

Head-Driven Simulation Model (HDSM) for Water Distribution System Calibration

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ABSTRACT: In order to reproduce the behavior of water distribution networks, calibration models have been proposed. They normally do not consider the relationship between pressure and leakage, as well as the dependence of demand on pressure in a water distribution system. In this paper, we seek to extend the calibration process through the development of a hydraulic simulation model based on leakage and pressure-dependent demands with support of the hydraulic simulator EPANET 2 (Rossman 2000). A hypothetical network was used to calibrate the model in terms of the absolute roughness of pipes and the parameters of the leakage model, simultaneously. The Simplex search method was used to improve the solutions obtained by Genetic Algorithms (GAs), successfully reproducing the nodal pressures and pipe flows values taken as reference to the calibration process.

1 INTRODUCTION

The validity of a hydraulic network model depends not only on the accuracy of its physical and geometric data but also on the accuracy of certain parameters such as pipe roughness coefficients and nodal demands. To render network simulation models useful they need to be calibrated.

Network model calibration efforts should generally encompass “basic” steps (Ormsbee & Lingireddy 1997) which includes identification of the intended use of the model, determination of initial estimates of the model parameters, collection of calibration data, evaluation of the model results, performing the macro level calibration, performing the sensitivity analysis and performing the micro level calibration. The last and most difficult step is micro level calibration, which involves the adjustment of demand loadings and pipe roughness until computed and observed field pressures and flow rates are in reasonable agreement.

Consequently, calibration of water distribution system models is, undoubtedly, an important and complex issue.

Several methods are proposed for the calibration of network models (Walski 1983, Bhave 1988, Ormsbee 1989, Boulos & Wood 1990, Lansley & Basnet 1991, Savic & Walters 1995, Lingireddy & Ormsbee 2002), but most of the existing calibration procedures focus on the computational problems related to optimization algorithms and the estimation of roughness factors. Little attention has been directed to the estimation of water loss parameters, although the systems that show major leakage problems are those that need calibration the most.

Water companies are well aware that there is a deficit between the total water produced from sources over a period of time and those recorded during the same period in consumer water meters. This difference, known as unaccounted for water, is due to different factors, such as measurement errors and leakage in pipes and connections (Martínez et al. 1999). Leakage from pipes and junctions can account for a significant proportion of the water that is fed into a distribution system, with figures usually ranging from 10% to 50% (Tucciarelli et al. 1999). Therefore, the use of existing hydraulic models to simulate hydraulic performance of the system is unrealistic,

because these models, based on the demand driven simulation method (DDSM), consider fixed values for nodal demands regardless of pressure variations.

In order to build a reliable water distribution network model the dependence of both leakage and demands on the pressure has to be considered simultaneously, through a head-driven simulation method – HDSM (Tabesh & Karimzadeh 2000).

Tucciarelli et al. (1999) proposed a simulation model used in the calibration procedure according to which the water losses are computed assuming that in the pipes of each zone there is a constant leakage per unit area of the pipes surface, based on the idea that the aging effect is uniform on all pipe walls. The authors assumed that the spatial distribution of the potential demand could be estimated with some degree of confidence based on the knowledge of the consumers served by each node in the network.

The same assumption was adopted here for the development of a hydraulic simulation model based on leakage and on pressure-dependent demand, with the hydraulic simulator EPANET 2 (Rossman 2000) support. A hypothetical network was used for calibration purpose in terms of the absolute roughness of pipes and the parameters of the leakage model. A hybrid GA-Simplex method is then implemented for resolution of the problem taking the advantage of the combination of local (Simplex method – Nelder & Mead 1965) and global (Genetic Algorithms) search methods. The proposed GA-Simplex method is then applied to a hypothetical network model in order to verify its ability to determine the optimal solution and to compare its performance to that of standard GA.

2 FORMULATION OF THE CALIBRATION PROBLEM

The indirect approach to solve the inverse problem of parameters identification of a water network model is usually set as the minimization of errors between true (measured for real systems or synthetic for hypothetical systems) and calculated state variables (pressures and discharges) as follows.

$$\min_Z OF = \sum_{t=1}^{n^{PD}} \left[\frac{\sum_{j=1}^{n_t^P} (P_{t,j} - P_{t,j}^*)^2}{\left(\sum_{i=1}^{n_t^P} P_{t,i}^* / n_t^P \right)^2} + \frac{\sum_{j=1}^{n_t^Q} (Q_{t,j} - Q_{t,j}^*)^2}{\left(\sum_{i=1}^{n_t^Q} Q_{t,i}^* / n_t^Q \right)^2} \right] \quad (1)$$

where n^{PD} = number of scenarios (in this paper equal to three: maximum, medium, and minimum daily consumption); P = computed pressure vector; Q = computed flow rate vector; P^* = true pressure vector; Q^* = true flow rate vector; and Z = decision variables vector corresponding to:

$$Z = (\varepsilon_1, \dots, \varepsilon_{n_\varepsilon}, \theta_1, \dots, \theta_{n_\theta}, \beta_1, \dots, \beta_{n_\beta}) \quad (2)$$

where ε = pipe roughness; n_ε = number of zones with constant roughness; θ = loss factor; n_θ = number of zones with constant loss factors; β = loss exponent; and n_β = number of zones with constant loss exponent. It can be observed that to decrease the level of parameterization of the problem it is assumed that both the pipe roughness and the leakage parameters are homogeneous within specified areas of the network, called zones.

3 HYDRAULIC SIMULATION MODEL

Nodal pressures and pipe discharges are evaluated through the hydraulic model of which the simulator EPANET 2 is an auxiliary module, which considers the dependence of both leakage and demands on pressure. Assuming that the total amount of supplied water (TS) can be divided in the total demand actually supplied to the consumers (TD) and leakage (V):

$$TS = TD + V \quad (3)$$

It can be observed that the proportion corresponding to leakage or actual demand in Equation 3 is not known.

Considering that the spatial demand factors are known and that the temporal factor (FT) refers to a unique pattern, the total demand potential (TDP) can be expressed as:

$$TDP = FT.TS^* \quad (4)$$

where TS^* is the reference total demand (monthly average).

Hence, the total demand will be:

$$TD = TDP - PNA \quad (5)$$

where PNA is the part of the potential demand not met due to restriction on pressure levels in the network.

Replacing equations (4) and (5) into (3), we have:

$$TS = FT.TS^* - PNA + V \quad (6)$$

The temporal factor can then be estimated, based on the prior estimates of PNA and V :

$$FT = \frac{TS + PNA - V}{TS^*} \quad (7)$$

where $PNA = (FT.TS^* - TD)_{\text{initial}}$; and V_{initial} .

So the temporal factor in the next iteration (FT_2) will be:

$$FT_2 = \frac{TS + FT_1.TS^* - TD_1 - V_1}{TS^*} \quad (8)$$

where FT_1 , TD_1 and V_1 are, respectively, the values of the temporal factor, total demand and leakage in the previous iteration. According to the scheme in Figure 1, the hydraulic simulator produces this temporal factor and, consequently, the proportion corresponding to leakage or actual demand in Equation 3.

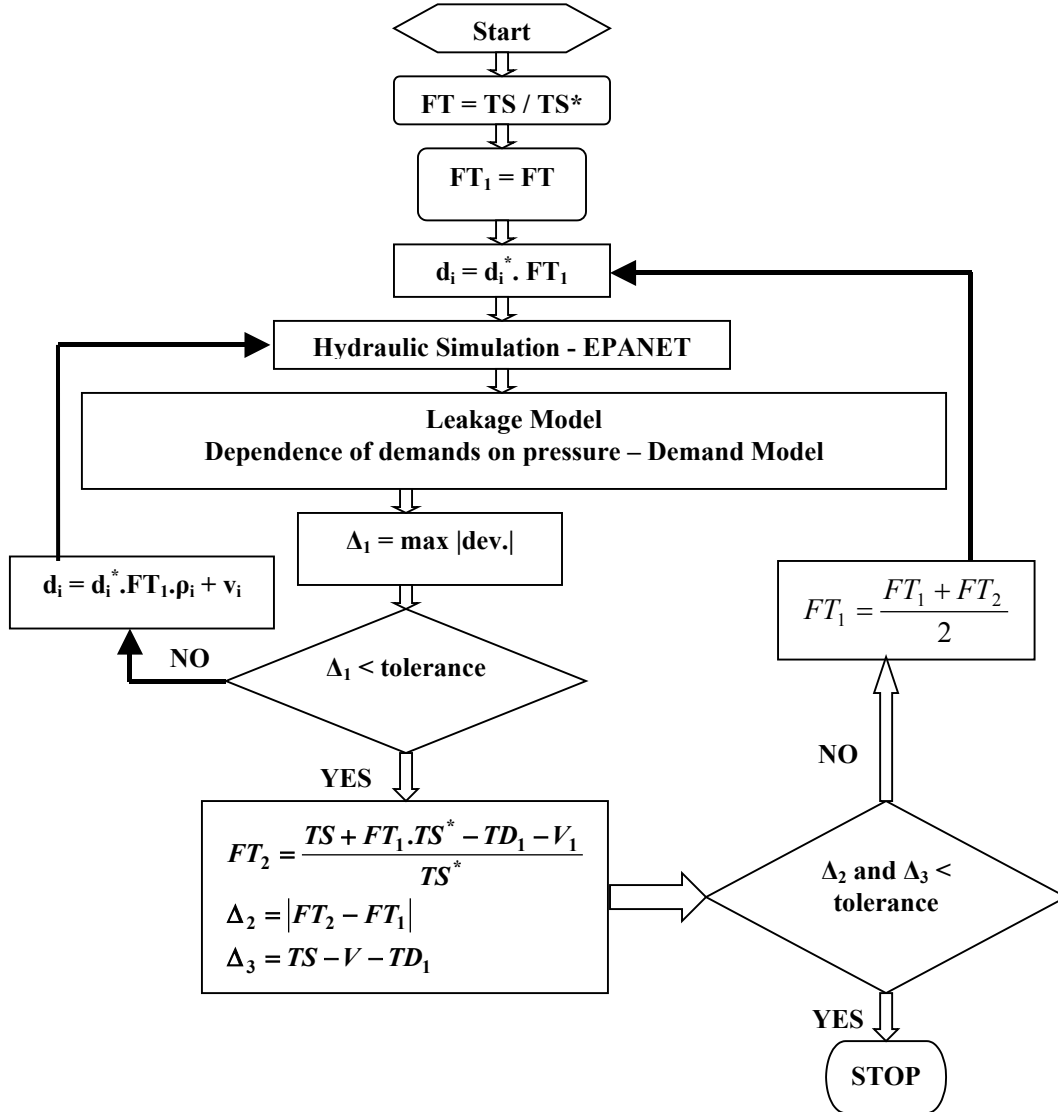


Figure 1. Flowchart of Proposed Hydraulic Simulator.

In Figure 1 we have:

Δ_1 = maximum deviation between previous pressures and real pressures in each node.

$$TS^* = \sum_{i \in N} d_i^* \quad (9)$$

$$TD = FT_1 \sum_{i \in N} d_i^* \cdot \rho_i \quad (10)$$

$$V = \sum_{i \in N} v_i \quad (11)$$

N = number of nodes.

ρ_i is the relationship between the demand actually supplied and the potential demand in node i .

Soares (2003) made an analysis of convergence of the head-driven models described in the literature (Fujiwara & Li 1998, Tucciarelli et al. 1999, and Tabesh & Karimzadeh 2000) concluding that the demand model proposed by Tucciarelli et al. (1999) is the most computationally efficient one. Thus, the spatial distribution factor ρ is assumed to be equal to:

$$\rho_i = 1 \quad \text{for} \quad P_i \geq P_i^{des}$$

$$\rho_i = \sin^2 \left(\frac{P_i}{2 \cdot P_i^{des}} \cdot \pi \right) \quad \text{for} \quad P_i^{min} \leq P_i \leq P_i^{des} \quad (12)$$

$$\rho_i = 0 \quad \text{for} \quad P_i \leq P_i^{min}$$

where P_i^{des} = minimum desired pressure to totally satisfy the demand; and P_i^{min} = absolute minimum pressure below which no flow can be discharged (in this paper it is equal to zero).

Leakage is computed based on the assumption that in each pipe there is a constant leakage per unit area of the pipe's surface (Tucciarelli et al. 1999), as expressed in the following equation:

$$v_i = (H_i - z_i)^\beta \sum_{j=1}^{M_i} \frac{\pi}{2} D_{ij} \theta_{ij} L_{ij} \quad (13)$$

where H_i = total water head at node i ; z_i = topographic elevation; β = loss exponent; M_i = total number of pipes linked to node i ; D_{ij} = pipe diameter; L_{ij} = pipe length; and θ_{ij} = leakage surface per unit pipe surface of the pipe linking nodes i and j .

4 HYBRID GA-SIMPLEX METHOD

In order to solve the inverse problem (1), a hybrid GA-Simplex was introduced and its performance compared to that of the standard GA. The idea was to link an effective global search method (GA) to an efficient local search method (Simplex method – Nelder & Mead 1965).

Computationally simple yet powerful search algorithms, Genetic Algorithms (GAs) are search methods that seek to reproduce mathematically the mechanisms of natural selection and population genetics, according to the biological processes of survival and adaptation (Goldberg 1989). The advantages of GAs over traditional search methods include the fact that they retain a population of well-adapted sample points, thus increasing the chance of reaching the global optimum (Reis et al. 1997). Moreover, these algorithms consider probability rules for the transition from one set of trial solutions to the next, and they have the flexibility of admitting many types of objective functions without requiring the continuity and existence of their derivatives.

GAs were first introduced into the area of water distribution network calibration by Savic & Walters (1995). Recently, Kapelan et al. (2000 and 2002) proposed two types of hybridization based on the GAs (global search method) and on Levenberg-Marquardt's method (local search method) to solve the inverse transient problem (network leak detection and roughness calibration).

In this paper the *GALib C++* (Wall 1996) library was used to develop the GA implementation. The library has a large number of built-in features: modeling different types of GAs, admitting various coding and selection schemes, several crossover and mutation operators, optional use of elitism, etc.

Davis¹ apud Michalewicz (1994) stated:

“When I talk to the user, I explain that my plan is to hybridize the genetic algorithm technique and the current algorithm by employing the following three principles:

- Use the current encoding in the hybrid algorithm.
- Hybridize where possible. Incorporate the positive features of the current algorithm in the hybrid algorithm.
- Adapt the genetic operators. Create crossover and mutation operators for the new type of encoding. Incorporate domain-based heuristics as operators as well.

[...] I use the term *hybrid genetic algorithm* for algorithms created by applying these three principles.”

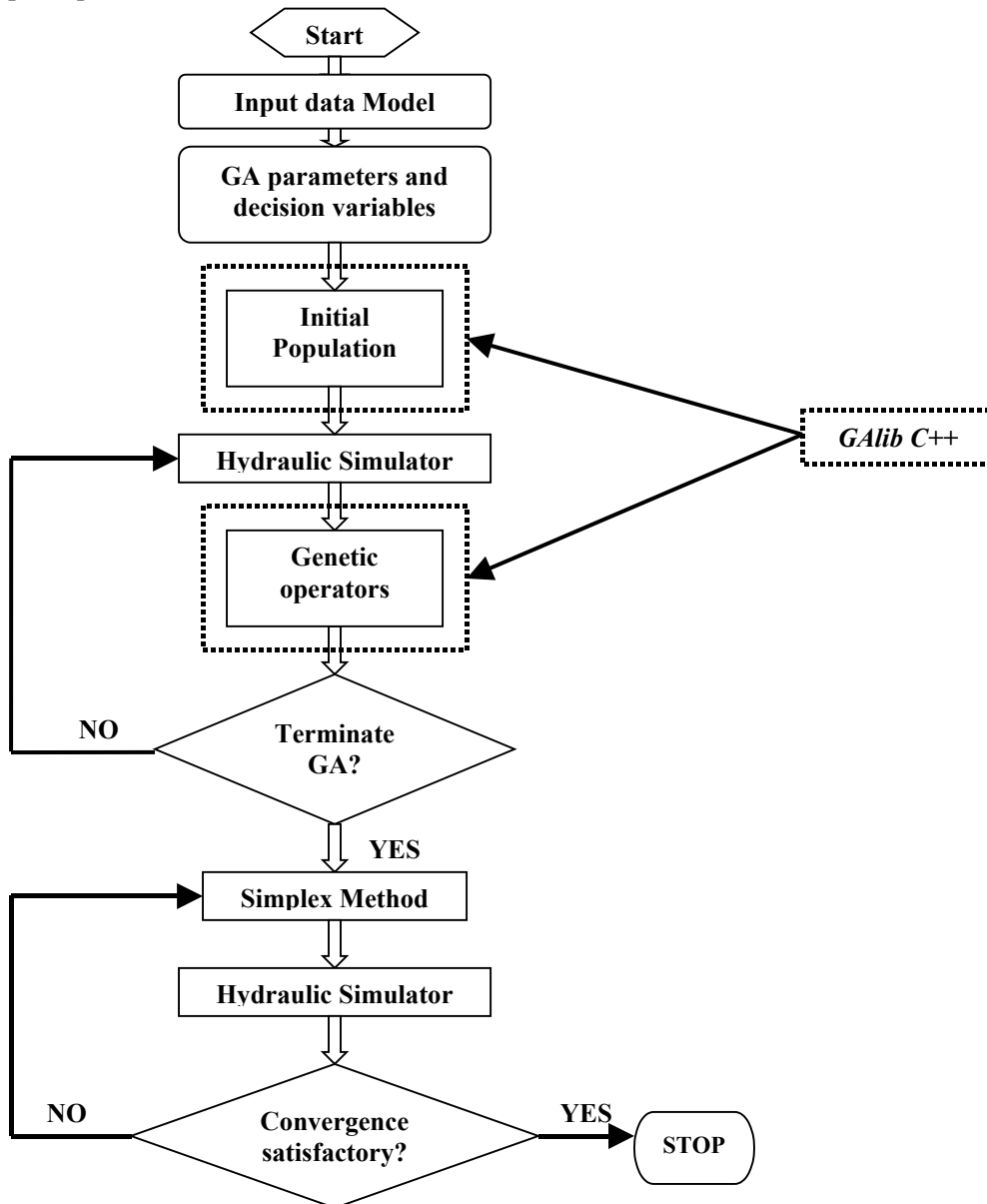


Figure 2. The Hybrid GA-Simplex Method Flowchart.

The simplest form of hybridization of GA and Simplex methods is a two-stage hybrid. The best solution found by GA, according to a certain convergence criterion, here established as the number of generations, is used as the starting point for the Simplex method (see Fig. 2). There-

¹ Davis, L. 1991 (Editor). *Handbook of Genetic Algorithms*, Van Nostrand Reinhold, New York.

fore, problems associated with the GA's slow convergence (large number of objective function evaluations) and the optimization method to converge to a local optimum can be reduced.

The *downhill simplex method* was developed by Nelder & Mead (1965) and it is one of the most popular direct-search methods among those which rely only on the function values to find the location of the optimum. This method does not require first- or second-order Taylor approximations to the function for its choice of search direction and it is important when gradient techniques cannot be applied or requires great computational effort such as objective functions of inverse problem.

Subrahmanyam (1989) extended the simplex algorithm of Nelder and Mead to handle nonlinear optimization problems with constraints. To prevent the simplex from collapsing into a subspace near the constraints, a delayed reflection is introduced for those points moving into the infeasible region. Subrahmanyam's technique has been used in this study because of the constraints in the variable decision vector (minimum and maximum values).

5 CASE STUDY

The proposed method was applied to the calibration of the hypothetical network model presented in Figure 3 (Tucciarelli et al. 1999).

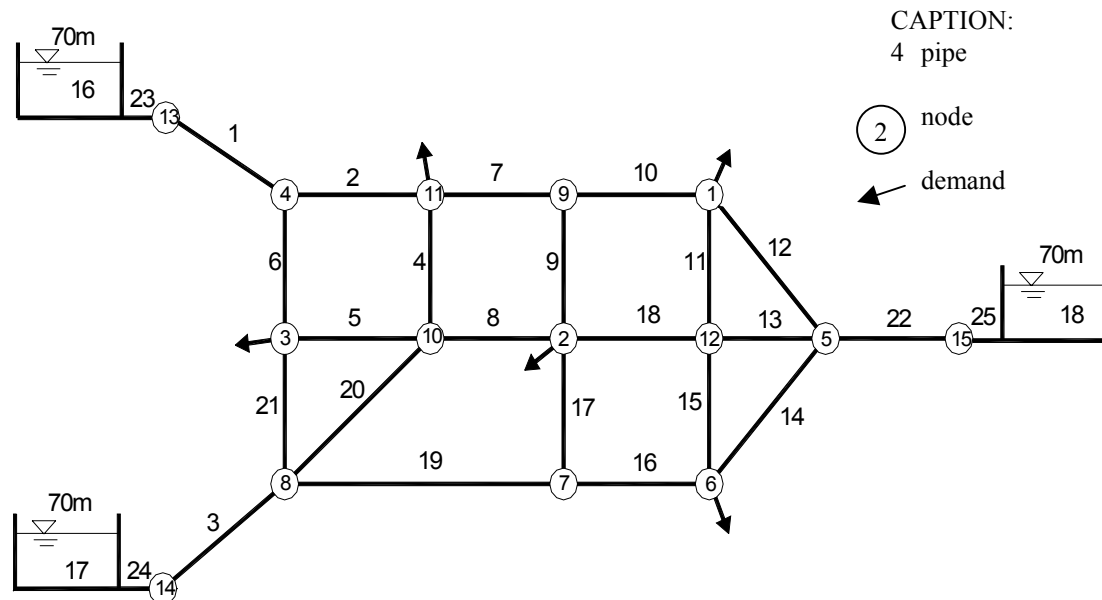


Figure 3. Case Study Network (Tucciarelli et al. 1999).

The gravity network has been grouped into three types of sectors: one is composed by three loss factor (θ) zones, other by one pipe roughness (ε) zone and the last one by one loss exponent (β) zone, as shown in Table 1. The third loss factor zone is assumed to have a known zero value (no leakage).

The location of the nodes with nonzero demand is shown in Figure 3, each one with a spatial distribution factor equal to 0.20.

Table 1. Network Input Data (Tucciarelli et al. 1999).

Loss Exponent (β)	Reference Demand (l/s)	Roughness (mm)	Loss factor		
			θ_1	θ_2	θ_3
1.253	180	3.153	7.504E-08	1.909E-07	0

Three scenarios were built in terms of the water levels in the reservoirs and total supply demands in order to provide pressure heads and flow rates for different network behaviors, as reported in Table 2. In the simulations it is used minimum pressure value $P^{min} = 0$ and desired pressure value $P^{des} = 15$ m.

Table 2. Scenarios Performed in the Simulations.

Scenario	Tank levels (m)	Supply Demand (l/s)		
		Reservoir 16	Reservoir 17	Reservoir 18
1	65.0	49.25	54.80	83.12
2	55.0	76.37	75.73	115.14
3	45.0	103.77	97.00	146.67

Synthetic pressure heads and flow rates were obtained through the application of the simulation model (Fig. 1). The set of values of flow rates and pressure heads used for calibration purpose were taken from the three pipes linking the network to the reservoirs and from five demand nodes according to Table 3.

Table 3. Pressure Heads in Five Nodes with Nonzero Demand.

Scenario	Pressure (m)				
	Node 1	Node 2	Node 3	Node 6	Node 11
1	38.15	42.26	42.31	36.83	41.20
2	25.60	28.14	31.17	25.55	28.60
3	12.16	12.65	19.38	13.73	14.98

6 RESULTS AND DISCUSSIONS

In order to compare the performances of the standard GA and the GA-Simplex optimization methods, three distinct initial population of solutions (represented by real strings) were run using an elitist (30%) generational GA, linear scaling of fitness, stochastic remainder sampling (SRS) as selection scheme, uniform arithmetic crossover with 70% probability and gene by gene Gaussian mutator with 1% probability. The number of generations used for standard GA was 500. Several tests (1, 5, 10, 30, and 50 generations) were performed to define that the best solution found by GA-Simplex only needed 10 generations.

Table 4 shows the minimum and maximum values admitted as well as the average values obtained for decision variables using both calibration procedures (GA and GA-Simplex). The average processing time spent for both procedures are also reported, showing that GA-Simplex is faster than standard GA. The GA CPU time is twenty times bigger than the hybrid and GA-Simplex presented better solutions than that found by the GA alone.

The case study demonstrates that the hybrid GA-Simplex method performs better than the standard GA in terms of both effectiveness and efficiency.

Table 4. Calibration Parameter Values found by GA and GA-Simplex Method.

Decision Variable	Search		True Value	Optimum Value	
	Min	Max		GA	GA-Simplex
ε (mm)	0.010	5.000	3.153	3.153	3.162
θ_1 (x10e-7)	0.050	3.000	0.750	0.648	0.792
θ_2 (x10e-7)	0.050	3.000	1.909	1.971	1.993
β	0.100	1.300	1.253	1.218	1.244
CPU Time				12.6 minutes	38 seconds

The values of pressures heads and flow rates computed are presented in Tables 5, 6, 7, and 8 for the three distinct initial population of solutions (1, 2, and 3) and for the two optimization methods (GA and GA-Simplex).

Table 5. Computed and True Pressure Heads (Standard GA).

Scenario	Node	Computed Pressures (m)			True Pressure (m)	Absolute Error (m)		
		1	2	3		1	2	3
1	1	37.88	38.07	38.18	38.15	0.27	0.08	0.03
	2	41.68	42.00	42.17	42.26	0.58	0.26	0.09
	3	42.18	42.28	42.31	42.31	0.13	0.03	0.00
	6	36.70	36.74	36.82	36.83	0.13	0.09	0.01
	11	40.96	41.18	41.28	41.20	0.24	0.02	0.08
2	1	25.27	25.54	25.83	25.60	0.33	0.06	0.23
	2	27.49	27.92	28.40	28.14	0.65	0.22	0.26
	3	31.04	31.16	31.28	31.17	0.13	0.01	0.11
	6	25.39	25.47	25.64	25.55	0.16	0.08	0.09
	11	28.31	28.59	28.87	28.60	0.29	0.01	0.27
3	1	11.89	12.17	12.64	12.16	0.27	0.01	0.48
	2	12.27	12.62	13.26	12.65	0.38	0.03	0.61
	3	19.25	19.41	19.70	19.38	0.13	0.03	0.32
	6	13.57	13.72	14.01	13.73	0.16	0.01	0.28
	11	14.71	15.01	15.53	14.98	0.27	0.03	0.55

It can be seen that the pressure heads obtained for the simulations with GA alone are close to the corresponding true values for nodal pressures, as illustrated in Table 5. The largest error is 0.65 m, produced in simulation 1, node 2, and scenario 2.

Table 6 presents the computed and true flow rates for the simulations with standard GA. The errors range from 0.0% (simulation 1, pipe 1, and scenario 3) to -2.5% (simulation 2, pipe 1, and scenario 1).

Table 6. Computed and True Flow Rates (Standard GA).

Scenario	Pipe	Computed Flows (l/s)			True Flow (l/s)	Relative Error (%)		
		1	2	3		1	2	3
1	1	50.06	48.00	48.33	49.25	1.6	-2.5	-1.9
	3	53.86	54.89	54.69	54.80	-1.7	0.2	-0.2
	22	83.24	84.30	84.16	83.12	0.1	1.4	1.3
2	1	76.62	75.62	75.66	76.37	0.3	-1.0	-0.9
	3	74.83	75.53	75.43	75.73	-1.2	-0.3	-0.4
	22	115.79	116.09	116.15	115.14	0.6	0.8	0.9
3	1	103.73	103.38	103.08	103.77	0.0	-0.4	-0.7
	3	96.59	96.76	96.57	97.00	-0.4	-0.2	-0.4
	22	147.09	147.25	147.80	146.67	0.3	0.4	0.8

Tables 7 and 8 permit the comparison between computed and true pressure heads and flow rates, respectively, when the hybrid GA-Simplex method is applied.

Table 7. Computed and True Pressure Heads (GA-Simplex).

Scenario	Node	Computed Pressures (m)			True Pressure (m)	Absolute Error (m)		
		1	2	3		1	2	3
1	1	38.15	38.16	38.15	38.15	0.00	0.01	0.00
	2	42.26	42.28	42.27	42.26	0.00	0.02	0.01
	3	42.31	42.31	42.31	42.31	0.00	0.00	0.00
	6	36.83	36.83	36.83	36.83	0.00	0.00	0.00
	11	41.19	41.20	41.20	41.20	0.01	0.00	0.00
2	1	25.60	25.61	25.60	25.60	0.00	0.01	0.00
	2	28.14	28.15	28.14	28.14	0.00	0.01	0.00
	3	31.17	31.17	31.17	31.17	0.00	0.00	0.00
	6	25.55	25.55	25.55	25.55	0.00	0.00	0.00
	11	28.60	28.61	28.61	28.60	0.00	0.01	0.01
3	1	12.16	12.16	12.16	12.16	0.00	0.00	0.00
	2	12.65	12.65	12.65	12.65	0.00	0.00	0.00
	3	19.38	19.38	19.38	19.38	0.00	0.00	0.00
	6	13.73	13.73	13.73	13.73	0.00	0.00	0.00
	11	14.97	14.98	14.98	14.98	0.01	0.00	0.00

Table 8. Computed and True Flow Rates (GA-Simplex).

Scenario	Pipe	Computed Flows (l/s)			True Flow (l/s)	Relative Error (%)		
		1	2	3		1	2	3
1	1	49.26	49.21	49.21	49.25	0.0	-0.1	-0.1
	3	54.77	54.83	54.82	54.80	0.0	0.0	0.0
	22	83.14	83.15	83.14	83.12	0.0	0.0	0.0
2	1	76.31	76.33	76.35	76.37	-0.1	-0.1	0.0
	3	75.74	75.76	75.75	75.73	0.0	0.0	0.0
	22	115.19	115.13	115.13	115.14	0.0	0.0	0.0
3	1	103.69	103.75	103.77	103.77	-0.1	0.0	0.0
	3	97.04	97.03	97.01	97.00	0.0	0.0	0.0
	22	146.69	146.66	146.66	146.67	0.0	0.0	0.0

The largest absolute error presented between computed and true pressure heads is 0.02 m, and the largest relative error between computed and true flow rates is -0.01%. It can be concluded that computed pressure heads and flow rates by the hybrid GA-Simplex method are very close to the true values and they are better than the computed pressure heads and flow rates by the GA alone.

7 CONCLUSIONS

This paper focuses on the development of a calibration hydraulic model using a hydraulic simulation model with the support of EPANET, which considers both leakage and pressure-dependent demands. The method was used to the evaluation of the water losses and actual demands using the data from a hypothetical network, but further studies are required, especially with field data.

Moreover, a hybrid GA-Simplex method is presented and its advantages like run-time savings and increased efficiency on determining calibration parameters are shown.

It should be observed that, sometimes, during the calibration process, the hydraulic simulator through EPANET could not be completed for certain combinations of parameters of the leakage model. It is surmised that this difficulty can be remedied by incorporating the leakage model into the hydraulic simulation code, avoiding the leakage calculations being conducted independently.

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