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Verification of Sampling Design for Water Distribution Networks Calibration

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Abstract

This paper presents the verification of sampling design problem for collecting data from a water distribution network. The aim is to compare the theory verification of model with the real one through developing a calibration procedure based on an optimization algorithm. At first, the multi-objective optimization model is assumed to be solved and the locations of measurement points are determined with different level of accuracy. Three approaches are considered for parameter uncertainty estimation in sampling design. With assuming the measurement points (i.e. the pressure heads) at each node, calibration procedure is made in order to adjust the best parameter (i.e. the pipe friction coefficients). Calibration is performed based on Genetic algorithm (GA) optimization approach. Determined Locations in the solutions of each scenario of sampling design are assumed to be the measurement points in each calibration procedure. Thus, the calibration results are compared in three scenarios with the same number of measurement. Comparison of the results is carried out based on the sum of squared deviations between all pressures calculated from the calibrated model and actual pressures with the real parameter. For the sets of the same measurement numbers, the best fitness solutions are selected based on the sum of squared error (SSE) criteria. The consistency of results for every specific number of measurements shows the robustness of methodology and its safe application to different cases.

Keywords: calibration, sampling design, field measurement

1-Introduction

Since development of the water distribution networks and making sensitive decisions in the investment sections of water supply, it is required extremely to accurately model the networks. Within this modeling, the correspondence between the results obtained from mathematical modeling and real conditions of the system is essential for modelers and decision makers. In other words, the results of mathematical model should have the least error and indicate the system operation with more reality. Therefore, the model must be calibrated in order to meet this purpose.

In order to calibration, field measurements of pressure and flow are necessary. The clients have some limitations in supplying the budget for collection of field measurements. Also, to meet the minimum error in calibration, it is required to collect more measurement data especially in spatial distribution. So, what the decision makers are interested to know, what are the relationships are between the number of field measurements and the accuracy resulted from their calibration.

Several authors have proposed various methods to obtain the relationship between the number and location of field measurement and the error resulted from their calibration. Although they have been presented different approaches for selecting the sampling points, rarely has the validation of the results been considered in the literature, may be because of the complexity of the optimization model.

Walski (1983) suggested monitoring pressure location should be away from water sources. Yu and Powell (1994) used a dynamic analysis for selecting the measurement points in which one additional point was added every stage. At the same time, Ferreri et al. (1994) proposed ranking of WDS nodes based on the sensitivity analysis of nodal heads relative to roughness parameters.

Meier and Barkdoll (2000) have addressed sampling design by choosing the fire flow test locations for potential points for calibration and used from genetic algorithm to find the best points. They have determined these flow tests as they are opened simultaneously. The objective function was to maximize the total of pipes with non-negligible flow velocity within the opening of the specific number of fire flow tests. The model has run for every number of fire flow tests each time, and the final results has been determined for each composition of fire flow tests up to ten points among the total of 189 potential hydrants. They have validated their model by comparing the results of optimization model and the best points of complete enumeration for each specific number of fire flow samplings. Of course, because numerous numbers of states are required for complete search, the authors had to validate their model for only four small types of measurement numbers.

Recent researchers have continued the route of sampling design by analyzing the sensitivity matrix of prediction variables relation to the parameters. In these approaches, the points that their predicted variables have the most sensitivity relation to parameter deviation are better candidates for sampling location. With this approach, parameter estimation and sampling design theory are accomplished.

Bush and Uber (1998) developed the sampling design theory with a sensitivity-based method to rank the measurement point for calibration. In addition to pressure measurement location, they determine concentration measurement location and also the effect of both. They proposed three methods based on the minimization of the parameter's confidence region volume for roughly sampling design. They showed that the measurement with both pressure and tracer concentration are more effective.

Lansey et al. (2001) proposed a three-step calibration procedure including parameter estimation, calibration assessment, and data collection design. With these looped steps, data collection plan are updated based on parameter estimation and propagation of parameter errors. The uncertainty of this model is calculated based on trace of the covariance matrix of the predictive heads.

Most recently, Kapelan et al. (2003) have introduced a multi-objective sampling design for calibration of the model. They have determined the relationship between the number of sampling pressure logger points versus its correspondent errors via a multi-objective approaches. In their objectives, they have considered the total cost of sampling design as the number of sampling points and the accuracy of the calibration results. The accuracy of the calibration is based on some theories obtained from the uncertainty of parameters and its estimation. Thus, they have addressed three different approaches as the model accuracy. Three different types of accuracy have been compared based on the results from the case study, and the best points are concluded as a theory basis.

This study extends the work of Kapelan et al. (2003) verifying three parameter uncertainty estimation approaches within the process of calibration. First, based on the Kapelan et al.'s approach, determining the sampling locations are developed. After obtaining the results of sampling design, calibration procedure is performed. Then, with assuming the measurement points (i.e. the pressure heads) at each node, calibration procedure is made in order to adjust the best parameter (i.e. the pipe friction coefficients). Calibration is performed based on Genetic algorithm (GA) optimization approach. Determined Locations in the solutions of each scenario of sampling design are assumed to be the measurement points in each calibration procedure. Thus, the calibration results are compared in three scenarios with the same number of measurement. Comparison of the results is carried out based on the sum of squared deviation between all pressures calculated from the calibrated model and actual pressures with the real parameter.

In the next section, the optimal sampling design is described. Then, model formulation is stated for both multi-objective sampling design and calibration of water network model. The proposed method for network calibration is explained in the next section. The methodology described then applied to the case study, and results of the model are presented and discussed.

2- Optimal sampling design

Selecting the sampling locations for data collection is an important issue in the calibration process. It can influence on the accuracy of calibration procedure. On the other hand, if sampling locations are not selected properly, it may cause that the lower correspondence between the measured and predicted variable. Therefore, considering the specific number of sampling locations, it is valuable to set a proper distribution of measurement devices on the potential locations with calibration purposes.

Optimal sampling design is accomplished by selecting the points that, after measuring data in those points and calibrating the model, will yield to minimum discrepancies in verification process. Verification is a process that the model results are compared with a set of conditions that were not used to estimate the parameters. Nevertheless, after verifying the model, the model results do not still match with the new data measurement. It shows that the model are still not well-estimated even with the best selection points; i.e. the parameter still have error in their estimation. Also, the less the parameters have error, the smaller the discrepancies between measured and calculated variables are generated. In other words, the parameters such as roughness coefficient have the errors in their estimation which is called uncertainty.

Therefore, In order to obtain the optimal sampling locations, one should find the point that has the most sensitivities relation to the variation of parameters. These points, if used for monitoring, can calibrate the model so that the model results are closely matched with the measurement locations, which can generate the most discrepancy; i.e. the points which have the most errors participate in the calibration; and will yield the parameters that are more compatible with those high-error points. With other data for verification, model results will have the smaller discrepancies because the parameters have been estimated with these data. Based on this uncertainty theory; three different approaches have been suggested for uncertainty modeling in sampling design.

In the first approach, the set of points are appropriate for monitoring that have the most sensitivities of predicted variables relation to parameter variations. This could be stated as follow:

$$Cur = J^T W J$$

Where J =Jacobian matrix of derivatives $\partial y_i / \partial a_K$ ($i = 1,..., N_o ; K = 1,..., N_a$) derivatives calculated for model predicted (dependent) variables $y(a)$ that spatially and temporally correspond to measurement y^*. N_o =total number of field measurement, N_a =number of calibrated parameter. Calculation of Jacobian matrix is possible from several ways as follow:

1- finite-difference method (Lansey et al. 2001)
2- sensitivity equation method (Bush and Uber 1998)
3-adjoint method (Kapelan et al. 2003)

The second approach finds those points that have the least variation of parameters with the specific variation of model results. The covariance matrix of the parameter, Cov_a, can handle this purpose and can be estimated by first-order approximation as follow:

$$Cov_a = \frac{E}{N_o - N_a}.Cur^{-1}$$

where E=optimal objective function value. The uncertainty of the *i*th calibration parameter is equal to the value of *i*th diagonal element of matrix Cov_a . .

In the third approach, propagation of error to the predicted values is considered. The set of points which has the minimum error in their predicted variables are the best options for monitoring. The first-order second-moment (FOSM) analysis can accurately estimate the covariance of the predicted uncertainty given the uncertainty of input. The prediction covariance matrix Cov_z can be estimated as follow:

$$Cov_z = J_z.Cov_a J_z^T$$

where J_z =Jacobian matrix of derivatives $\partial z_i / \partial a_K$ that $i = 1,...,N_z$, $K = 1,...,N_a$, N_z =number of predicted variables of interest. Jacobian matrix J_z is a matrix of $N_z \times N_a$ dimensions and matrix Cov_z is defined as a $N_z \times N_z$ dimension. Like matrix Cov_a, the uncertainty of predicted variables is the diagonal element of matrix Cov_z .

Based on these approaches, uncertainties of point selection are modeled. An optimization algorithm can solve this model and can present the best points for installing the measurement devices. In the next section, the process of model formulation for finding the best points is presented. After finding the best solution, each method of handling uncertainty present a different set for optimum sampling location. In order to see which one of the set is more proper, verification of the model is required. The verification should include the process of calibration with the best solution of each type. An approach that can obtain the minimum error in calibration can indicate to the best solution.

3-Model Formulation

At first step, two objective functions are formulated in order to solve the sampling locations. The first objective mimics the uncertainty of the model and based on this objective the measurement points are selected from the set of potential points in the field. The second objective restricts the number of selecting point in each step. After obtaining the model, a trade-off between the number of solution and the corresponding accuracy for Pareto-optimal solutions are determined. At second stage of this paper, verification process is initiated. Verifying the optimal sampling locations is carried out with calibration process.

As mentioned above, three different types of fist objective function could be stated as follow:

$$Max \quad F_1 = \left[\det\left(Cur\right)\right]^{1/(2N_a)}$$

$$Min \quad F_1 = \frac{1}{N_a}\sum_{i=1}^{N_a} Cov_{a,ii}^{1/2}$$

$$Min \quad F_1 = \frac{1}{N_z}\sum_{i=1}^{N_z} Cov_{z,ii}^{1/2}$$

These objectives are called CAO1, CAO2 and CAO3, respectively. The other objective function is limitation of the number of sampling locations that can be stated as bellow:

$$Min F_2 = N$$

The number of sampling devices (N) are related to the number of observation (N_o) as temporally and spatially. In our case, because that observation are done in each time step, therefore these relationship is as $N_o = N \times t$, where t is the number of measurement times.

4-Network model Calibration

Verification process is accomplished with calibration based on the optimization algorithm. In this study, optimization algorithm used for calibration is an evolutionary technique which better known as genetic algorithm (GA). In GA, the objective function is minimized so that the best parameters are estimated. Assuming that some measurements are available, the GA minimizes the sum of the square differences between the measured and computed variables. Measurement and computed variables can be pipe flows, nodal pressure heads and tank levels that are variables in various operational conditions. In this paper, nodal pressure heads are the only variables that are compared. Mathematically, the objective function used in this algorithm is as follow:

$$Min\ E = \sum_{j=1}\sum_{i=1}^{N} w_{ij}[Y^*_{ij} - Y_{ij}(X)]^2$$

where: E= objective function that must be minimized; t= number of operational conditions; N = number of pressure head measured locations; W_{ij} = weighting factor for location i and operation condition j with respect to their importance or accuracy; Y^*_{ij} = observed pressure head at node i and operational condition j ; $Y_{ij}(X)$ = calculated pressure at node i and operational condition j ; The GA decreases the objective function with altering the friction coefficient parameters so that measured and calculated pressures are to closely match in each operational condition.

The constraints of this optimization model are mainly the simulation equations of the model. Simulation equations include two groups of mass balance for each node and energy equations of each loop. Since most of the simulation models in water network models is solved with numerical methods and needs iteration algorithm, it is required to establish a linkage between simulation and optimization model. Thus, constraints are satisfied from the simulation model, so that, the equations of simulation model are solved iteratively and the results of pressure heads are returned back to the optimization model in each step. Therefore, the optimization model have to search between the feasible search space and examine the various decision variables to find better solution that can satisfy the simulation model and minimize the objective function. The decision variables are friction coefficients of the pipes.

In this paper, an optimization program written in C language has been linked to the source code of EPANET hydraulic simulation program. The source code of EPANET was written in C language and was compatible to every optimization model that is written in C language. (Rossman, 2000)

GA is one the best search algorithm that has the ability to do this task. GA was developed by Holland (1975) at the University of Michigan. It can mimic the adaptation of natural systems, and provide a robust and efficient way to search complex parameter spaces for ever better solutions to an optimization problem (Goldberg 1989).

At first step in GA, decision variable encoding was introduced. The encoding scheme is a string of integer values. These genes represent the values of friction factors of pipes as integer values. The fitness function of GA is the objective function as mentioned above. Next, proper operations, including selection, crossover, mutation and elitism, were determined and refined after some experimental implementations. In the next section, we describe the case study and some of the assumptions for implementing the model.

5- Case Study

Verification of sampling design is applied on a case study of Anytwon city in U.S.A. that has been used many times in the previous works. This case study was used in the literature for the purpose of calibration by Ormsbee(1989), Lansey and Basnet(1991) and also for the purpose of sampling design by Kapelan et al.(2003). The network schematic is shown in Fig. 1. The distribution system consists of 34 pipes and 16 nodes that their characteristics are given in tables 1 and 2. In order to group the pipe friction factor into smaller numbers, five groups are considered that is shown table 3. The friction coefficient of pipes is expressed as Hazen Williams C factor.

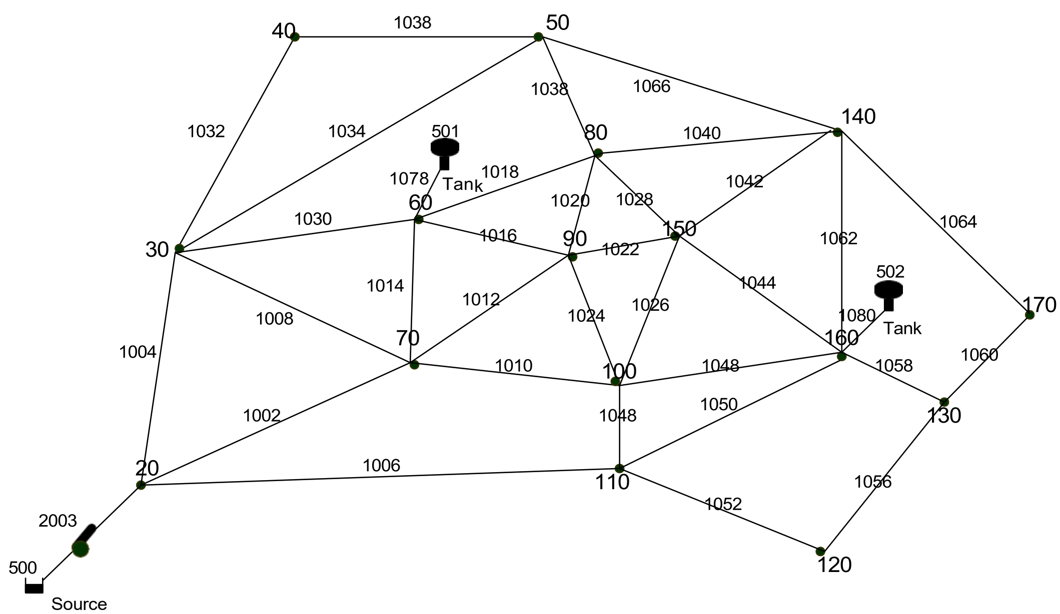

Fig.1. Water Distribution Network

Table1. Properties of the network pipe

No.	ID	Length (m)	Diameter (mm)	HW roughness coefficient	No.	ID	Length (m)	Diameter (mm)	HW roughness coefficient
1	1002	3657	406	120	18	1036	1830	254	120
2	1004	3657	406	120	19	1038	1830	254	120
3	1006	3657	406	120	20	1040	1830	254	130
4	1008	2743	305	70	21	1042	1830	203	130
5	1010	1830	305	120	22	1044	1830	203	90
6	1012	1830	254	70	23	1046	1830	305	90
7	1014	1830	305	70	24	1048	1830	203	90
8	1016	1830	254	70	25	1050	1830	254	90
9	1018	1830	305	70	26	1052	1830	203	90
10	1020	1830	254	70	27	1056	1830	203	130
11	1022	1830	254	70	28	1058	1830	254	130
12	1024	1830	254	70	29	1060	1830	203	130
13	1026	1830	305	70	30	1062	1830	203	130
14	1028	1830	254	90	31	1064	3656	203	130
15	1030	1830	254	120	32	1066	3656	203	130
16	1032	1830	254	120	33	1078	30.5	305	110
17	1034	2730	254	120	34	1080	30.5	305	110

Table2. Node Information

No.	Identification	Elevation (m)	Demand (L/s)
1	20	6.23	31.51
2	30	15.24	12.52
3	40	15.24	12.52
4	50	15.24	31.51
5	140	24.4	12.52
6	170	36.6	12.52
7	130	36.6	12.52
8	120	36.6	31.51
9	110	15.24	12.52
10	160	36.6	31.51
11	100	15.24	12.52
12	150	36.6	12.52
13	80	15.24	31.51
14	90	15.24	63.83
15	70	15.24	31.51
16	60	15.24	50.9
Total			403.95

Three pumps are available at the reservoir and pump water to the distribution system. The pump characteristic curves for three pumps are the same and are as follow (flow (L/s) and heads (m)): (0.0, 91.4), (252.5, 82.3), (504.7, 55.2). Both tanks have bottom elevations of 65.5 m and overflow elevation of 77.7 m; i.e. the tanks have 12 m height. The water level at the reservoir is fixed at an elevation of 3.04 m. Five loading conditions, including a normal demand loading and four separate fire demand loadings, are available for implementing of sampling design and calibration. For each fire demand loading, water required for fire demand is added to the nodes as assumed to be 82.48 L/s (node 40), 107.17 L/s (node 90), 31.49 L/s (node 120), and 82.48 L/s (node 140). The tanks are half-full (6.1 m) for the normal demand loading while they are full (12 m) for each fire flow loading.

Table3. Roughness coefficients of pipe grouping

Pipe Grouping	HW roughness coefficient
1	120
2	70
3	90
4	130
5	110

6- Results and Discussions

At the first step, it is required that sampling design problem is solved for the distribution system. Total nodes (16 nodes) are possible locations for monitoring. Total assumed parameters are 5 because of five friction groupings of pipes. Assuming $N_a = 5$, the multi-objective genetic algorithm was run to find the trade-off between the number of point locations and their associated accuracy. In each number of point locations for pressure logger, the best arrangement of location's position is determined based on the minimum parameter uncertainty. Table 4 shows the results of point location obtained from the third approach of first objective function based on the work of Kapelan et al.(2003).

Table4. Multi-objective genetic algorithm solution of sampling design problem

Pareto-Optimal Front for CAO3																
Number of monitoring locations	Network nodes															
	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
3	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0
4	0	0	1	0	0	0	0	1	0	1	1	0	0	0	0	0
5	0	0	1	0	0	0	0	1	0	1	1	0	0	0	1	0
6	0	0	1	0	0	0	0	1	0	1	1	0	0	0	1	1
7	0	0	1	0	0	0	0	1	1	1	1	0	0	0	1	1
8	0	0	1	0	1	0	0	1	1	1	1	0	0	0	1	1
9	0	0	1	0	1	0	0	1	1	1	1	1	0	0	1	1
10	0	0	1	0	1	0	0	1	1	1	1	1	1	0	1	1
11	0	0	1	0	1	1	0	1	1	1	1	1	1	0	1	1
12	0	0	1	0	1	1	0	1	1	1	1	1	1	1	1	1
13	0	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1
14	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
15	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

In order to verify the results, a calibration procedure was done. For the purpose of calibration, it is necessary to be available the measurement point of pressure at all nodes. Thus, the pressure calculated from the actual friction coefficients are assumed to be the measurement pressures at all nodes. These measurement pressures are shown in column 2 of table 7. It is also required to assume the initial friction coefficients for all pipes. Therefore, the value of 100 was assumed for Hazen Williams's roughness factor.

For each number of monitoring locations, an optimization model was run to calibrate the model based on those specific numbers of location. The position of locations predefined based on the solution obtained from sampling design. Thus, various runs are necessary for calibrating the model. Results of calibration procedure for all different number of monitoring locations are presented in table 5 and Fig. 2.

Table5 . Comparison of Calibration results for different uncertainty approaches

Number of monitored points	Objective function of calibration model		
	CAO1	CAO2	CAO3
1	93.30	93.30	93.30
2	136.74	137.21	96.90
3	29.91	78.72	65.75
4	9.95	64.38	9.95
5	9.54	22.99	9.54
6	10.93	29.00	10.93
7	14.28	5.95	14.28
8	5.51	3.05	6.77
9	2.60	2.05	2.25
10	2.02	4.46	2.02
11	0.43	1.74	0.43
12	1.60	0.78	1.60
13	1.75	0.39	0.39
14	0.32	0.32	0.32
15	0.17	0.17	0.17

Comparison of results can be carried out based on their objective function. All types of number of monitoring points are compared with the same objective function. After calibrating for each measurement points, the objective function is calculated based on the sum of squared deviations between all the pressures of the calibrated model and the actual pressures. The pressures obtained from the calibrated model for four-monitoring position, for instance, are shown in table 6. Also, the corresponding friction coefficients of calibrated model are shown in table 7. The monitoring points in the hydrant are also compared with these scenarios. The hydrants are at nodes 40, 90, 120 and 140.

The pipe grouping mentioned above was used in sampling design problem. It is impossible to apply the pipe grouping for calibration approach because all types of calibration will converge to the exact solution in each run. The reason is probably for small number of parameters to be calibrated (five pipe grouping). Therefore, despite the sampling design problem was solved with only 5 pipe grouping, the calibration process was run for all pipe frictions. It means that the parameter to be calibrated increase from 5 to 34 unknown parameters. In other words, this resulted in 34 decision variables. Thus, the number of genes required in a chromosome of GA is 34 genes.

As shown in table 6, the average percent deviation is 6.3% for initial pressure and was reduced to 0.4% for scenario CAO1 pressure, to 0.7% for scenario CAO2, to 0.4% for scenario CAO3 pressure and to 0.6% for hydrants that are comparable to the work of Ormsbee (1989) (1.3% final pressure).

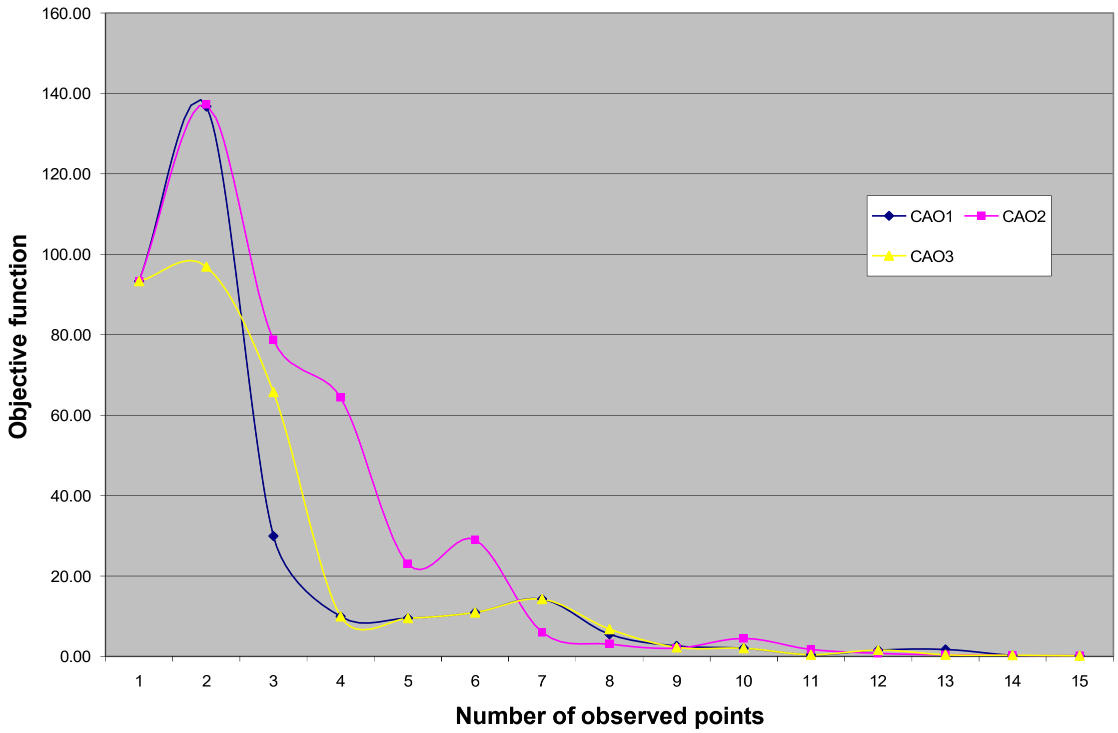

Fig.2. Objective functions of all possible states of four-point subset measurements

Table 6. Calibration results of node pressures with GA optimization

Node ID	Mean actual pressure (m)	Initial pressure (m)	Final pressure (m) (4 points for monitoring)			
			CAO1	CAO2	CAO3	Hydrant
20	85.65	85.58	85.75	85.8	85.75	85.88
30	66.07	62.64	65.9	66.16	65.9	65.79
40	59.98	57.98	59.98	58.76	59.98	59.98
50	59.19	56.27	58.63	58.47	58.63	58.76
60	61.21	56.36	61.18	61.16	61.18	61.19
70	65.49	61.06	65.16	64.8	65.16	64.61
80	58.46	55.61	58.41	58.46	58.41	58.47
90	56.75	55.63	56.75	58.04	56.75	56.76
100	61.85	57.04	61.72	61.86	61.72	61.71
110	70.41	66.16	70.41	68.26	70.41	68.19
120	34.73	32.41	34.73	34.74	34.73	34.73
130	36.66	32.63	36.12	36.54	36.12	36.21
140	48.76	46.32	48.54	48.76	48.54	48.76
150	37.5	34.49	37.52	37.77	37.52	37.68
160	39.82	35	39.76	39.82	39.76	39.78
170	35.6	32.1	34.77	35.45	34.77	35.09

Table 7. Calibration results of friction coefficients with GA optimization

Pipe ID	Actual C-factor	Initial C-factor	Final C-factor (4 points for monitoring)			
			CAO1	CAO2	CAO3	Hydrant
1002	120	100	123	110	123	98
1004	120	100	106	125	106	117
1006	120	100	119	90	119	101
1008	70	100	101	118	101	118
1010	120	100	116	133	116	134
1012	70	100	83	100	83	71
1014	70	100	96	83	96	71
1016	70	100	61	109	61	64
1018	70	100	82	69	82	76
1020	70	100	65	94	65	71
1022	70	100	80	67	80	72
1024	70	100	61	75	61	76
1026	70	100	71	74	71	81
1028	90	100	102	73	102	101
1030	120	100	78	114	78	94
1032	120	100	130	99	130	129
1034	120	100	88	97	88	95
1036	120	100	117	98	117	117
1038	120	100	116	115	116	109
1040	130	100	133	139	133	136
1042	130	100	131	131	131	130
1044	90	100	138	80	138	125
1046	90	100	109	76	109	66
1048	90	100	97	93	97	103
1050	90	100	77	76	77	94
1052	90	100	102	105	102	116
1056	130	100	123	117	123	105
1058	130	100	105	117	105	97
1060	130	100	103	119	103	103
1062	130	100	114	132	114	137
1064	130	100	97	129	97	118
1066	130	100	112	116	112	138
1078	110	100	90	77	90	121
1080	110	100	79	128	79	93

The GA was run in each time until no improvement is met. After some experiment, the number of generation for each run was set to 1000 generation. For example, improvement of fitness function for one point monitoring at node 170 is shown in fig. 3. As it can be seen, improvement after about 500 generation does not exist. The proper operation such as mutation and crossover, after some examinations, are set to 0.1 and 0.25, respectively. The population size of each generation was considered to 100 individuals.

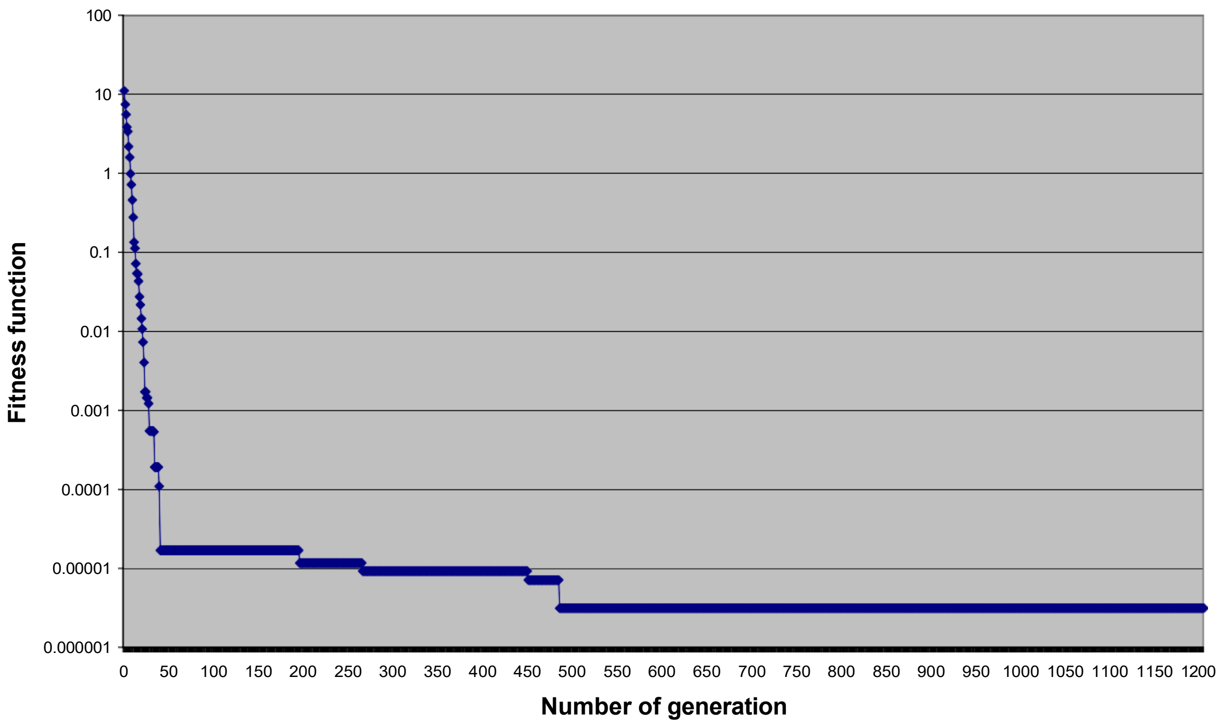

Fig. 3.Improvement of fitness function for calibration with monitoring node of 170(one-point monitoring)

7-Summary and conclusion

Sampling design problem has advanced and multi-objective genetic algorithm has been used for finding the sampling locations in water distribution system. In this paper, an algorithm of calibration based on GA was developed to verify the sampling design solutions. The calibration includes an optimization model that has been linked to the hydraulic simulation package EPANET. GA successfully calibrated the network of Anytown city after up to 1000 generations.

In the procedure, for each specific number of sampling locations, GA found the calibrated model and compared between three approaches of parameter uncertainty estimation. As shown in the figures and tables, between three approaches of parameter estimation, CAO3 has better behavior in meeting the optimum calibration. The points which CAO3 offers show the more confidence in comparison to other approaches. Also, as it can be seen in table 6, the average percent deviation of pressure from their real values is reduced to less than 1% in each of the scenarios and also when only hydrant measurements are existed.

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