DIAGNOSING ERROR PRONE APPLICATION OF OPTIMAL MODEL CALIBRATION

By Zheng Yi Wu and Thomas M. Walski
Haestad Methods Solution Center, Bentley Systems Inc., 27 Siemon Co. Drive, Watertown, CT06795, USA
Email: zheng.wu@bentley.com

Abstract

Optimization tools have been developed for automatic calibration of water distribution models. The tools are often based upon a powerful genetic algorithm optimization and seamlessly integrated with hydraulic and water quality modeling systems. It provides the advanced features for engineers and modelers. In spite of the power of the GA modeling, some users report that the optimal calibration tool has not worked effectively for practical model calibration. This paper presents a case study on uncovering the causes of problems in automated calibration and proposes an approach for effectively applying the optimization calibration method. The case study involves a real water distribution system. The model is constructed by experienced modeling engineers and an optimization calibration tool is applied to calibrating the model. However, the initial application of the calibration tool did not make any improvement at all over the uncalibrated model. A detailed analysis has been conducted to diagnose the problems with the model calibration. This study uncovers an error prone application of the optimization-based calibration tool and illustrates effective procedures for applying the calibration tool to a real water distribution model. The procedure and steps have been found efficient at improving model calibration. They may also serve the general guidelines for calibrating water distribution models even without use of optimization.

Keywords
Water distribution systems, computer model, calibration, optimization

1. INTRODCUTION

A water distribution model is useful only if it is calibrated to replicate the hydraulic characteristics of a real water system. However, because of the large number of potential unknowns and uncertainties that exist in a water distribution model, it is not possible to analytically solve for model parameters. Optimization methods are proposed for facilitating the model calibration. The early endeavourer was made to applying linear and nonlinear optimization techniques to model calibration (Meredith 1983; Ormsbee & Chase 1988; Lansey and Basnet 1991). Over last decade many successful applications of a genetic algorithm (GA) to solving model calibration problems have been carried out for water resource systems. Wang (1991) applied a genetic algorithm to the calibration of a conceptual hydrology model. Wu (1994), Wu and Larsen (1996) presented a genetic algorithm approach for automatic calibration of MOUSE, an integrated hydrology and hydrodynamic modeling system (DHI 1993). Savic and Walters (1995) applied a genetic algorithm to the calibration of a water distribution model. Many others showed a great deal of promise in that GAs were robust and weren't trapped by local minima. There are numerous variations of genetic algorithms. Wu and Simpson (1996; 1997 and 2001) found that the fast messy GA (Goldberg et al. 1989 and 1993) has been the most efficient GA for the optimization of a water distribution system. The fast messy genetic algorithm has employed as an effective search algorithm for developing the evolutionary calibration methods (Wu et al. 2001; 2002a and 200b). The essential difference among all the calibration approaches is not the GA itself, but the calibration framework, namely how a model calibration is formulated and implemented so that engineers are allowed to flexibly set up model calibration to best reflect various engineering conditions. A versatile GA-based optimization calibration tool is developed in Darwin Calibrator (Haestad 2002).

2. OPTIMAL CALIBRATION

An optimal calibration method is to facilitate the calibration process under practical conditions. The method needs to be flexible enough to enable a modeler to perform model calibration for various calibration needs under different operating scenarios. Optimization technique is to automatically search for the best-fit water distribution model parameters including:

1. Pipe roughness factor f_i for pipe group i, all the pipes within one group will be either set to the same roughness coefficient or multiplied the same multiplier with the original roughness coefficients;
2. Demand adjustment multiplier $m_{j,t}$ for junction group j at time step t, the demands of all the junctions within the same demand group are multiplied with the same adjustment multiplier;
3. Link operation status $s_{k,t}$ for link k (pipes, valves and pumps) *at* time step t.

The fittest parameters are obtained by minimizing the discrepancy between the model predicted and the field observed values of junction pressures (hydraulic grades) and pipe flows for given boundary conditions such as tank levels, control valve setting and pump speeds. The optimized calibration is then defined as a nonlinear optimization problem for a given time step t as the following.

Search for: $$\vec{X} = (f_i, m_{j,t}, s_{k,t}) \qquad i = 1,\ldots,NI;\ j = 1,\ldots,NJ;\ k = 1,\ldots,NK. \tag{1}$$

Minimize: $$F(\vec{X}) \tag{2}$$

Subject to: $$\overline{f_i} \le f_i \le \underline{f_i} \tag{3}$$

$$\overline{m_{j,t}} \le m_{j,t} \le \underline{m_{j,t}} \tag{4}$$

$$s_{k,t} \in \{0,1\} \tag{5}$$

Where $\vec{X}$ represents a set of model parameters, $\overline{f_i}$ and $\underline{f_i}$ are the upper and lower limits of roughness factor for pipe group i, $\overline{m_{j,t}}$ and $\underline{m_{j,t}}$ are the upper and lower limits for demand adjustment multiplier for junction group j at time step t, NI is the number of roughness groups, HJ is the number of demand junction groups, NK is the number of uncertain-status links and $F(\vec{X})$ is the objective function that measures the goodness-of-fit between the field observed values and the model simulated values.

The objective function is defined as the fitness (also called goodness-of-fit score) or the distance between the model simulated and the field measured values of junction HGLs and pipe flows. In order to equivalently consider the contribution of both HGL and flow to the objective function, the difference between the observed and the simulated HGL is converted into the dimensionless fitness score by using user-specified the factor (*Hpnt*) of fitness point per unit hydraulic head. Similarly, the flow difference is also converted into the fitness score by user-specified factor (*Qpnt*) of fitness per unit flow. This permits flexible evaluation of both pipe flow and junction hydraulic head in one calibration run. Three fitness functions are defined as:

Objective type I: minimize the sum of difference squares

$$F(\vec{X}) = \sum_{t=1}^{T} \frac{\sum_{nh=1}^{NH} w_{nh} \left(\frac{Hs_{nh}(t) - Ho_{nh}(t)}{Hpnt} \right)^2 + \sum_{nf=1}^{NF} w_{nf} \left(\frac{Qs_{nf}(t) - Qo_{nf}(t)}{Qpnt} \right)^2}{NH + NQ} \tag{6}$$

Objective type II: minimize the sum of absolute differences

$$F(\vec{X}) = \sum_{t=1}^{T} \frac{\sum_{np=1}^{NH} w_{nh} \left| \frac{Hs_{nh}(t) - Ho_{nh}(t)}{Hpnt} \right| + \sum_{nf=1}^{NF} w_{nf} \left| \frac{Qs_{nf}(t) - Qo_{nf}(t)}{Qpnt} \right|}{NH + NQ} \tag{7}$$

Objective type III: minimize the maximum absolute difference

$$F(\vec{X}) = \arg\max_{t,nh,nf}\left\{\left|\frac{Hs_{nh}(t)-Ho_{nh}(t)}{Hpnt}\right|,\ \left|\frac{Qs_{nf}(t)-Qo_{nf}(t)}{Qpnt}\right|\right\} \tag{8}$$

where $Ho_{nh}(t)$ designates the observed hydraulic grade of the nh-th junction at time step t, $Hs_{nh}(t)$ is the model simulated hydraulic grade of the nh-th junction at time step t, $Qo_{nf}(t)$ is the observed flow of the nf-th link at time step t, $Qs_{nf}(t)$ is the simulated flow of the nf-th link at time step t, $Hpnt$ denotes the hydraulic head per fitness point while $Qpnt$ is the flow per fitness point, NH is the number of observed hydraulic grades and NQ is the number of observed pipe discharges, W_{nh} and W_{nf} represent a normalized weighting factor for observed hydraulic grades and flows respectively. They are given as:

$$W_{nh} = w(Hloss_{nh} / \sum Hloss_{nh}) \tag{9}$$
$$W_{nf} = w(Qo_{nf} / \sum Qo_{nf}) \tag{10}$$

where $w()$ is a function that can be linear, square, square root, log or constant and $Hloss_{nh}$ is the head loss at observation data point nh. An optimized calibration can be conducted by selecting one of three objectives. The model parameters are optimized by using a genetic algorithm while minimizing the selected objective function.

3. CALIBRATION STUDY

The model undertaken for calibration represents a real water system, as shown in Fig. 1, containing 407 pipes, 294 nodes, 2 wells (each is connected to a pump) and 2 storage tanks (one in the south near the wells and the other is to the far north of the system). A total system demand for the average day is 444.04 gpm while the total of the maximum day demand is 1066.22 gpm. A ratio of 2.4 is observed for the maximum day demand to average day demand. Static pressure, flow rate and residual pressure have been collected along with pump status (on/off) and tank levels for each of 14 fire flow tests (fire flow varies in a range of from 720 to 1,500 gpm. The time was not provided for each of the fire hydrant flow tests, which is deemed important for taking into account demand variation during the day.

3.1 Error Prone Application

The model was initially set up for applying GA-based calibration tool, the setup included:

1. 28 usable field data sets, both static and fire flow tests are specified together with corresponding tank level and pump status as well as the demand adjustment to account for the flow rate at the flowing hydrant.
2. Demand multiplier is set to 1.0;
3. 407 pipes are grouped into six roughness groups according to the original roughness C values by the following criteria:
    a. C-value < 70;
    b. 70 ≤ C-value < 80;
    c. 80 ≤ C-value < 110;
    d. 110 ≤ C-value < 120;
    e. 120 ≤ C-value < 130;
    f. C-value ≥ 130;
4. All junctions are grouped into one demand adjustment group.

With the input as above, calibration improvement was not achieved by using the GA-based optimization calibration tool. An endeavor has been made to trouble shoot the model calibration.

3.2 Diagnoses

A comprehensive diagnoses on the model calibration was undertaken in all aspects of field data set, optimal calibration setup and the also the calibration steps as follows.

3.2.1 Data Verification

The first step was taken to validate the field data including static and residual pressures as well as tank levels and pump statuses. Tank levels for T-South and T-North, pump status for PMP-5000 and PMP-3141 are served as boundary conditions for each data set, fire flow is specified as an additional demand. The main finding was that the pump status for some field data sets was inconsistent with the base scenario or data sheet provided. The mismatched pump status has been corrected according to the data sheet and also verified by performing the hydraulic run of corresponding scenario. However, this correction alone did not result in good calibration results although it did improve the goodness-of-fit between the observed values and model simulated values. Further effort has been made to justify roughness grouping and demand grouping.

3.2.2 Roughness Grouping

As mentioned earlier, 6 pipe groups were established according to the original C values. It has been noticed that the pipes within one group are scattered throughout the system. No individual group of pipes shows any hydraulic sensitivity to a field data set. In addition, 6 roughness groups represent 6 calibration variables (unknowns) that are to be calibrated for 14 field data sets of either static or fire flow. In this case, the number of data sets (known) is greater than the number of calibration parameters (unknown), so that the calibration problem is over-constrained. It restrains the calibration process from identifying sensible solution.

Pipe grouping is provided for reducing the number of calibration variables. All the pipes within the same group will be applied either the same C value or same multiplier to the original C values. To effectively calibrate a hydraulic model, a roughness group must be carefully selected to form an equivalent hydraulic link that is sensitive to a certain field data set/point. Adjusting the roughness values of one roughness group should be sensitive to the field-observed pressure and thus it ensures that calibration adjustment contributes hydraulic head loss to the field data points. Only in this way will changing the roughness of a group of pipes be sensitive to the observed pressure and thus enable the observed to match the simulated values. Therefore, sensible C value can be achieved and good agreement between the observed and simulated can be obtained. The steps undertaken to identify sensitive pipes and make roughness group are as follows.

1. Perform a steady state hydraulic run with a significant demand at a pressure data location (such as a fire flow testing location).
2. Enable pipe flow direction arrows for all the pipes.
3. Group those pipes that contribute most of the flow to the node. You may also divide them into several groups according to their diameters.

It is highly recommended that the grouping process start with the node that is near to the water source, and then progressively move to the next testing node.

For this particular model pipes have been regrouped by following the above procedure, starting at fire flow test F-20 at junction J-9 as shown in Fig. 1, which is the closest to the source tank T-North. Six pipes are aggregated into Roughness Group-20 including p-6, p-12, p-33, p-5357 and p-5360, which are the upstream pipes of junction J-9 and contribute the flow (thus the headloss) to the testing node. The next fire flow test number could be fire flow test F-18 at J-42 or fire flow test F-17 at J-54. The calibration sequence of the rest field data sets will be fire flow test F-19 at J-5084, F-13 at J-189, F-12 at J-213, F-15 at J-102, F-14 at J-195, F-9 at J-300, F-8 at J-5222, F-5 at J-5024, F-6 at J-447, F-7 at J-396 and F-10 at J-309. This sequence allows you to group the pipes from the source to the distribution system for the filed data points. It also allows you to calibrate the model progressively for each roughness group.

3.2.3 Demand Grouping

Initial calibration setup contained one demand group that includes all the demand junctions. This essentially requires that the demands are adjusted or calibrated for all the nodes, including the fire flow nodes, by applying one demand multiplier. This is a problematic demand grouping for this case since the demand is measured and a known value at fire flow node. Adjusting the demand at the fire flow nodes, along with the non-fire flow nodes, just skews the correct loading conditions at the fire flow nodes that contribute more than 50% of the maximum-day demand in this system. Thus, the fire flow nodes should be excluded from demand adjustment groups when calibrating the model against fire flow tests.

3.3 Progressive Calibration

Apart from correcting the erroneous pump operation status in field data input, insensitive roughness groups, faulty demand group, progressive calibration approach is further adopted as an effective procedure to demonstrate how to achieve good calibration results by applying optimal calibration tool.

Progressive calibration is undertaken by optimizing one roughness group at one calibration run while just using the most sensitive field data set. It starts with the calibration of those roughness groups that are associated with the field data set/points near to a primary water source, then proceeds gradually with the adjacent roughness group and field data set. This allows the modeler to progressively calibrate the model from sources into a distribution system. A general procedure for conducting progressive calibration is given as:

1. Create one optimized calibration run for the field data sets that are near the main water sources.
2. Set the minimum and maximum bounds for the calibration group(s) that are sensitive to the field data set(s).
3. Set the minimum and maximum bounds the same for the rest of groups, using 1.0 for un-calibrated groups and the calibrated value for the groups that are calibrated. The same minimum and maximum bound will force GA to use the bound value for the roughness group.
4. Exclude the fire flow node from the demand group.
5. Run optimal calibration with preferred criteria.
6. Proceed the rest of model calibration by creating a child optimized calibration run and repeating step 2 to 5 for the adjacent roughness group and field data sets.

For this model calibration, fire flow test F-20 at junction J-9 and Roughness Group-20 were chosen as the first calibration run. It is identified as a good starting point since it is near to the tank T-North, the main water source when the hydrant at junction of J-9 is flowing. To optimize one adjustment group Roughness Group 20 using only field data set F-20, the minimum and maximum values for all the other roughness groups were set to 1.0. It forces GA to apply roughness multiplier of 1.0 to the other roughness groups. It essentially keeps the C value as it is for all the other pipes. A good calibration results were obtained with the minimum HGL difference of 0.02 ft between the observed and simulated values, roughness multiplier of 1.05 and demand multiplier of 1.05. The resulted demand multiplier represents the demand variation in comparing to the representative demand alternative when the field-testing was carried out. Having calibrated F-20, the next adjacent calibration group Roughness Group-18 has been calibrated using field data set of fire flow test F-18 at junction J-42. During this process, the minimum and maximum values for roughness Group-20 were set to 1.05 while the other groups are set to 1.0. Calibration run has also resulted in good calibration results, 0.001 ft HGL difference and roughness multiplier of 1.1. The process has been repeated by generally following the progressive procedure and the calibration sequence outlined early. A child calibration can be created from previous calibration run. This way the model calibration progressively proceeded from sources into the system. It has significantly improved the calibration results as shown in Figure 2.

4. CONCLUSIONS

This study illustrates a fruitful calibration process from many perspectives. Although it does not intend to achieve a completely calibrated model, the investigation has identified and corrected the faulty pump operating status, insensitive roughness group and conflict demand group. It proposed an effective calibration procedure including generating sensible roughness adjustment grouping (pipe roughness and junction demand) and the progressive calibration process. The procedure and steps have been found particularly efficient at improving calibration by using the optimization calibration tool. They may also serve a general guideline and reference for calibrating water distribution models even without using optimization techniques. This study also uncovered that the optimal calibration method needs to be improved in its robustness to effectively handle faulty field data and efficiently avoid error-prone applications.

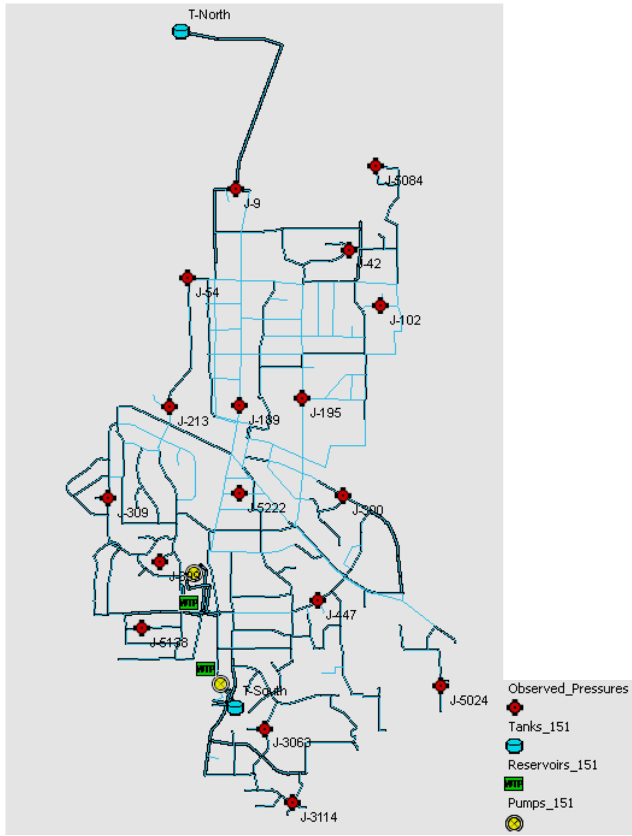

Figure 1 Layout of water distribution model undertaken for calibration

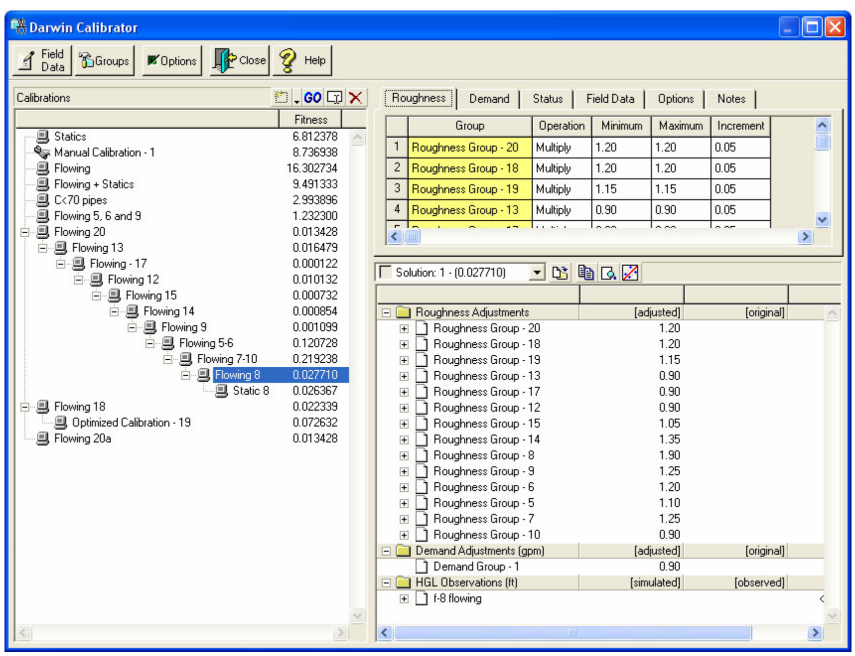

Figure 2 Darwin Progressive Calibration by Creating Multi-layer Inherited Calibration Runs

Reference

DHI Water and Environment (1993) *MOUSE User Guide and Technique Reference*, Agern Allé 5, DK-2970, Hørsholm, Denmark.

Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison Wesley, Reading, MA.

Goldberg, D. E., Korb, B., & Deb, K. (1989). "Messy genetic algorithms: Motivation, analysis, and first results." *Complex Systems, 3*, 493-530.

Goldberg, D. E., Deb, K., Kargupta, H., & Harik G. (1993). "Rapid, Accurate Optimization of Difficult Problems Using Fast Messy Genetic Algorithms." *IlliGAL Report No. 93004*, Illinois Genetic Algorithms Laboratory, University of Illinios at Urbana-Champaign, Urbana, IL 61801, USA.

Haestad Methods (2002) *WaterCAD Software Manual*, Bentley Systems Incorporated, Haestad Methods Solution Center, Watertown, CT06795, USA.

Lansey, K. and Basnet, C. (1991) "Parameter Estimation for Water Distribution Networks." *Journal of Water Resources Planning and Management,* 117(1), 126.

Meredith, D., (1983) "Use of Optimization in Calibrating Water Distribution Models," *Proceedings of ASCE Spring Convention,* Philadelphia, PA.

Ormsbee, L. and Chase, D.V. (1988) "Hydraulic Network Calibration using Nonlinear Programming." *Proceedings of International Symposium on Water Distribution Modeling*, Lexington, KY.

Savic, D. A. and Walters, G.A. (1995) "Genetic Algorithm Techniques for Calibrating Network Models." Report No. 95/12, Center for Systems and Control Engineering, University of Exeter, UK.

Walski, T. M. (2000) "Model Calibration Data: The Good, The Bad and The Useless," *J. AWWA,* 92(1), p. 94.

Walski, T. M. (2001) "Understanding the adjustments for water distribution system model calibration." *Journal of Indian Water Works Association*, April-June, 2001, pp151-157.

Walski, T. M., Chase, D.V. and Savic, D.A. (2001) *Water Distribution Modeling,* Bentley Systems, Incorporated, Haestad Methods Solution Center, Watertwon, CT06795, USA.

Wang, Q. J. (1991) "The Genetic Algorithm and its Application to Conceptual Rainfall-Runoff Models." *Water Resources Research*, Vol.27, No.9, pp2467-2482.

Wu, Z. Y. (1994) *Automatic Model Calibration by Simulating Evolution*, H.H. 191, International Institute for Infrastructure, Hydraulic and Environmental Engineering, Delft, the Netherlands.

Wu, Z. Y. and Larsen, C. L. (1996) "Verification of hydrological and hydrodynamic models calibrated by genetic algorithms." *Proc. of the 2nd International Conference on Water Resources & Environmental Research*, Vol. 2, Kyoto, Japan, pp175-182.

Wu, Z. Y. and Simpson, A. R. (2001) "Competent Genetic Algorithm Optimization of Water Distribution Systems." *Journal of Computing in Civil Engineering*, ASCE, Vol 15, No. 2, pp89-101.

Wu, Z. Y., Boulos, P. F., Orr, C. H., and Ro, J. J (2000) "An Efficient Genetic Algorithms Approach to an Intelligent Decision Support System for Water Distribution Networks." in *Proceedings of the Hydroinformatics 2000 Conference*, July 26-29, Iowa, IW.

Wu, Z. Y., Walski, T.M., Mankowski, R., Herrin, G., Gurrieri, R. and Tryby, M. (2002a) "Calibrating Water Distribution Models via Genetic Algorithms." Proceedings AWWA Information Management Technology Conference, Kansas City, Mo.

Wu, Z. Y., Walski, T. M., Mankowski, R., Herrin, G., Gurrieri,, R., Tryby, M. (2002b) "Impact of Measurement Errors on Optimal Calibration of Water Distribution Models." *Proceedings of the International Conference on Technology Automation and Control of Wastewater and Drinking Water Systems,* Gdansk, Poland.