

Optimal Calibration Method for Water Distribution Water Quality Model

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7 A water quality model is to predict water quality transport and fate throughout a
8 water distribution system. The model is not only a promising alternative for analyzing
9 disinfectant residuals in a cost-effective manner, but also a means of providing
10 enormous engineering insights into the characteristics of water quality variation and
11 constituent reactions. However, a water quality model is a reliable tool only if it predicts
12 what a real system behaves. This paper presents a methodology that enables a modeler
13 to efficiently calibrate a water quality model such that the field observed water quality
14 values match with the model simulated values. The method is formulated to adjust
15 the global water quality parameters and also the element-dependent water quality
16 reaction rates for pipelines and tank storages. A genetic algorithm is applied to optimize
17 the model parameters by minimizing the difference between the model-predicted
18 values and the field-observed values. It is seamLessly integrated with a well-developed
19 hydraulic and water quality modeling system. The approach has provided a generic
20 tool and methodology for engineers to construct the sound water quality model in
21 expedient manner. The method is applied to a real water system and demonstrated
22 that a water quality model can be optimized for managing adequate water supply to
23 public communities.

24 Key Words: Water distribution; Water supply; Water quality model; Chlorine decay;
25 Simulation; Calibration; Optimization; Genetic algorithm.

26 INTRODUCTION

27 Drinking water quality is essential to public heath. Although water treatment
28 is a common practice for supplying good quality of water from a source,
29 maintaining an adequate water quality throughout a distribution system
30 is a daunting task. The challenges remain in the complex pipe geometry,

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31 sophisticated network connectivity, various system operation controls, tem-
32 poral and spatial variation of water demand, and also intriguing constituent
33 reaction in bulk water and in between the water and pipe walls. Sampling
34 and continuously monitoring water quality at appropriate locations have
35 played an important role to minimize the risk of inadequate water quality
36 to public health, however, but sampling only presents a limited picture of
37 water quality in that there are only a few monitoring points and mon-
38 itoring cannot be used to predict future conditions or perform “what if”
39 analyses due to the limited coverage and the high cost. Thus, using a well-
40 developed hydraulic and water quality model is an important approach for
41 simulating the hydraulic and water quality dynamics for all elements in a
42 system.

43 Water quality modeling has become an increasingly common practice for
44 water utilities around world. It is formulated as a mathematical model and
45 developed as computer-based tool to predict water quality transport and fate
46 within a water distribution system according to the network flow dynamics.
47 The model is not only a promising technology for predicting disinfectant
48 residuals in a cost-effective manner, but also a means of providing enormous
49 engineering understanding in the dynamics of water quality variation and the
50 sophisticated process of constituent reactions that occur in water distribution
51 systems. The early development of water quality models was based upon the
52 steady-state hydraulic simulation of mass conservation law. The models^[1-4]
53 determined the water quality spatial distribution of a constituent throughout
54 a pipeline network under static hydraulic conditions.

55 Although the steady-state water quality model proved to be useful for
56 investigating the overall movement of a contaminant under constant con-
57 ditions, the system hydraulics is constantly changing in tank levels, valve
58 settings, pump operating status and nodal demand. Therefore, the need for
59 the models that represent the dynamics of contaminant movement led to
60 the development of better water quality models under temporally varying
61 conditions. Dynamic models of water quality in distribution systems explicitly
62 take into account of changing in flows through pipelines and storage facilities
63 over an extended period of time. A number of solution methods^[5-9] are
64 developed for dynamic water quality models. They can be classified spatially as
65 either Eulerian or Lagrangian and temporally as time-driven or event-driven
66 methods. Each of these methods assumes that a hydraulic model determines
67 the flow direction and velocity in each pipe at specific time intervals over an
68 extended period. Within each interval, referred as hydraulic time step, the pipe
69 flow velocity remains constant, the simulation of a constituent movement and
70 reaction proceeds in a smaller time step (so-called water quality time step).
71 Thus the dynamic approach is more realistic than steady-state methods in
72 simulating systematic condition of water quality transportation and reaction
73 in distribution networks.

74 However, a water quality model is an effective and reliable analysis tool
75 only when the constituent reaction and decay/growth mechanisms are properly
76 defined. This can only be achieved by calibrating the water quality model using
77 the field observed and lab-tested water quality data. Like hydraulic model
78 calibration, water quality model calibration is a time-consuming and tedious
79 process by manually adjusting model parameters. In this article, a competent
80 genetic algorithm-based calibration approach for calibrating a water quality
81 model is presented. It provides modelers a flexible optimization modeling tool
82 to facilitate the water quality model calibration task. In order to develop an
83 effective calibration method, it is important to understand the insights into
84 water quality model formulation. A brief overview of water quality model is
85 given next.

86 WATER QUALITY MODEL

87 Water quality model for a water distribution system is based upon Reynolds
88 transport theorem (RTT) and formulated for one-dimensional, unsteady small
89 fluid parcel as follows.

$$\frac{\partial C}{\partial t} + V \frac{\partial C}{\partial x} = R(C) \quad (1)$$

90 where C is the concentration of a constituent; t is time; V is the flow velocity;
92 x is the distance and R represents the constituent reaction relationship. Water
93 quality model for a water distribution system used in this paper is based
94 upon a parcel tracking algorithm.^[8,9] It tracks the change in water quality
95 of discrete parcels of water as they move along pipes and mixes together at
96 junctions between fixed-length time steps. During a simulation, the water
97 quality in each parcel is updated to reflect any reaction that may have occurred
98 over the time step. The water from the leading parcels of pipes with flow
99 into each junction is blended together, along with any external inflow to the
100 junction, to compute a new water quality value at the junction. The volume
101 contributed from each parcel equals the product of its pipe's flow rate and the
102 time step. If this volume exceeds that of the leading parcel then the leading
103 parcel is destroyed and the next parcel in line behind it begins to contribute its
104 volume. New parcels are created in pipes with flow out of each junction. The
105 parcel volume equals the product of the pipe flow and the time step.

106 To reduce on the number of parcels, a new parcel is formed if the new
107 junction quality differs by a user-specified tolerance from that of the last parcel
108 in the outflow pipe. If the difference in quality is below the tolerance then the
109 size of the last parcel is simply increased by the volume of flow released into
110 the pipe over the time step with no change in quality. Initially each pipe in
111 the network consists of a single parcel whose quality equals the initial quality
112 assigned to the upstream node. The water quality simulation tracks the growth

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113 or decay of a substance by reaction as it travels through a distribution system.
 114 To do this, it needs to know the rate at which the substance reacts and how
 115 this rate might depend on substance concentration. Reactions can occur both
 116 within the bulk flow and with material along the pipe wall. Bulk fluid reactions
 117 can also occur within tanks.

118 Bulk Reaction

119 Bulk flow reactions are the reactions that occur in the main flow stream
 120 of a pipe or in a storage tank, unaffected by any processes that might
 121 involve the pipe wall. A water quality model simulates these reactions using
 122 n -th order kinetics, where the instantaneous rate of reaction (R in unit of
 123 mass/volume/time) is assumed to be concentration-dependent, given as:

$$R(C) = K_b C^n \quad (2)$$

124 where K_b is a bulk rate coefficient; C is reactant concentration (mass/volume)
 125 and n is a reaction order. K_b has units of concentration raised to the $(1-n)$
 126 power divided by time. It is positive for growth reactions and negative for decay
 127 reactions. It also considers reactions where a limiting concentration exists on
 128 the ultimate growth or loss of the substance. In this case the rate expression
 129 for a growth reaction becomes
 130

$$R(C) = K_b (C_L - C) C^{(n-1)} \quad (3)$$

131 where C_L = the limiting concentration. For decay reactions $(C_L - C)$ is replaced
 132 by $(C - C_L)$.

134 Thus, there are three parameters (K_b , C_L , and n) that are used to
 135 characterize bulk reaction rates. Different values of these parameters lead to
 136 different kinetic models. They need to be carefully calibrated for the pipes and
 137 tanks in a water distribution system.

138 Wall Reaction

139 In addition to bulk flow reactions, constituent reactions occur with mate-
 140 rial on or near the pipe wall. The rate of this reaction is dependent on the
 141 concentration in the bulk flow and pipe wall conditions, given as:

$$R(C) = (A/V) K_w C^n \quad (4)$$

142 Where K_w is a wall reaction rate coefficient and (A/V) is the surface area per
 143 unit volume within a pipe. It converts the mass reacting per unit of wall area
 144 to a per unit volume basis. n is the wall reaction order taking value of either
 145 0 or 1, so that the unit of K_w is either mass/area/time or length/time. Both K_w
 146 and n are site specific and need to be calibrated for water distribution pipes.
 147

148 CALIBRATION FORMULATION

149 To calibrate a water quality model for analyzing any constituent (not just Chlorine decay), it is important to adjust the parameters that govern the reaction
150 mechanism. It includes bulk reaction and pipe wall reaction parameters.
151

152 Bulk Water Reaction Calibration

153 Bulk reaction rate is conventionally obtained by conducting bottle test
154 in a laboratory, namely taking bottles of sample water and measuring the
155 constituent concentration of the bottle water over time test to determine the
156 bulk water reaction rate. For chlorine decay, one can measure the residual
157 of chlorine over time, so that bulk reaction/decay can be gauged by the bottle
158 test. Bottle test is recommended for determining the bulk reaction coefficient
159 such as chlorine decay factor. It provides a good baseline value and reference
160 for constructing a water quality model. Although bulk reaction coefficient can
161 be attained by bottle test, real bulk reaction may vary from one portion of a
162 system to another due to dynamic flow conditions and mixing of multiple water
163 sources. The real bulk reaction mechanism needs to be calibrated throughout
164 a distribution system. Bulk water reaction is generally characterized by three
165 parameters including:

- 166 (i) Bulk reaction coefficient K_b ;
- 167 (ii) Bulk reaction order n_b ;
- 168 (iii) Concentration limit C_L .

169 Bulk reaction parameters need to be adjusted for both pipe and tank
170 elements. The pipes that are of the similar characteristics are allowed to be
171 grouped into one calibration group for bulk reaction coefficient adjustment.
172 The bulk reaction groups are set up in a similar fashion to the roughness
173 group,^[10] prescribed with minimum, maximum values and an increment for
174 each pipe group and tank. The same reaction parameters are applied to the
175 pipes in one calibration group. This reduces the number of the calibration
176 parameters. Tank bulk reaction coefficient is calibrated individually for each
177 storage facility. By adjusting all the parameters (K_b , n_b and C_L), a water
178 quality model can be calibrated to simulate the bulk water reaction of not
179 only chlorine decay, but also the other reaction mechanisms such as first-
180 order saturation growth, two-component second-order growth, two-component
181 second-order decay and the other reaction mechanisms.

182 Pipe Wall Reaction Calibration

183 Pipe wall reaction is characterized by the wall coefficient (K_w) and reaction
184 order (n_w). Both parameters are closely related to pipe material and pipe wall

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185 physical conditions such as encrustation and tuberculation of corrosion prod-
186 ucts. Two methods are developed for calibrating pipe wall reaction mechanism.

187 **Direct Calibration**

188 Direct calibration is to directly optimize the pipe wall reaction coefficient
189 and reaction order for a group of pipes. Since the wall reaction mechanism is
190 expected to have the same behavior for the pipes of the same characteristics
191 (age, material and location). Similar to the roughness calibration group,^[11]
192 pipes of the same characteristics are allowed to be aggregated and treated as a
193 set of common calibration parameters, wall coefficient and order are calibrated
194 between the minimum and maximum values with an increment specified by a
195 modeler.

196 **Correlation Calibration**

197 Alternatively, pipe wall reaction can be calibrated by adjusting a corre-
198 lation factor. It is well known that as metal pipes age their roughness tends
199 to increase due to encrustation and tuberculation of corrosion products on
200 the pipe walls. This increase in roughness produces a lower Hazen-Williams
201 C -factor or a higher Darcy-Weisbach roughness coefficient, resulting in greater
202 frictional headloss in flow through the pipe. There is some evidence^[12] to
203 suggest that the same processes that increase a pipe's roughness with age also
204 tend to increase the reactivity of its wall with some chemical species, particu-
205 larly chlorine and other disinfectants. Each pipe's wall reaction coefficient (K_w)
206 can be a function of the coefficient used to describe its roughness. A different
207 function applies depending on the formula used to compute headloss through
208 a pipe:

$$\text{Hazen-Williams: } K_w = F/C \quad (5)$$

$$\text{Darcy-Weisbach: } K_w = -F/\log(e/d) \quad (6)$$

$$\text{Chezy-Manning: } K_w = F*N \quad (7)$$

209 where C is Hazen-Williams C -factor; e is Darcy-Weisbach roughness, d is
210 pipe diameter, N is Manning roughness coefficient and F is the coefficient
211 of correlation of wall reaction and pipe roughness. The coefficient F must
212 be developed from site-specific field measurements and will have a different
213 meaning depending on which headloss equation is used. The advantage of
214 using this approach is that it requires only a single parameter F , to allow wall
215 reaction coefficients to vary throughout the network in a physically meaningful
216 way. This is because a hydraulic model must be calibrated before undertaking a
217 water quality model calibration. Therefore, pipe roughness should be a known
218 value for water quality model calibration. In this case, modelers may choose to
219

220 just calibrate the correlation factor for Chlorine pipe wall reaction mechanism.
 221 Correlation factor adjustment can also be conducted for a group of pipes or
 222 globally for an entire system.

223 One calibration solution represents one set of parameters that define
 224 the bulk water reaction and pipe wall reaction mechanism. Each possible
 225 solution is passed to a hydraulic and water quality model which produces the
 226 simulation results of water quality concentrations in a system. The simulated
 227 concentration values are compared with the observed values. The comparison
 228 is quantified as a goodness-of-fit between the simulated and the observed
 229 values. The goodness-of-fit is defined as a fitness or calibration objective
 230 function in the following section.

231 Calibration Objectives

232 The objective of water quality model calibration is to minimize the
 233 difference between the field observed and the model simulated constituent
 234 concentrations. Assume the field observed concentration be represented by
 235 $C_i^{obs}(t_j)$ at time t_j for monitoring location i and collected over N time steps
 236 at M locations while the model simulated concentration is noted as $C_i^{sim}(t_j)$.
 237 The calibration objective can be measured in many different ways formulated
 238 as follows.

239 Minimize difference square:

$$Fitness = \frac{\sum_{i=1}^M \sum_{j=1}^N (C_i^{obs}(t_j) - C_i^{sim}(t_j))^2}{N \times M} \quad (8)$$

240

241 Minimize absolute difference:

$$Fitness = \frac{\sum_{i=1}^M \sum_{j=1}^N |C_i^{obs}(t_j) - C_i^{sim}(t_j)|}{N \times M} \quad (9)$$

242

243 Minimize absolute maximum difference:

$$Fitness = \max_{i,j} |C_i^{obs}(t_j) - C_i^{sim}(t_j)| \quad (10)$$

244

245 Minimize sum of absolute mean difference:

$$Fitness = \sum_{i=1}^M \frac{\sum_{j=1}^N |C_i^{obs}(t_j) - C_i^{sim}(t_j)|}{N} \quad (11)$$

246

247 When chemical concentration is collected at a sampling/monitoring station, it
 248 may not be measured at a regular time step. To compare between the observed
 249 and simulated concentration, the simulated result must be obtained for the
 250 same time as the observed value is collected. When the simulation time step

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251 does not exactly match the time step of data collection, the simulated concen-
252 tration is attained by interpolating the results at two adjacent computation
253 time steps for the same monitor location/node. The coefficients for bulk water
254 and pipe wall reaction can be calibrated for pipe groups while the reaction
255 orders and concentration limit are global parameters for a system.

256 Water quality calibration, formulated as above, is a nonlinear implicit
257 optimization problem. It is solved by using the same methodology for hydraulic
258 model calibration by Wu et al.^[10,11] In fact, the hydraulic calibration has been
259 extended to include the calibration of water quality parameters by means of
260 the competent genetic algorithm.^[13]

261 SOLUTION METHODOLOGY

262 The implementation of water quality calibration algorithm is illustrated in
263 Figure 1. The information flows in both directions between the end-user and
264 the data storage and thus enables engineers to effectively manage the data and
265 calibrate a model by exploiting the powerful combination of GA optimizer and
266 hydraulic network simulator, both are embodied into one modeling system.
267 It consists of a user interface, calibration evaluation module, GA optimizer,
268 hydraulic and water quality simulation model.

269 A user interface on a personal computer or other workstation lends the
270 user the ability to enter the field observed data, select the representative de-
271 mand loading, corresponding boundary conditions (including pump operating
272 status, valve settings and tank levels) and calibration criteria. It enables a
273 modeler to intuitively set up calibration, persistently conducting calibration
274 tasks and graphically presenting results.

275 An initial calibration model is established by performing the extended pe-
276 riod hydraulic simulation. The results are saved in the file that is repetitively
277 used for water quality analysis of each calibration solution. A calibration run
278 may proceed by either interactively adjusting calibration parameters (manu-
279 ally set a value for each parameter), that is to bypass the genetic algorithm
280 optimizer, or presenting the data to GA optimizer to automatically search
281 for the optimal and near optimal calibration solutions. Without activating
282 the GA optimizer, the user-estimated model parameters are submitted to the
283 hydraulic and water quality simulator. It predicts the water quality responses
284 that are passed back to calibration evaluation module. The goodness-of-fit is
285 calculated and reported to a user. Modelers can estimate the parameters and
286 iterate over the process to enhance model calibration. In contrast, calibration
287 can proceed with GA optimizer searching for the optimal solution. The GA
288 optimizer will automatically generate and optimize the calibration solutions.
289 Each trial solution, along with the selected data sets, corresponding loading
290 and boundary conditions, is submitted to hydraulic network simulator for

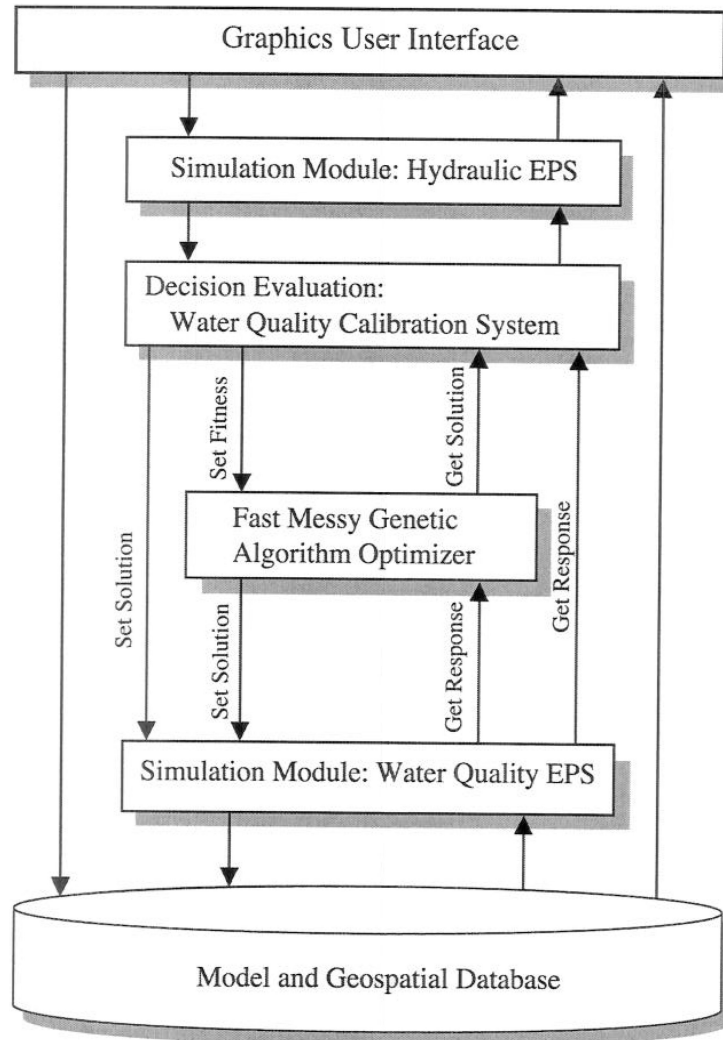


Figure 1: Darwin water quality calibration framework and data flow.

291 predicting the water quality results. The model simulated results are passed
 292 back to the calibration evaluation module and used to calculate the fitness for
 293 the solution. It enables the GA-optimizer to evolve the calibration solutions.

294 In addition, all the input data including the field data, calibration results
 295 and calibration run settings including the number of top solutions to be
 296 reported, optimization stop criteria and GA parameters are consistently per-
 297 sisted in a modeling database along with the simulation model. This permits
 298 engineers to revisit the calibration process any time. It also helps modelers to
 299 better manage a project over time. The integrated implementation provides the

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300 powerful features of hydraulic and water quality network modeling paradigm.
301 It has been applied to the optimization of the water quality model for chlorine
302 decay study by Vasconcelos et al.^[12]

303 CASE STUDY

304 Oberlin system, as shown as in Figure 2, has been demonstrated as an example
305 of applying the calibration method to construct an accurate water quality
306 model. Oberlin zone is a relatively isolated system receiving water from one
307 source. It is a portion of Harrisburg water system within United Water service
308 area. There is no storage facility in the zone. The isolated Oberlin zone was
309 used for the project of chlorine decay kinetics study^[12] funded by America
310 Water Works Research Fund (AWWARF). Chlorine concentration data were
311 collected at 27 locations over 35 hours for capturing the balance of water
312 quality state. This field data set provides an excellent example for water
313 quality calibration. Both bulk water and pipe wall reaction parameters are
314 calibrated to minimize the difference between the observed and simulated
315 chlorine concentrations.

316 For chlorine reaction coefficients (bulk water and pipe wall) are adjusted
317 for pipe groups. All the pipes are grouped into three groups. For each group,
318 pipe wall correlation factor is specified within a range of -1000.0 and -100.0
319 with increment of 5.0 . Bulk reaction coefficient is set up within a range of -2.0
320 and -0.1 in unit of $(\text{mg/L})^{(1.0-n)/s}$ with increment of 0.05 . Reaction orders are
321 treated as global model parameter, so that they are adjusted for the entire
322 zone. Bulk reaction order is between 1 and 5 while pipe wall reaction order can
323 be either 0 or 1 .

324 Any of the four fitness functions can be selected to run water quality
325 calibration. However, to compare the results with the previous study, fitness
326 type of minimizing the sum of absolute mean differences is applied to this
327 case study, namely, the fitness of calibration solution is calculated as the sum
328 of absolute mean differences between the observed mean and the simulated
329 mean over 35 hours for all the 27 locations. The Darwin Calibrator run
330 is performed to optimize the water quality parameters. The comparison is
331 presented, as in Figure 3, for both free chlorine decay and the calibrated
332 average absolute errors of all monitor locations. The results obtained
333 illustrate that it effectively improved the goodness-of-fit between the observed
334 and predicted water quality when comparing to the free chlorine decay (all
335 the points would fall on a straight line if agreement was perfect). Without the
336 calibration on water quality model, the field observed water quality near the
337 source appears to match well with the simulated results as shown in Figure 4.
338 This is due to the fact that there is not much reaction/decay has occurred in
339 the bulk water, and between the pipe wall and water right after chlorine is put

Model to Predict Water Quality Transport 11

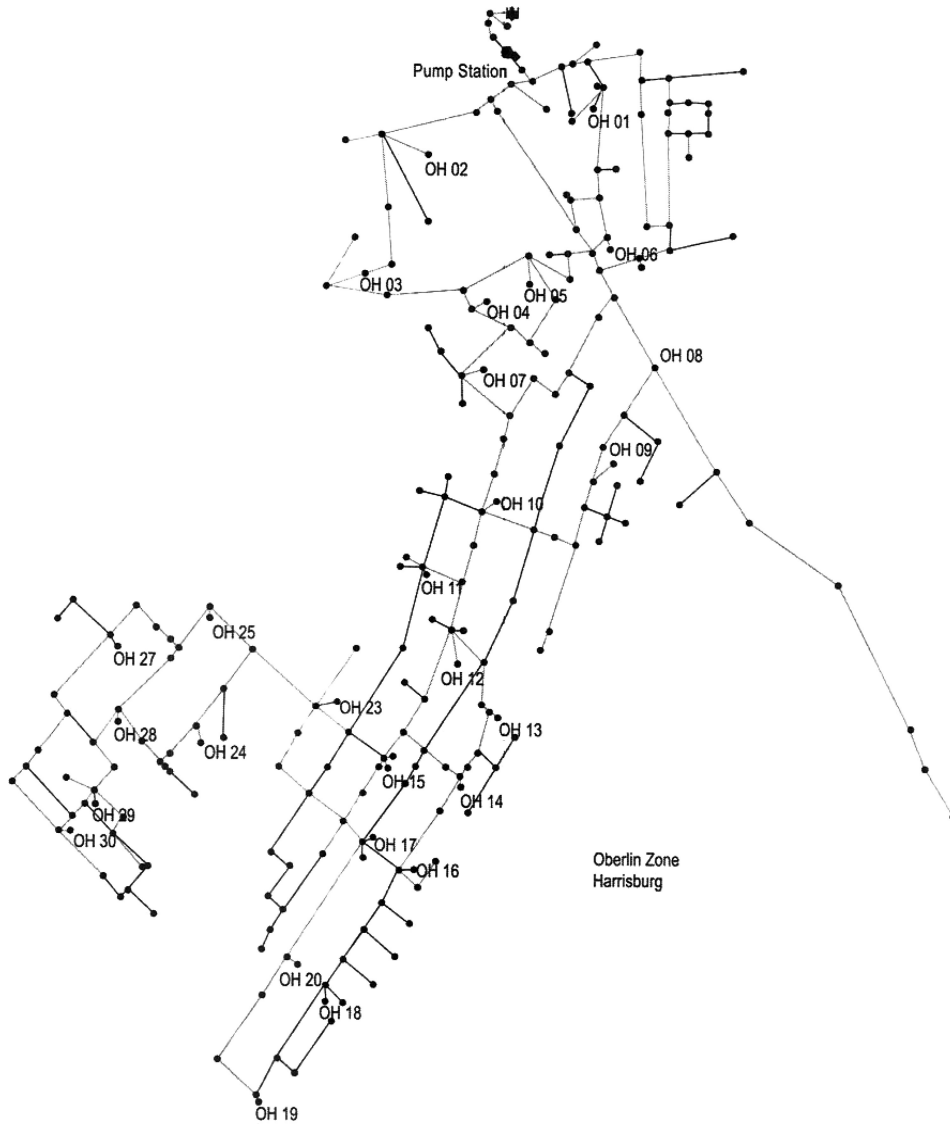


Figure 2: Oberlin zone of Harrisburg Water Distribution System.

340 into the system at the source (booster station in this case). Water quality at
 341 the outskirts of the system, however, is quite different from the nodes near the
 342 pump station. Figure 5 implies that significant chlorine decay has taken place
 343 from the source into the distribution system. Without good calibration on the
 344 water quality model, the field observed chlorine residual is away mismatched
 345 with the model simulated. Figures 3 and 5 demonstrate that the calibration

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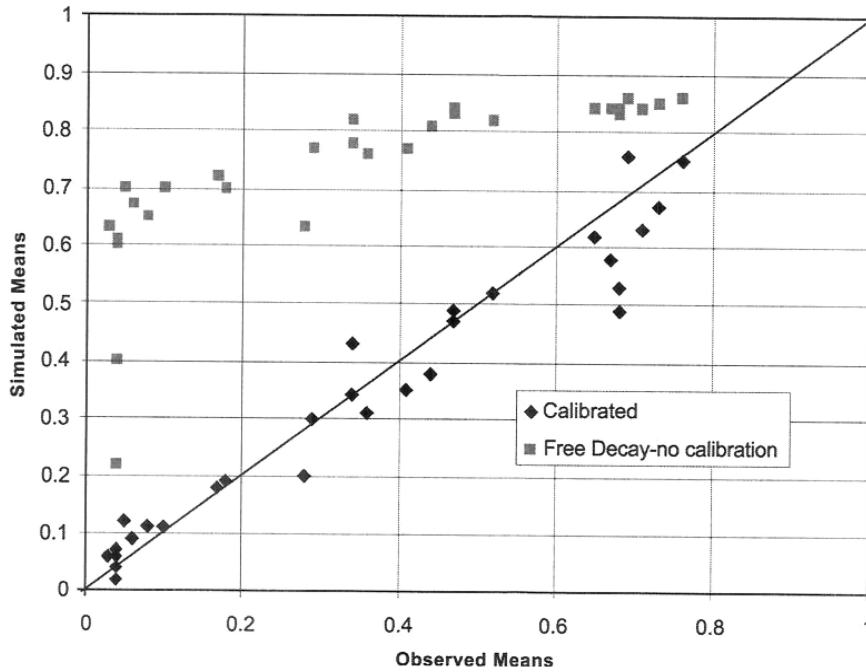


Figure 3: Comparison the observed and simulated mean of chlorine concentrations over 35 hours at 27 sampling locations.

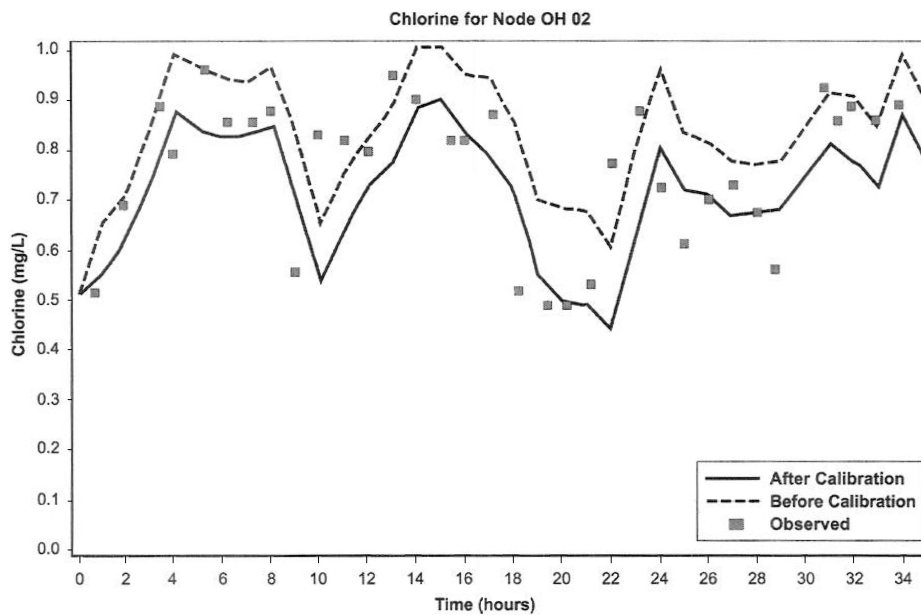


Figure 4: Comparison of the field observed and the model simulated chlorine concentration at node OH 02 near the water source (booster station).

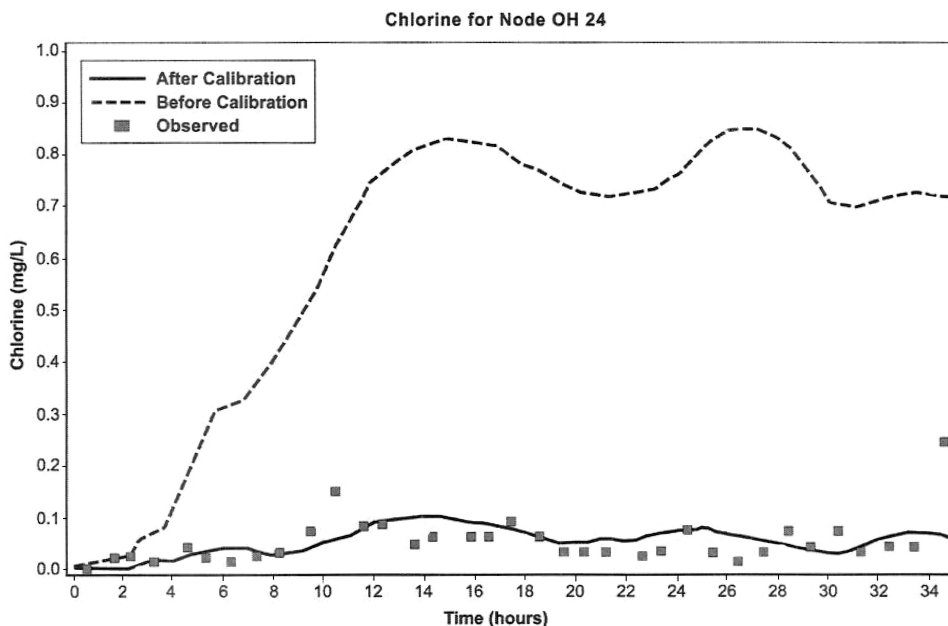


Figure 5: Comparison of the field observed and the model simulated chlorine concentration at node OH 24 the outskirts of system.

346 approach successfully enhances the chlorine residual agreement, particularly
 347 for the nodes far apart from the source.

348 Three top calibration solutions are presented in Table 1 and compared with
 349 previous study. The best fitness of 1.309 with average difference of 0.045 mg/L
 350 has been achieved for 27 sampling stations over 35 hours while the previous
 351 study resulted in the fitness of 2.467 with average of 0.086 mg/L. It clearly
 352 indicates that the better calibration solutions have been obtained by using the
 353 optimal calibration method. The solutions are ranked by the fitness value, the
 354 sum of absolute mean differences, which is resulted in by different correlation
 355 factor between pipe wall coefficient and roughness for pipe groups. The average
 356 of absolute mean differences is the same for all three solutions. It is no
 357 doubt that genetic algorithm calibration effectively improved the water quality
 358 model for this case study and a better solution has been obtained than the
 359 conventional approach. However, an accurate water quality model cannot be
 360 expected to be achieved by simply performing optimization calibration run. An
 361 insightful analysis must be undertaken for understanding the solution and
 362 the data points where the relatively greater discrepancies are resulted in. This
 363 is usually caused by poor data quality and abnormal model representation.
 364 Optimization modeling tool may help engineers quickly to reveal the weakest
 365 where good engineering judgment is applied to investigate the possible errors,

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Table 1: Comparison of optimal calibration solutions to previous study.

Items	Optimal solution I	Optimal solution II	Optimal solution III	Vasconcelos et al. ^[12]
Fitness (sum of absolute mean differences)	1.3090	1.3106	1.3119	2.4670
Average absolute mean difference (mg/L)	0.0450	0.0450	0.0450	0.0860
Bulk reaction order	2	2	2	1
Wall reaction order	0	0	0	0
Bulk				
Pipe group 1	-1*	-1	-1	-0.232
Reaction				
Pipe group 2	-1	-1	-1	-0.232
Coefficient				
Pipe group 3	-1	-1	-1	-0.232
Wall				
Pipe group 1	-800	-795	-785	-660
Correlation				
Pipe group 2	-470	-470	-470	-660
Coefficient				
Pipe group 3	-600	-600	-600	-660

*Negative sign indicates chlorine decay (not growth).

366 which is an indispensable task to model calibration due to no perfect data exist
367 for a real system.

368 **DISCUSSIONS**

369 The results of example water quality model calibration have shown the effective-
370 tiveness of competent genetic algorithm for solving nonlinear constrained opti-
371 mization problem. Conventionally, water quality model calibration is achieved
372 by manually adjusting pipe wall reaction coefficient along with bottle test in
373 a laboratory, which determines the bulk reaction order (either 0 or 1) and the
374 bulk reaction rate. For the chlorine decay model, pipe wall reaction coefficient
375 may be globally adjusted by using a correlation factor to roughness. It can
376 simplify the complexity and reduces the work load for manual calibration. The
377 previous study demonstrated that some good calibration results have been
378 achieved for chlorine decay model of a relatively small system. However, it
379 is unknown if the approach is applicable to a large real system with multiple
380 water sources of mixed water quality. In addition, the correlation factor method
381 only proved to be applicable to chlorine decay. For real water distribution
382 system, water quality can be maintained by using other chemicals, pipe wall
383 reaction rate may not be the same for all pipes, the bulk reaction can be
384 in any order (not just 0 or 1) and also bulk reaction coefficient varies from
385 location to location due to mixed water quality from different water sources.
386 Thus the simplified approach of just calibrating pipe wall coefficient by a

387 correlation factor is unlikely be able to handle all the complexity of a real water
388 quality model. In contrast, the water quality calibration approach developed
389 in this paper is generic and flexible method taking into account combination
390 of different water quality parameters. It is able to consider the element-
391 dependent reaction parameters (for both pipe and tank) and any reaction order.
392 With the capability of grouping the pipes of similar characteristics, modeler is
393 able to calibrate a water quality model of any constituent.

394 To achieve a good water quality calibration, a well calibrated EPS
395 hydraulic model is essential before starting water quality calibration. The
396 accuracy of water quality simulation relies on the hydraulic simulation results.
397 A hydraulic simulation must be performed priori to a water quality analysis.
398 It is the hydraulic simulation that provides the necessary flow and velocity
399 information of each element to determine how a constituent is transported
400 and reacted throughout a distribution system. This indicates that hydraulic
401 calibration must be conducted before embarking on water quality model
402 calibration, and also hydraulic model calibration must be carried out for
403 extended period simulation. If there are errors in the hydraulic model, then
404 forcing the water quality parameters to achieve calibration may result in a
405 model that appears calibrated due to compensating errors.

406 CONCLUSIONS

407 Water quality modeling is an important means of providing system-wide infor-
408 mation on water quality for evaluating routine system operation policy, thus
409 maintaining and improving water quality throughout a system. Calibrating
410 such a model ensures that a water quality model predicts what is happening
411 in a real system. The approach presented in this paper has provided a generic
412 tool and methodology for calibrating a water quality model of any constituent.
413 It relieves modeler from trial and error process and thus enables engineers
414 to construct an accurate model for effectively managing water quality in
415 distribution systems to comply the public health.

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