# DETERMINING THE ACCURACY OF AUTOMATED CALIBRATION OF PIPE NETWORK MODELS

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## Abstract

*Methods to automatically calibrate water distribution system models have been available for some time but it is very difficult to prove that any method is correct. Since at any one time the ability to know all the usage and flow conditions in a real system is impossible, obtaining all of the data needed in a real water distribution system to obtain an accurate and complete data set for model calibration is unrealistic. To test the ability of automated calibration methods to predict the actual conditions in a water system a laboratory scale physical model of a water distribution system was constructed and an automated water distribution model calibration program, employing genetic algorithms, was used to calibrate the model of that system.*

*The results indicated that the automated calibration methods worked well in estimating pipe roughness, demands and locating closed valves. More specifically, the automated calibration model exactly matched the measured flows and pressures in the system. It was able to identify whether a valve was closed and where the demands were located. If given sufficient data, it was able to identify pipe roughness. The only problems occurred when the number of unknowns greatly exceeded the number of measurements. The model worked equally well regardless of whether the head loss equation used was the Hazen-Williams, Darcy-Weisbach or Manning equation. In all, automated calibration was successful.*

*The paper describes how the lab data were collected, and how the calibration program matched the lab data and provides some suggestions for users of an automated water distribution calibration model.*

## Keywords

Water distribution modeling, calibration, genetic algorithm, optimal calibration, pipe roughness

## 1. BACKGROUND

Water distribution models are frequently used both for design and operation by virtually all water utilities. The value of these models is directly related to how well the model represents the real water distribution system. Utilities improve the quality of their model through a process known as model calibration in which: 1. model results are compared with field measurement of system parameters and 2. the model is adjusted to better match the real system (Herrin, 1997; Walski, et al., 2003). However, making the appropriate adjustments to the model is often difficult because there are so many parameters to be

adjusted. It is often difficult to determine which parameter is causing the problem or if the problem actually lies with the field data (Walski, 1990). Problems with calibration can be traced to a large number of sources including incorrect pipe roughness, inaccurate demands, incorrect valve status, and erroneous field data.

Calibration has traditionally been a manual trial-and-error process where the modeler estimates the parameter adjustment that might bring the model into agreement with field data. These trials continue until the modeler is satisfied with calibration or cannot justify additional effort to further improve the model. Ideally, this manual calibration process can be improved by having the computer take over much of the trial-and-error work in calibration. Unfortunately it is difficult if not impossible to tell how well a model has been calibrated because it is nearly impossible to know the exact water consumption by each customer, the exact roughness for each pipe, or the correct setting of each valve at the time when the field measurements were obtained. Because the correct value of every parameter in a model is not known, it is impossible to know if any automated (or manual) calibration process is actually correct.

In this study, a laboratory-scale physical model of a distribution system was constructed and an automated calibration model was used to determine the model input parameters. The values from the automated calibration model were compared with the measured values obtained from the lab model. This paper discusses the literature on automated calibration, presents the Darwin Calibrator (the automated calibration program used in this study), describes the physical model constructed in a laboratory, and presents the results of the comparison between the physical model observations and the Darwin Calibrator results.

## 1.1 Literature Review

Model calibration has traditionally been a trial-and-error process. Because of the large number of potential unknowns, it is not possible to analytically solve all calibration parameters. Early methods to calibrate models (Shamir and Howard, 1968; Walski, 1983; Ormsbee and Wood 1986, Bhave, 1988) often used an approach where the number of unknowns matches the number of observations so that an explicit solution could be determined. This required a great deal of judgment to determine how to group the unknowns. This resulted in the use of models that could be erroneous if the assumptions used to group unknowns were invalid. Therefore, some form of optimization needed to be used when calibrating models so that it was not necessary to solve a number of equations equal to the number of unknowns. Meredith (1983) produced the first optimization model for calibration which was based on linear programming.

With the advance of computing technology and optimization techniques, more automated calibration methods were developed. Most methods for automated calibration relied on optimization and fall under the general category of “parameter estimation”. By using input values known as “state variables” such as measured flows and heads, the model can determine “control or decision variables” such as pipe roughness or demand. Ormsbee (1989) and Ormsbee and Chase (1988) applied optimization to calibrate models. Lansey and Basnet (1991) developed an optimization model which could match field observations but noted that sufficient quantities of high quality data were necessary to make it work well. This concurred with Walski’s observation (1986, 2000) that sufficient head loss is needed in the system for automated calibration to work, which was successfully illustrated in a sample system (Walski, 2001). Araujo and Lansey (1991) and Lansey et al. (2001) quantified how measurement errors propagated through the model calibration processes.

Methods to evaluate and optimize model calibration vary widely. Datta and Sridharan, (1994) and Reddy, Sridharan, and Rao (1996) used least squares methods to arrive at calibrated models. Greco and Del Giudice (1999) used a “sensitivity matrix” to minimize the least squares difference between observed and

predicted values. Lingireddy and Ormsbee (1998) developed a method using neural networks for model calibration.

Wang (1991) was the first to apply a genetic algorithm to the calibration of a conceptual hydrology model. Wu (1994) developed a genetic algorithm approach for automatic calibration of an integrated hydrology and hydrodynamic modeling system. Savic and Walters (1995) developed a genetic algorithm method for water distribution model calibration. Genetic algorithm methods showed a great deal of promise in that they were robust and weren't hampered by local minima. Wu et al. (2002a) developed the Darwin Calibrator which used a competent genetic algorithm paradigm (Wu and Simpson 2001) which included the ability to identify correct values for demand and valve status as well as pipe roughness.

Because it is not possible to accurately know the roughness of every pipe and demands at every node in a real water system, the methods described above could only be tested against hypothetical solutions (i.e. the "correct" solution was generated by a model).

## 1.2 Calibration Using a Genetic Algorithm Program

The Darwin Calibrator is the genetic algorithm program used in this study. It is an add-on program to WaterCAD and WaterGEMS programs (Haestad Methods, 2006). The Darwin Calibrator uses a genetic algorithm approach developed by Wu and is described in papers by Wu et al. (2002a, 2002b).

Once the user has constructed a model of a water distribution system, the user enters field data. The user then decides on which parameters could be adjusted to achieve calibration and any boundary conditions associated with the system at the time the data were collected. Field data consists of flows and head (hydraulic grade line elevations) through the system. Boundary conditions refer to water levels in tanks and the operational status of pumps and valves.

In any real system there can be hundreds or thousands of unknowns and only a relatively small number of field observations. Wu et al. (2002b) has observed that when the number of unknowns greatly exceeds the number of useful observations, there is little confidence in the calibration results. There are too many solutions that can match the observed flows and heads. However, it is not likely that pipes with similar characteristics will have very different roughness values or nodes in a given area of the system will need large adjustments to achieve calibration. It is likely for automated calibration to be successful that pipes and nodes being adjusted be placed in "groups". This reduces the size of the problem, makes it possible to find the optimal solution and avoids issues where several identical pipes would end up with very different roughness values because of small inaccuracies in field measurement.

The correctness of the solutions obtained using genetic algorithms is quantified using what is called the "fitness" of the solutions. The fitness is based on the difference between observed and predicted values for the hydraulic grade line (HGL) and flow. There are typically three methods for calculating fitness: least squares, least absolute difference value, and least maximum error. The method used in this paper, unless otherwise stated, is least squares where the fitness is determined as

$$F = \frac{1}{w_H}\sum (H_{mod} - H_{obs})^2 + \frac{1}{w_Q}\sum (Q_{mod} - Q_{obs})^2$$

where $F$ = fitness
$H_{mod}$ = model value for head, L
$H_{obs}$ = observed value for head, L
$Q_{mod}$ = model value for flow, $L^3/T$

$Q_{obs}$ = observed value for flow, $L^3/T$
$w_H$ = weighting factor for head, $L^2$/fitness unit
$w_Q$ = weighting factor for flow, $(L^3/T)^2$/fitness unit

Unless stated otherwise, the head weighting was 0.305 while the flow weighting was 0.631.

One of the issues with genetic algorithm type searches is that there is some uncertainty as to when to stop the solver. Three general criteria are used to stop the run:

1. Fitness within user specified tolerance: if the fitness is excellent, the solver is satisfied and stops.
2. Maximum number of iterations: if the maximum number is exceeded, the best solution(s) found thus far is shown.
3. Maximum number of non-improvement generations: if the solution stops improving after this number of generations, the solver cannot improve fitness and stops.

For initial runs, the user is encouraged to set the tolerances high and the maximum iterations low to make the solver run faster, but for final runs, the user should set the tolerance very low and the maximums very high to get the best accuracy.

## 2. LABORATORY EXPERIMENTS

Because it is not possible to know the exact flows and pipe properties in a real system, a laboratory model system was constructed in the Wilkes University (Wilkes-Barre, Pennsylvania) laboratory. The dimensions of the piping system are shown in Figure 1. The piping consisted of nominal 1-inch (25 mm) and 1½-inch (38 mm) PVC pipe with actual internal diameters of 1.044 and 1.609 inches (26.5 and 40.8 mm) measured using a micrometer. Pipe sizes were selected to be small while still maintaining turbulent flow conditions during all experiments. Figure 2 shows a photograph of the actual pipe network with the manometer board in the center.

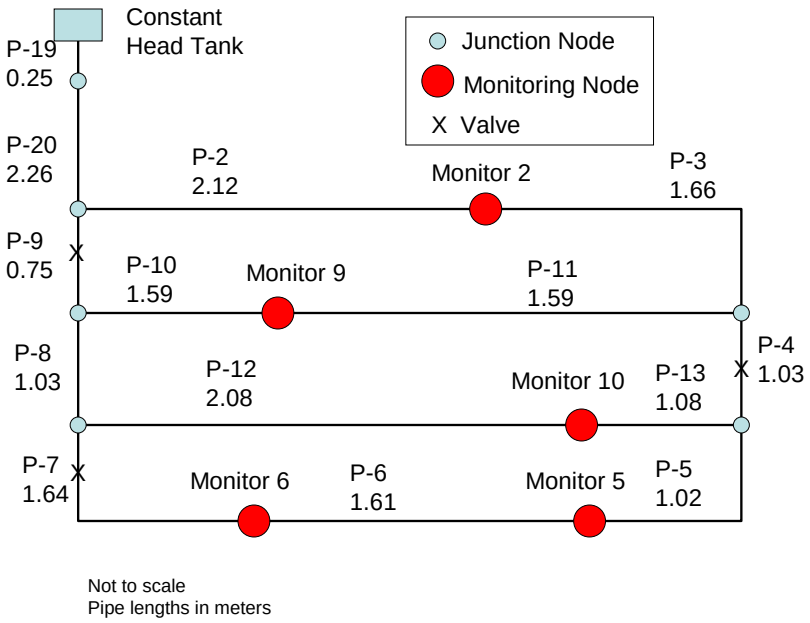


Figure 1. Schematic of original lab pipe network

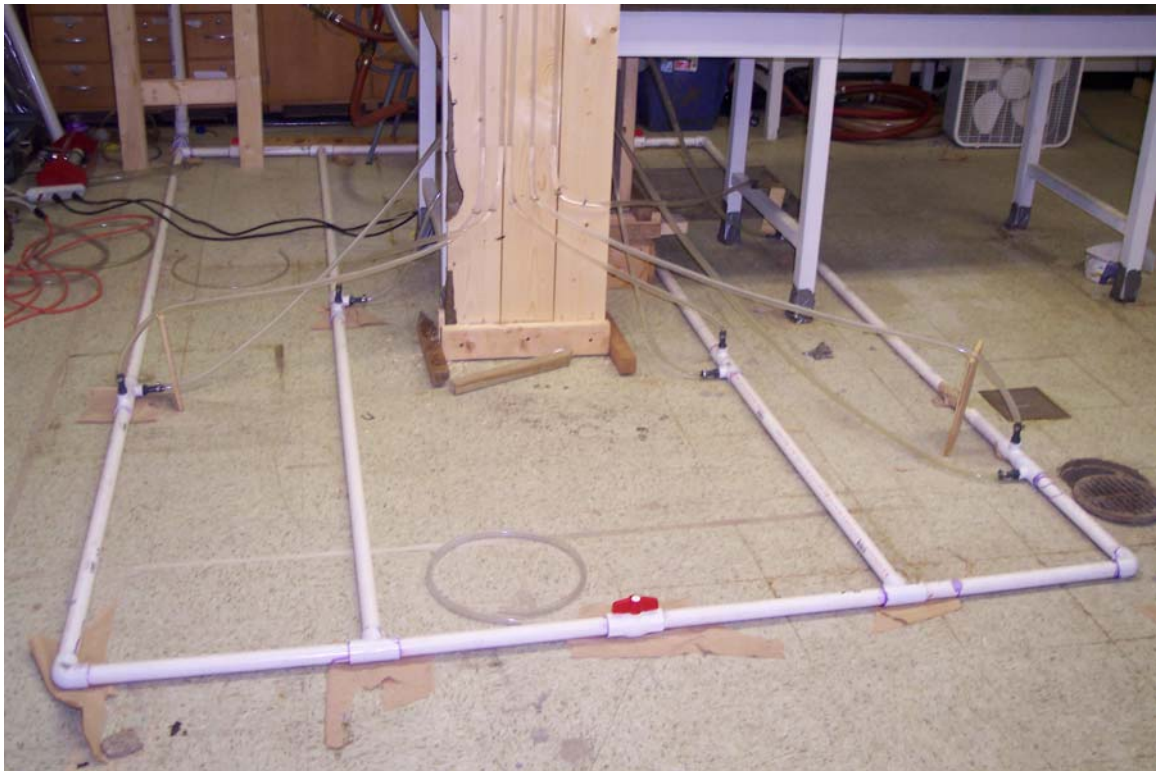

Figure 2. Pipe network used to generate data

The water in the system was supplied by a constant head tank. All water drained back to a sump and was recycled to the constant head tank. Three full port ball valves (in pipes P-4, P-7, and P-9) were initially included in the piping to make it possible to reconfigure the piping network from one run to the next and to test Darwin's ability to find closed valves.

There were five demand/monitoring nodes in the network. Each of these contained two T's as shown in Figure 3. One tap (at the side of the pipe) corresponded to the water user and was a location where flow was measured by recording the time it took to fill a container of known volume. The other T (tap on top of the pipe) was connected to a central manometer board shown in Figure 4 where the hydraulic grade line elevation could be directly measured.

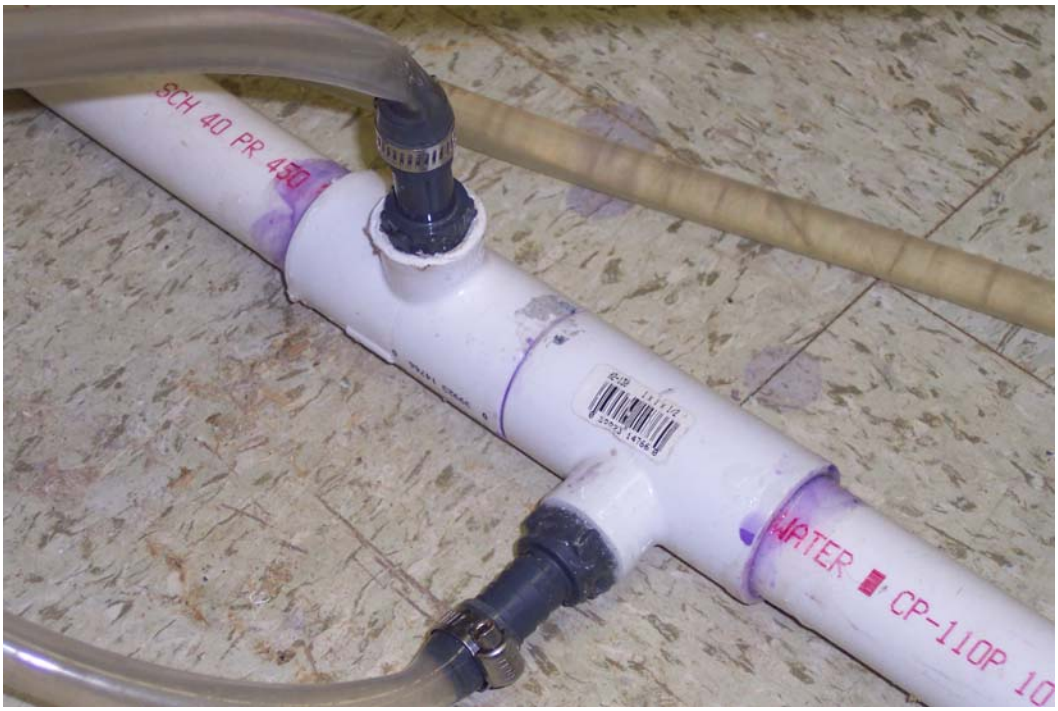


Figure 3. Monitoring and water use node

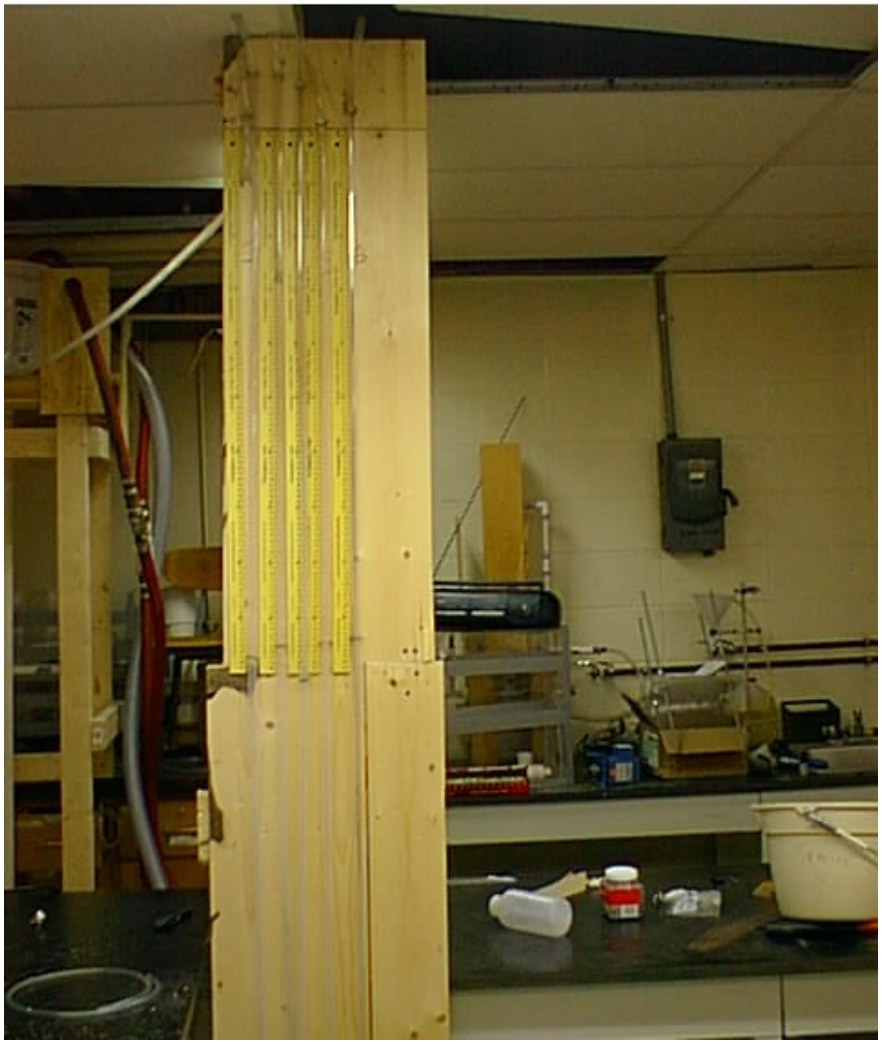

Figure 4. Manometer used to measure heads

Several experimental runs of the lab model were conducted for all combinations of valve settings. In general six sets of measurements were taken for each condition and the average value was used for this analysis. Most runs were made with all of the outlets open although some runs were made with all but one of the outlets closed. All runs corresponded to steady state conditions so there were no unsteady flow or transient effects.

## 3. ANALYSIS

Once the data were collected and the computer model of the system was constructed, the Darwin Calibrator was used to determine the calibration parameters. With data collected from the physical lab model, it was possible to set up numerous cases for which the Darwin Calibrator was tested. In general, there were 14 pipe roughness values, five demands and three valve settings that could be determined (i.e.

22 decision variables). Depending on the run, these values were determined using information about the three valve settings, five HGL measurements, and five measured demands. In some cases, the valve status (open/closed) and demands were treated as either known or unknown. In many of the runs, all of the pipes were placed in one group because all of the pipes should have the same internal characteristics. In other runs, 14 separate groups were set up to determine if Darwin would give similar results for each pipe. In still other runs, pipes were placed in groups depending on their location within the system.

A large number of cases were set up and solved using the Darwin Calibrator. The cases that provided the most insight into its performance for automated calibration are presented in the sections below. As expected, the Darwin Calibrator did an excellent job in matching the measured HGL values (state variables). The root mean square error (RMSE) between observed and model HGL values is usually on the order of the precision of the readings. However, because of the under constrained nature of the calibration problem, it was more difficult to match the model parameters for roughness and demand (decision variables). This is especially evident in runs with large numbers of groups.

The lab model differs from most distribution systems because the exact internal diameter is known. In real systems, the exact internal diameters are not known and nominal diameters are typically used. Only in small pipes is this difference really significant. Minor losses can usually be ignored in real water distribution systems because they account for only a small portion of the total head loss. However in this pipe network they could be significant and their impact was considered in some runs. Finally, in real systems the velocity head changes are negligible. In this system, the use of the HGL instead of energy grade line may have introduced error in some specific cases. The individual cases are presented in the sub-sections below.

## 3.1 Determining Roughness

The initial runs showed a range of results for the optimal value for C-factor. Because the pipes did not change between runs, this was less than ideal — one would expect a single correct C-factor. This indicated some nonuniformity in C-factors across the system and required some special work to account for this anomaly which distorted some otherwise good results.

When the pipes were placed in 14 separate groups, the pipes around node J-1 (junction of P-2, P-9, and P-20; see Figure 1) had lower C-factors. When the pipes were placed in a single group, runs with a higher flow had significantly lower C-factors. Plotting total flow from the reservoir vs. C as shown in Figure 5 showed that runs with pipe P-9 with the valve open had lower C-factors.

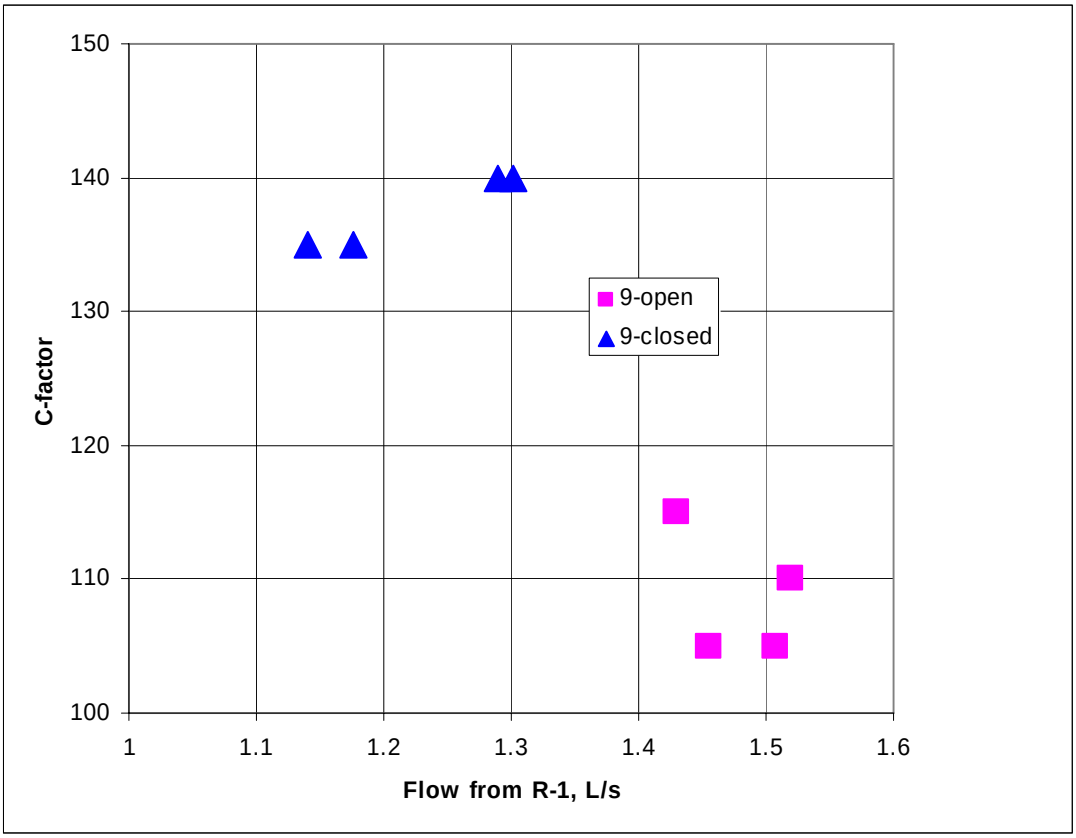


Figure 5. C-factor based on varying status for pipe P-9

This indicated that something odd was occurring in pipe P-9. Since this was a pipe with a valve in it and is from the 90-degree angle of the tee near vertical pipe from the supply tank, the supposition was that the valve was not opening completely or the minor losses due because of the tee are much higher than expected. As a follow up to the initial testing, a fourth valve was place in the system in pipe P-3 and it was closed so that all of the flow from the source passed through pipe P-9. In this case a calculated C-factor of 70 for P-9 and values on the order of 120 to 130 for all other pipes, supported the supposition that a minor loss is significant in P-9. Because the high head loss in this pipe was needed to be accounted for, a minor loss coefficient was assigned to this pipe for all later runs.

To determine the minor loss in P-9, a series of model runs were made with differing assigned minor loss K values for this pipe. A single system-wide C-factor was determined using all data sets. As shown in Figure 6, as K increased, the global C-factor had to increase to offset other losses. The fitness of the solution was at its best with a minor loss K of 4 and a C-factor of 141.

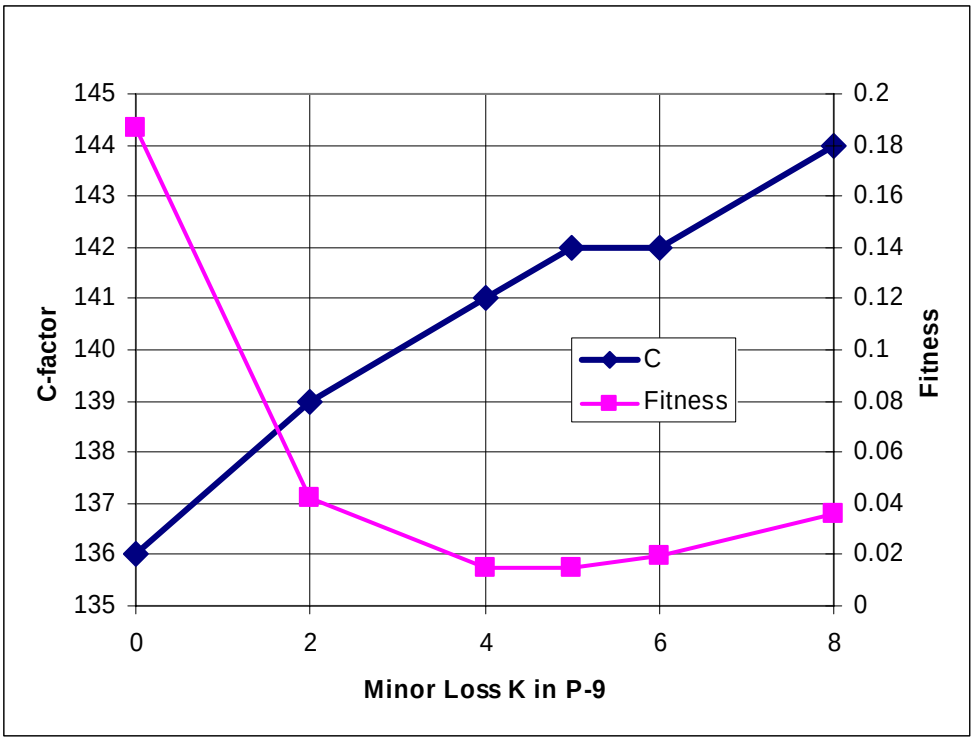


Figure 6. Effect of minor loss K on roughness and fitness

For the remaining runs a minor loss coefficient (K) value of 4 is used for P-9 unless otherwise noted. This value was required to account for the reduction from 38 to 25 mm (1.5 to 1 in.) with two right angle bends at the upstream end of P-9. Minor losses were ignored in the other bends. Based on these initial runs the "correct" value for the C-factor is 141 and other solutions will be judged with regard to how well they approach this value.

## 3.2 Individual Pipes vs. Spatial Grouping

In running an optimal calibration model it is tempting to set up a separate group for each pipe to allow the maximum flexibility in finding solutions. In this study there would be 14 groups. Ideally, if the correct C-factor is 141, all of the groups would end up with 141 as the predicted C-factor. However, in runs with 14 groups, while the Darwin Calibrator matched the heads exactly, there were many combinations of C-factors that worked. The program does not only save a single solution but can save many of the good solutions it determines ranked by the fitness value. The best solution and several representative solutions are shown in Table 1 below. The "solution number" refers to the rank of the solution based on the least-squared fitness value. Solution 12 has the 12$^{th}$ best fitness of all considered.

Table 1. C factors for several solutions

| Solution Number | 1 | 5 | 8 | 12 |
|---|---|---|---|---|
| Fitness Value | 0.00258 | 0.00296 | 0.00341 | 0.00407 |
| Pipe 2 | 145 | 144 | 144 | 144 |
| Pipe 3 | 152 | 151 | 152 | 150 |
| Pipe 4 | 151 | 180 | 150 | 152 |
| Pipe 5 | 180 | 147 | 180 | 180 |
| Pipe 6 | 154 | 180 | 114 | 172 |
| Pipe 7 | 115 | 180 | 175 | 175 |
| Pipe 8 | 146 | 119 | 140 | 117 |
| Pipe 9 | 103 | 116 | 100 | 116 |
| Pipe 10 | 138 | 147 | 135 | 180 |
| Pipe 11 | 112 | 113 | 110 | 112 |
| Pipe 12 | 156 | 175 | 152 | 180 |
| Pipe 13 | 123 | 125 | 164 | 101 |
| Pipe 19 | 141 | 157 | 180 | 180 |
| Pipe 20 | 131 | 132 | 130 | 130 |

While each of the solutions in the table represent good solutions and the agreement between observed and predicted heads are on the order of the precision of measurement, the table shows that there are many good solutions, some of which have unusual values for the C-factor. However, the length weighted averages of the C-factor is near 141 for all cases.

The reason for the range of C-factors is that there is no way to distinguish between pipe C-factors when there are no measurement of head between monitoring points. For example, pipes P-19, P-20 and P-2 are in series but there is no measurement between the pipes. Therefore, there are an infinite number of combinations of C-factor that will give the correct head at the end of those three pipes. The weighted average C-factor is near 141 but the software cannot distinguish between 141-131-145, 180-130-144 or 141-141-141 for P-19, P-20, and P-2 respectfully. The implication here in terms of modeling is that creating an excessive number of groups does not improve the solution if there is not sufficient data for an optimal calibrator to distinguish between the groups. Intelligent grouping is the key to using automated calibration models.

One approach to create spatial groups has been to group pipes according to the monitoring point (or flow test). In this case pipes leading up to a monitoring point would be in one group, pipes between this monitor and another monitor would be the second group, etc. The calibration process would be to determine the C-factor for the first group, then that value would be fixed and the C-factor for the second group would then be determined. For the physical lab model, groups are shown in Figure 7 and are labeled Grp2, Grp9, Grp10 and Grp56 based on the monitoring point locations. Monitoring points 5 and 6 were combined because there is very little head loss between the two points.

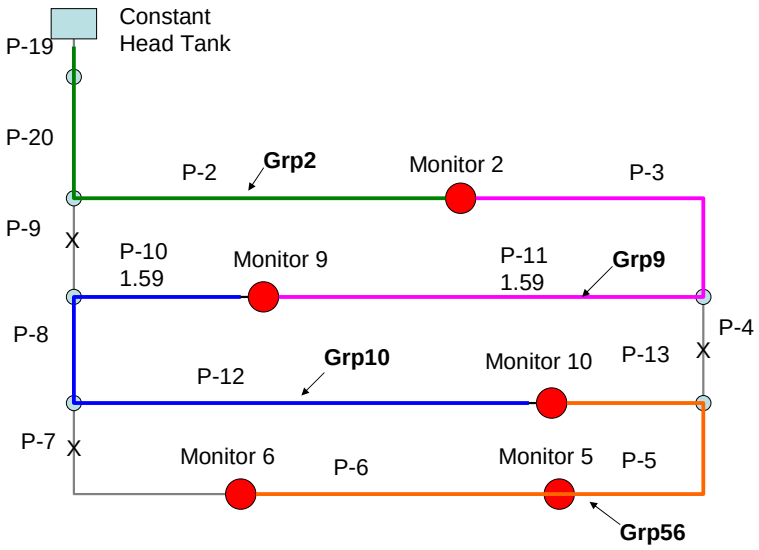


Figure 7. Spatial grouping of pipes

In this example, all data collected was when all of the flow goes to the monitoring point. For example, for monitoring point 2, only data for the case where P-9 is closed is used. When each value for C-factor is determined incrementally, the values are shown in Table 2 below.

Table 2. Solution with four groups

| Group | C-factor |
|---|---|
| Grp2 | 143 |
| Grp9 | 140 |
| Grp10 | 127 |
| Grp56 | 140 |

This showed that it is possible to move through the system and solve for roughness one area at a time. With this approach, the run times are faster because the number of groups being adjusted is small. This is logical where pipes differ spatially. For instance, if older pipes are located in the south part of town, there is no sense in adjusting their roughness using flow tests from the north part of town.

### 3.4 Effect of Using Discrete Increment Values

In the genetic algorithm solver, the unknowns are not continuous variables but are discrete variables. C-factors such as 140, 141, 142, etc. are determined and values such as 141.3486 are not determined unless the increment was set to 0.0001, which would result in a prohibitively large set of possible solutions. To determine the effect of the increment size on the solutions the increment was set to 1, 2, 5 and 10. Those solutions and the associated fitness values are shown in the Table 3 for the case with four spatial groups. For the case with an increment of 10, the range started at 60 (60, 70, etc.) for one run and 65 (65, 75, etc.) for the next.

Table 3. C-factors determined using different values for each increment

| Increment | 1 | 2 | 5 | 10(60) | 10(65) |
|---|---|---|---|---|---|
| Grp2 | 146 | 146 | 145 | 150 | 145 |
| Grp9 | 125 | 124 | 125 | 120 | 125 |
| Grp10 | 143 | 144 | 145 | 150 | 145 |
| Grp56 | 140 | 144 | 140 | 130 | 135 |
| Fitness Value | 0.000023 | 0.000057 | 0.000076 | 0.001382 | 0.000088 |

As one would expect, as the increment size decreased, the fitness value (agreement between model and observed values) improved. Another interesting point is that the runs with an increment of 10 yielded different solutions depending on whether the values such as 60, 70 80, etc were used instead of values like 65, 75, 85, etc. This appears to be just a quirk of this problem, but if large increments are used, the user may want to adjust the ranges to test the sensitivity of the solution to the ranges used. The lesson learned in these runs were that intelligently reducing the range of allowable roughness values will enable the solver to have a better chance to find the right value. However, if the increment size is decreased too much, the number of possible solutions greatly increases without providing a more correct value. Generally calculating a C-factor close one is unrealistic in the field so it is impractical to use an increment size less than one.

## 3.5 Finding Closed Valves

One of the key tests of the calibrator was the test of its ability to find closed valves in the pipe network. To test this, 8 different combinations of valves were tested in the lab as listed in Table 4 below. Calibration runs were set up to determine a single global C-factor with the three valves which each could have the status of open or closed.

Table 4. Summary of Valve Status Runs

| 4 | 7 | 9 | Global C-factor |
|---|---|---|---|
| O | O | O | 140 |
| C | C | C | 139 |
| C | O | C | 139 |
| C | O | O | 134 |
| O | C | C | 145 |
| O | C | O | 138 |
| C | C | O | 147 |
| O | O | C | 144 |

O = open; C = closed

Figure 8 summarizes the results of the runs to locate closed valves. They show that in all cases, the HGL predicted by the model (solid line) matched the HGL observed in the pipe network (points with same color as line). The results also show that while similar C-factors were determined for each case, there is some variation in the correct solution due to the accuracy of the measurements. The HGL in the physical lab could only be measured to a precision of approximately one centimeter due to the slight unsteady water level in the manometer. The differences between observed and predicted HGLs were at most one to two centimeters which corresponded to a variation of up to 6 C-factor units for the “correct” value of 141. The “position” (x-axis) in the figure refers to the distance from the constant head tank when all valves are closed.

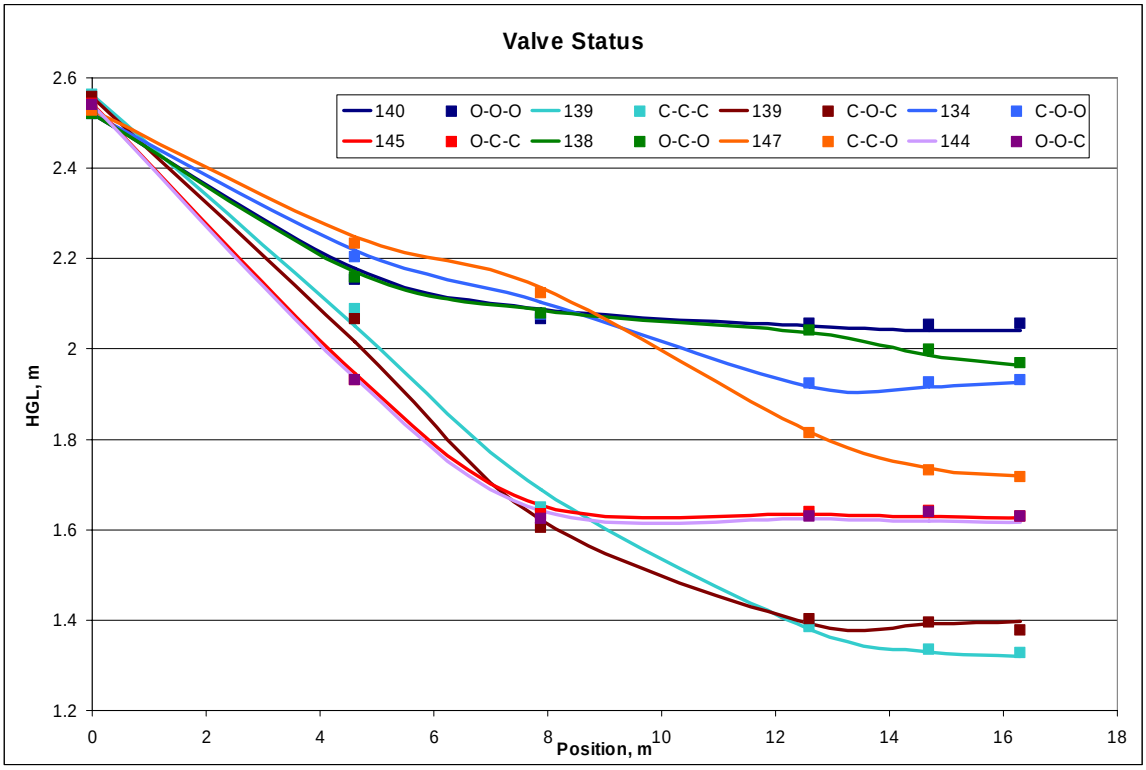


Figure 8. Correlation between observed and model HGL valves for different valve positions

Out of the eight runs, the Darwin Calibrator correctly matched the valve status in seven. The single run where the initial solution had one valve wrong involved the case were valve 4 was open and 7 and 9 were closed (O-C-C). In that run, status for valves 4 and 9 were correctly predicted but incorrectly stated that valve 7 was open. The problem was caused by the fact that with valve 7 open, virtually no flow in the pipe P-7 was observed, such that the solutions with 7 open and closed were virtually identical. The lesson here is that in order to determine the status of a valve, the flow pattern should be such that a significant amount of flow would pass through the valve if it were open.

## 3.6 Determining Demands

The ability of the Darwin Calibrator to determine demand flow rates were tested as shown in Table 5. With only the HGL information provided, numerous solutions were found where roughness and demands compensated for each other, i.e. a high value for the C-factor can offset a high value for the demand. Therefore, for most subsequent runs, the totalized flow was also provided. This is a reasonable piece of information since, for most systems, the total water plant or well production flow is known. Without some input as to total inflow from the source, the solver had difficulty determining the magnitude of flow because roughness errors could offset demand errors.

The table consists of pairs of columns for each test. The first with the values measured in the lab and the second the results of the model. In all there were four tests. The first used all 8 possible combinations for the valve status and all outlets were open. Only the demands for the data set where all valves are open are shown. The second data set was for the case where all the operable valves were open and all the outlets were open. The third case consisted of the data set when all three operable valves were shut. The final case consisted off all three valves shut with only Monitor 6 (the last outlet) open.

Table 5. Results of runs to evaluate the effectiveness of determining demands. (Flow rates have units of L/s.)

| Open Valves | 8 Combinations | | 4-7-9 | | None | | None | |
|---|---|---|---|---|---|---|---|---|
| Open Outlets | All | | All | | All | | Mon6 | |
| Outlet Node | Lab | Model | Lab | Model | Lab | Model | Lab | Model |
| Monitor 2 | 0.30 | 0.28 | 0.30 | 0.29 | 0.30 | 0.19 | 0 | 0 |
| Monitor 5 | 0.28 | 0.33 | 0.28 | 0.32 | 0.18 | 0.18 | 0 | 0.02 |
| Monitor 6 | 0.30 | 0.20 | 0.30 | 0.30 | 0.18 | 0.18 | 0.33 | 0.31 |
| Monitor 9 | 0.30 | 0.30 | 0.30 | 0.33 | 0.21 | 0.33 | 0 | 0 |
| Monitor 10 | 0.33 | 0.40 | 0.33 | 0.27 | 0.27 | 0.26 | 0 | 0 |
| Total Flow | 1.51 | 1.51 | 1.51 | 1.51 | 1.14 | 1.14 | 0.33 | 0.33 |
| C-factor | | 143 | | 141 | | 144 | | 139 |

In general, the C-factor and total demand were predicted accurately. It was somewhat less accurate at assigning demands to the individual nodes. This can be expected because while the predicted HGL is sensitive to the total flow demand, it is somewhat less sensitive to the exact placement of that demand. Similarly, in a real water system, it is impossible to know exactly which customer(s) are using water when any data are collected.

## 3.7 Other Head Loss Equations

Thus far, the Hazen-Williams equation has been used for head loss and the Darwin Calibrator has solved for the C-factor. To examine the use of other head loss equations, the pipes were grouped into four groups as described earlier and the cases with all eight valve combinations and the single case with all valves open were run. Either the Manning or Darcy-Weisbach equations were used for head loss where Darwin solved for Manning's n or the equivalent sand grain roughness height using the Swamee-Jain formula. The results are shown in Table 6 below.

Table 6. Results for Manning's n and Darcy-Weisbach roughness height in mm.

| | Manning's n | | Darcy-Weisbach | |
|---|---|---|---|---|
| Group | 8 Combinations | All valves closed | 8 Combinations | All valves closed |
| Grp2 | 0.008 | 0.007 | 0.006 | 0.011 |
| Grp9 | 0.006 | 0.009 | 0.061 | 0.076 |
| Grp10 | 0.008 | 0.007 | 0.021 | 0.016 |
| Grp56 | 0.006 | 0.010 | 0.001 | 0.006 |

The values for Manning's n were very low but are consistent with a small pipe with a C-factor of 140. The solutions for equivalent sand grain roughness height are reasonable for smooth small pipe but show an unexpectedly large range. However, in the range of Reynolds numbers and relative roughness for this network, it takes very large changes in roughness to make even a tiny change in friction factor. (On the Moody diagram, many lines converge in this region.) This explains the large range for roughness values. In terms of friction factor (f), all the f-values were around 0.03.

## 3.8 Nominal vs. Actual Diameters

In the runs thus far, the actual internal diameters were used for pipes. For many cases, the user will only know the nominal diameters. Using the same case (all valves closed—four groups—least squares fitness), the Darwin Calibrator was used to solve for the C-factor. One would expect the C-factors to be related to the ratio of diameters using the Hazen-Williams equations as

$$C_{(nom)} = C_{(actual)} \left( \frac{D_{(actual)}}{D_{(nom)}} \right)^{2.63}$$

The results shown Table 7 are consistent with what one would expect. The ratio between actual and nominal C-factors should be on the order of 1.12 based on the measured internal diameter of the pipe used in the physical model.

Table 7. Comparing solutions based on minimal and actual diameters. Ratio is determined as the Nominal value divided by the Actual value.

| | Actual | Nominal | Ratio |
|---|---|---|---|
| Grp2 | 146 | 160 | 1.10 |
| Grp9 | 125 | 148 | 1.18 |
| Grp10 | 143 | 154 | 1.08 |
| Grp56 | 140 | 164 | 1.17 |

The calculated ratio has a range of 1.08 and 1.18 which is consistent with the expected ratio of 1.12. In larger pipes, as found in real water distribution systems, the differences between nominal and actual diameters are usually much smaller than those encountered in the small pipes used in this study and the resulting ratio would be closer to 1. These results indicate that the use of the nominal pipe diameter in a real water distribution system does not lead to substantial errors.

## 4.0 SUMMARY

This paper showed the ability of genetic algorithms as embodied in the Darwin Calibrator to determine values for the pipe roughness, valve status, and demand for a pipe network where the flows and valve status would be known much more precisely than is likely possible for real systems. Overall, the solver worked well although several potential pitfalls in its use were identified. The most significant is trying to use more pipe groups than the data can support. In this case many possible combinations of C-factors were possible. Also when trying to determine the valve status in a case where very little flow would pass through the valve, in one case, the calibrator inaccurately predicted whether the valve was opened or closed. The Darwin Calibrator worked well regardless of whether the Hazen-Williams, Manning, or Darcy-Weisbach formulas were used. When determining demands, it is important to specify some flow, such as the total inflow to the system at sources, in order to keep the search focused in the right range of flows.

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