1} Q_{ij} + \frac{8 f_{vij}}{g \pi^2 d_{ij}^4} \left|Q_{ij}\right| Q_{ij} \tag{6}$$

where

$$r_{ij} = 0.27853 C_{ij} d^{2.63} L_{ij}^{-0.54} \tag{7}$$

The second term in Eq. (6) is required only if there is a valve between nodes. Here $Q_{ij}$ ($m^3$/sec) is pipe discharge from node $i$ to $j$, and $Q_{ij} = -Q_{ji}$; | | means absolute value, $H_i$ (m) and $H_j$ (m) are hydraulic pressures at nodes $i$ and $j$; $\alpha = 0.54$ is a numerical constant, $f_{vij}$ is valve loss coefficient; $g$ is acceleration of gravity; $C_{ij}$ Hazen-Williams coefficient, $d_{ij}$ (m) is diameter of the pipe, and $L_{ij}$ (m) is pipe length.

In this study, the coefficient of valve loss, $f_{vij}$ is calculated using the following equation.

$$f_{vij}(\theta) = \begin{cases} 165226 \times 10^{-0.18\theta} & (0 \le \theta < 13) \\ 3696 \times 10^{-0.06\theta} & (13 \le \theta < 40) \\ 221 \times 10^{-0.03\theta} & (40 \le \theta \le 100) \end{cases} \tag{8}$$

where $\theta$ (%) is the valve openings. Eq. (8) is taken for the typical type of electrically motor valves used in Fukuoka City water distribution network.

## SCE-UA ALGORITHM

The Shuffled Complex Evolution (SCE) method is a general purpose global optimization evolutionary programming technique which combines the strengths of the simplex procedure with the concepts of controlled random search, competitive evolution and the concepts of complex shuffling [10].

The synthesis of these concepts makes the SCE algorithm not only effective and robust, but also flexible and efficient. The use of deterministic strategies permits the SCE algorithm to make effective use of the response surface information to guide the search. Robustness and flexibility is taken care of by the use of random elements. The implicit clustering strategy guides to the most promising region of the search space. The use of the systematic complex strategy helps to ensure a relatively robust search that is guided by the structure of the objective function. Readers not familiar with SCE strategy may refer to the details of this algorithm in Duan *et al.* [10].

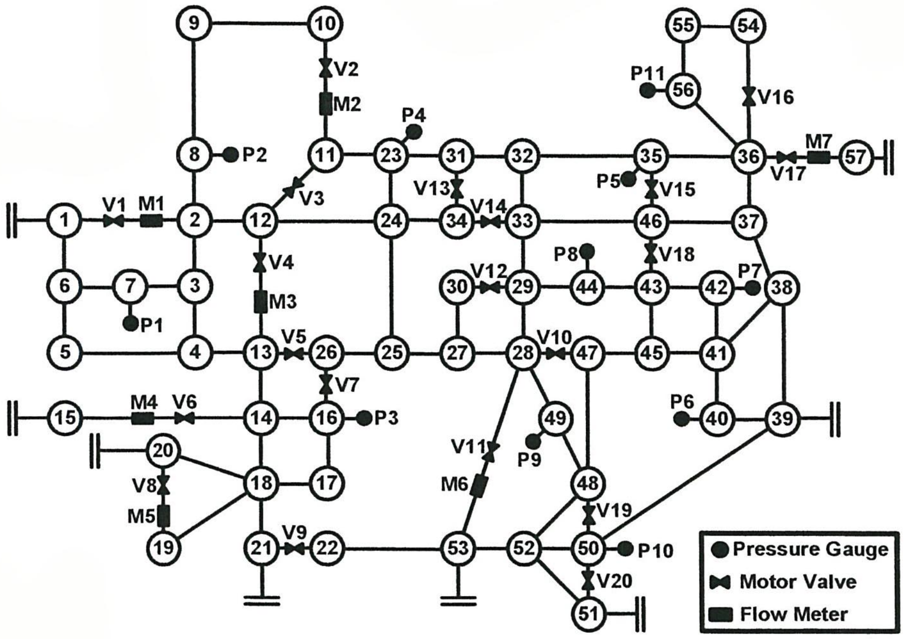


Figure 1. Block 12 of the Fukuoka City water supply network

## APPLICATION

**Network specifications and data used**

The water supply network of Fukuoka city is divided into 21 blocks and the area served by each block takes into consideration separate water distribution areas, differences in land elevation, location of rivers and railroads, as well as local differences in water usage. In the supervisory city water network motor valves are operated by remote control while pressure gauges and flow meters fitted to distribution pipes are monitored. The values of flow rate passing each flow meter, the opening percentage of each motor valve and the pressure intensity at each pressure gauge are recorded every minute. Block 12 as one of the main blocks of the city network is selected to illustrate the performance of the proposed model. The initial number of nodes and pipes in this block are 1133 and 1645, respectively, after selecting pipes with diameter greater than or equal 100 mm. A skeletonized figure of Block 12 containing 57 nodes and 83 pipes is shown in Figure 1. The calibrated parameters used in this study are related to the 57 network node and divided into 49 water demands, and 8 pressure head at the nodes which received inflows from outside the network (nodes 1, 15, 20, 21, 39, 51, 53 and 57). For the telemeters attached to the network, there are 7 flow meters (M1, ..., M7), 11 pressure gauges (P1, ..., P11) and 20 electrically motor valves (V1, ..., V20).

The analyzed data of this study are based on hourly data for all flow meters, pressure gauges, and motor valves for a randomly selected day (Saturday, 9$^{th}$ of November 2002). Therefore the number of loading conditions $k_{max}$ in Eq. (1) is 24.

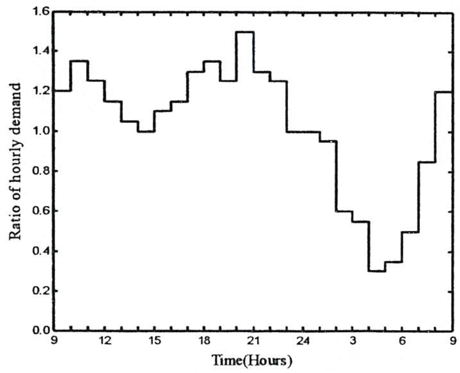


Figure 2. Variation of daily demand

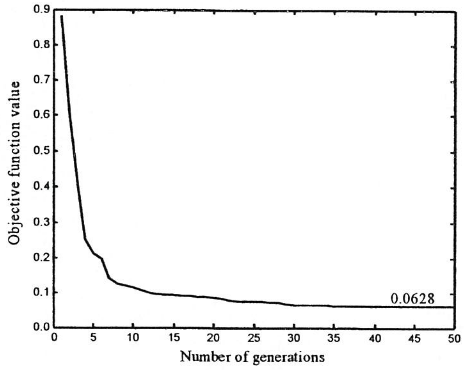


Figure 3. Course of evolution

**SCE parameters**

The number of variable to be optimized using SCE algorithm; $n_{opt} = 57$, which is the total number of network nodes. In the SCE the followings are the used parameter values; number of complex $p = 20$, number of complex population $m = 2n_{opt}+1 = 115$, number of sub-complex population $q = n_{opt}+1 = 58$, the user defined parameter which determines how many offspring should be generated $\beta = m = 115$ and the number of generation inside the extermination room $\alpha = 1$. All previous values are the suggested ones [10].

**Computational details**

SCE is applied to minimize the objective function of Eq. (1) subjected to the different constraints mentioned in the model formulation section. The nodal demand at each node is multiplied by an adjustable hourly demand as shown in Figure 2. The ratio of hourly nodal demand is calculated by estimating the total network consumption from the reading of the all flow meters attached to the pipes of the network. The typical daily demand pattern shown in Figure 2 is assumed to be fixed for all the nodes of network. Hazan-Williams coefficient for all pipes is assumed constant and equal to 130.

At each loading condition the percentage values of the 20 valves opening are the real values recorded for the corresponding period simulation. The overall procedure outlined before has been coded in Matlab language and applied on PC computer.

## RESULTS AND DISCUSION

SCE algorithm is applied for the above-mentioned problem. Figure 3 shows the best value of objective function in each generation up to 50 generations, the number of function evaluations in each generation varies between 2000 and 5300 at each of those function evaluation the number of solving the hydraulic network is equal to the number of loading conditions. The number of function evaluation are varied through different generation due to some internal tests related to a competitive complex evolution algorithm which is a sub-algorithm embedded in the SCE.

Table 1. Calibration results

| Telemeter | Flow meters ($m^3$/hr) | | | | | | | Pressure gauges (m) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 |
| Minimum Value | 74 | -243 | -1247 | -375 | 0 | -709 | -648 | 20.5 | 22.5 | 25 | 23.6 | 24.2 | 22.2 | 22.5 | 21.1 | 22.5 | 21.6 | 24.9 |
| Maximum Value | 341 | 0 | -153 | -47 | 0 | -159 | 720 | 31 | 33 | 37.8 | 33.7 | 33.8 | 32.1 | 32.7 | 31.2 | 32.8 | 31.8 | 34.3 |
| Max. Abs. Error (%) | 35.1 | -- | 24.6 | 16.6 | -- | 26.9 | 11.6 | 10.0 | 34.2 | 32.9 | 12.1 | 8.5 | 17.9 | 22.6 | 21.5 | 16.2 | 9.9 | 10.3 |
| Average Error (%) | 10.9 | -- | 8.5 | 4.2 | -- | 8.1 | 2.1 | 5.2 | 11.6 | 10.9 | 3.2 | 2.0 | 5.4 | 7.5 | 6.2 | 5.9 | 4.4 | 4.3 |

From Figure 3 we could investigate that the optimal solution is reached after 34 generation which correspond to 112,458 function evaluations. One of the main factors that affects to total number of function evaluations and therefore the computational time is the selection of different constraints mentioned in Eq. (4) and Eq. (5); at each node we should apply one of those two constraints to narrow the search in the most promising region of the search space.

Table 1 summarize the main calibration results of the application problem, this table shows the minimum and maximum observed values for the different telemeters attached to the network and the corresponding absolute maximum and average percentage of error over the several loading condition. The maximum absolute error recorded in matching the observed values over all telemeters varies between 8.5% and 35.1%, while the average error recorded varies between 2% and 11.6%. For flow meter M2 and M5 those percentage of error could not be calculated because the reading of those flow meter is zero in some loading conditions.

Figure 4 and Figure 5 show the 24-hour related results to the observed and calibrated data of a typical flow meter (M1) and a typical pressure gauge (P1), respectively. As can be seen from the figures the correlation between observed and computed values is in good agreement. Similar conclusion has been conducted for the remaining flow meters and pressure gauges.

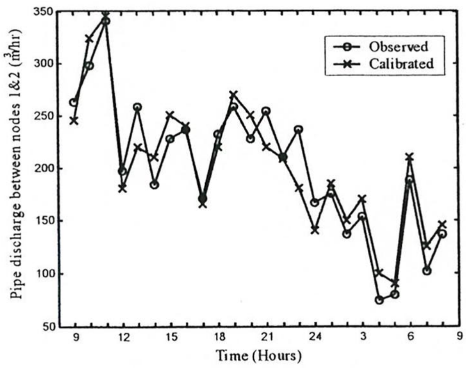


Figure 4. Discharge at flow meter M1

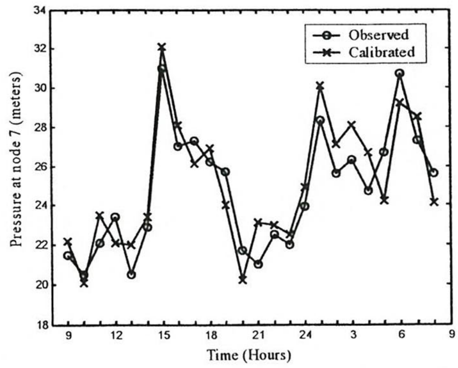


Figure 5. Pressure at pressure gauge P1

## CONCLUSIONS

An implicit methodology for the calibration of water distribution networks has been presented to estimate the different nodal parameters of a water distribution network. The proposed model is formulated by using SCE as an optimization algorithm. The model minimize the error obtained between the observed and calculated variables over an extended period simulation which present a typical daily operation for a certain block of Fukuoka City water distribution network.

The good results obtained from the application indicate that the robust search characteristics of SCE are suited for the problem of water distribution network calibration. We think that better solutions could be obtained if an internal improvement of SCE has been done, to ensure this point we are now trying a sensitivity analysis study for the different SCE parameters and its effect on the final matching solutions between observed and computed solutions.

Poorly defined constraints could affect the computational time and may lead to nodal demand and pressure head values that are not reasonable.

### REFERENCES

1. Mays, L.W., "*Water distribution system handbook*", McGraw-Hill, (1999).
2. American Water Works Associated Research Committee on Distribution Systems, "Water distribution and applied development needs", *J. of AWWA*, Vol. 66, No. 6, (1974), pp 385-390.
3. Awad, H., Kawamura, A., and Jinno, K., "Effective and efficient technique for nodal demands prediction in water supply network", *Proc. XXX IAHR Congress*, Thessaloniki, Greece, Theme B, (2003), pp 255-262.
4. Walski, T.M., "Case study: Pipe network model calibration issues", *J. Water Resour. Plng. And Mgmt., ASCE*, Vol. 112, No. 2, (1986), pp 238-249.
5. Bhave, P.R., "Calibrating water distribution network models", *J. Environ. Engrg., ASCE*, Vol. 114, No. 1, (1988), pp 120-136.
6. Ormsbee, L.E., and Wood, D.J., "Explicit pipe network calibration", *J. Water Resour. Plng. And Mgmt., ASCE*, Vol. 112, No. 2, (1986), pp 166-182.
7. Boulos, P.F., and Wood, D.J., "Explicit calculation of pipe network parameters", *J. Hydr. Engrg., ASCE*, Vol. 116, No. 11, (1990), pp 1329-1344.
8. Ormsbee, L.E., "Implicit network calibration", *J. Water Resour. Plng. And Mgmt., ASCE*, Vol. 115, No. 2, (1989), pp 243-257.
9. Haestad Methods, Walski, T.M., Chase, D.V., Savic, D.A. Grayman, W., Beckwith, S., Koelle, E., "*Advanced Water Distribution Modeling and Management*", 1st edition, Haestad Press, (2003).
10. Duan, Q., Gupta, V.K. and Sorooshian, S., "Effective and efficient global optimization for conceptual rainfall-runoff models", *Water Resources Res.*, Vol. 28, No. 4, (1992), pp 1015-10.