Improved EPANET Hydraulic Model with Optimized Roughness Coefficient using Genetic Algorithm

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Abstract

The process of calibrating hydraulic models for water distribution systems (WDS) is crucial during the model-building process, particularly when determining the roughness coefficients of pipes. However, using a single roughness coefficient based solely on pipe material can lead to significant variations in frictional head losses. To address this issue and enhance computational efficiency, this study proposes a single-objective procedure that utilizes Genetic Algorithm (GA) for optimizing roughness coefficients in the EPANET hydraulic model. EPANET-GA incorporates an automated calibration process and a User Graphic Interface (GUI) to analyze the water head pressures of WDS nodes. Notably, the proposed method not only optimizes roughness coefficients based on pipe material but also spatial characteristics of pipes. To demonstrate the effectiveness of this method, the study builds a hydraulic analysis model for the Zhonghe and Yonghe district of the Taipei Water Department, integrating graph theory's connectivity and the GIS database. The model was optimized with 34,783 node items, 30,940 pipes, and 140 field measurements. Results show that the optimized roughness coefficient produces a high correlation coefficient (0.9) with the measured data in a certain time slot. Furthermore, a low standard error (8.93%) was acheived compared to 24-hour monitoring data. The proposed method was further compared to WaterGEMs, and the study concludes that the proposed model provides a reliable reference for the design and routing scenario of WDS.

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Introduction

In the present day, hydraulic simulation models have become widely utilized for analyzing the behavior of water distribution systems (WDS), as noted by (Zanfei et al., 2020)(Sitzenfrei et al., 2020). The calibration of water distribution models involves adjusting network parameters, such as pipe roughness and nodal demand(Savic et al., 209AD), to minimize the disparities between simulated results and real measurements. Over the last thirty years, calibration has been a popular research topic among WDS analysts, and there have been numerous publications on this subject in scientific and engineering literature. In their work, Savic et al. (2009) conducted a comprehensive review of the calibration of water distribution network models and classified the calibration methods into three categories.

The first category involves iterative procedure models, where unknown parameters are updated at each iteration by solving the set of steady-state mass balance and energy equations using obtained water heads and/or flows at nodes(Rahal et al., 1980)(Walski, 1983)(Walski, 1986)(Bhave, 1988). However, this approach tends to have a slow convergence rate and is only suitable for handling small-scale problems(Bhave, 1988).

The second category includes explicit models, also known as hydraulic simulation models, which rely on solving an extended set of steady-state equations that include initial equations and additional ones derived from available measurements(Zanfei et al., 2020). An objective function or cost function is typically applied to minimize the disparities between measured and model-predicted variables(Savic et al., 209AD). However, this method requires a large quantity of observation data to accurately estimate calibration parameters(Walski, 2000). Nevertheless, simplifications of the model should be made to find a reasonable solution.

The third category of calibration methods involves implicit models that are generally based on optimization techniques. The calibration variables for these models encompass a broad range of parameters, such as nodal demand and pipe roughness(*Calibrating water distribution model via genetic algorithms*, 2002), or valve status and leak parameters(Laucelli et al., 2010)., 2011). A variety of optimization methods have been employed to address the relevant calibration problem, including the general reduced gradient method(Shamir, 1974)(Lansey & Basnet, 1991), the Gauss-Newton method("WLS method for parameter estimation in water distribution networks", 1996), the Levenberg-Marquardt method(Liggett & Chen, 1994), the extended complex method of box(Ormsbee, 1989), linear and non-linear programming(Greco & Del Giudice, 1999), the Kalman filtering method(Todini, 1999), and the simulated annealing method(Tucciarelli et al., 1999). However, there are trade-offs and no general guidance exists regarding which optimization technique is preferable for a specific calibration problem.

Various optimization techniques have been proposed for model calibration utilizing genetic algorithms (GAs)(Zanfei et al., 2020)(Savic & Walters, 1995)("An improved genetic algorithm for pipe network optimisation", 1996)(Vítkovský & Simpson, 1997)("Leak detection and calibration using transients and genetic algorithms", 2000)(Tang et al., 1999)(Kapelan, 2002)(Lingireddy & Ormsbee, 1998)(Meirelles et al., 2017). GAs have been shown to be efficient in assessing sensitivities, managing extensive calibrations, and integrating additional calibration parameter types and constraints into the optimization process. Recently, researchers have explored the use of evolutionary computer techniques to calibrate hydraulic models, with a focus on leakage estimation (Di Nardo et al., 2014)(Covelli et al., 2015) and water demand(Do et al., 2016).

However, the roughness coefficient is a primary parameter that contributes to uncertainty in model outputs, and different equations may yield vastly different estimates of frictional head losses, depending on the pipe size and water flow rate(Jamil, 2019)(Hashemi et al., 2020). The Darwin Calibrator in the commercial WaterGEMs has been developed utilizing GA to enable the adjustment of model parameters and modification of the roughness of pipe groups and junction demand during the calibration process(Z.Y. et al., 2004). However, WaterGEM did not account for the spatial characteristics of pipes in WDS calibration.

Regarding the previous requirements and limitations, this study proposes an enhanced method that employs Genetic Algorithm to optimize the roughness coefficient while incorporating the spatial factor and actual junction demand in the EPANET hydraulic model. Notably, EPANET is a freely available software that models the water quality and hydraulic behavior of water distribution piping systems(Shiu & Chung, 2022). Furthermore, a case analysis is carried out in the study to illustrate how the proposed technique can enhance the operational effectiveness by minimizing the difference between the simulated and observed values. The proposed method is further compared to WaterGEMs to provides a reliable reference for the design and routing scenario of WDS.

Materials and Methods

Overall concept

This study aims to collaborate with an EPANET-based hydraulic model algorithm, which is a useful and accessible tool for users to build automated processes and handle critical system parameters, such as nodes, links, demand, properties, pumps, reservoirs, and roughness. The study presents a modified approach for calibrating the roughness coefficient in a hydraulic model using a Graphic User Interface (GUI) and a

Genetic Algorithm (GA). GA approach is applied in the field to reduce the difference between the observed and predicted values, and it can be used as a valuable reference for future water supply deployment in emergency situations or for adjusting water supply at monitoring centers. Moreover, the water analysis model can identify leaking pipe sections in the network, thereby improving the maintenance efficiency of the pipe network for the adiministation.

Genetic Algorithms (GAs) are biologically motivated adaptive computer techniques based on natural selection and genetic operators(Wang, 1991)(Babovic et al., 1994). These algorithms are often used to solve complex optimization problems(Zanfei et al., 2020)(Meirelles et al., 2017)(Di Nardo et al., 2014)(Do et al., 2016)(Mambretti & Orsi, 2016). The computing framework in this study begins with data preprocessing, transforming the spatial database of the study area into the initial model, which includes a set of initial roughness coefficients denoted as C. These coefficients are estimated using theoretical or empirical formula, such as the Hazen-Williams equation shown in Equation (1)(Williams & Hazen, 1909), which is an empirical relationship between the flow of water in a pipe and the physical properties of the pipe, as well as the pressure drop caused by friction:

$$V = k\ C\ R^{0.63}\ S^{0.54}$$

(1)

where V is velocity (in ft/s for US units, in m/s for SI units), k is a conversion factor for the unit system (k = 1.318 for US units, k = 0.849 for SI units), R is the hydraulic radius (in ft for US units, in m for SI units), and S is the slope of the energy line (head loss per length of pipe or hf/L).

The roughness coefficient C of a pipe is a dimensionless number that depends on the pipe material, and in this study, the pipe roughness is categorized based on the fabrication material, including cast iron, plastic, and stainless steel. The roughness of new cast iron pipes is 130, while the roughness of 20-year-old pipes is 95, and 30-year-old pipes are 82.5. For plastic pipes, regardless of the age, the roughness is set at 150. For stainless steel pipes, the roughness of new riveted steel pipes is 110. The roughness of other pipelines is 100(ToolBox, 2012).

The process of calibration involves adjusting the roughness coefficient value C through EPANET and optimization techniques to minimize the difference between predicted pressures P and measured pressures, resulting in the creation of a corrected INP file for EPANET. Figure 1 illustrates the overall concept, while Equation (2) represents the objective function used for genetic algorithm correction:

$$F(x) = min \sum_{i=1}^{n} (P - \Delta P)^2$$

(2)

The objective function, F(x), is defined as the minimized sum of the water pressure difference squared, where P represents the actual measured value and ΔP represents the model predicted value. The model predicted value is obtained by adjusting the C value of each pipeline and substituted into EPANET.dll for calculation.

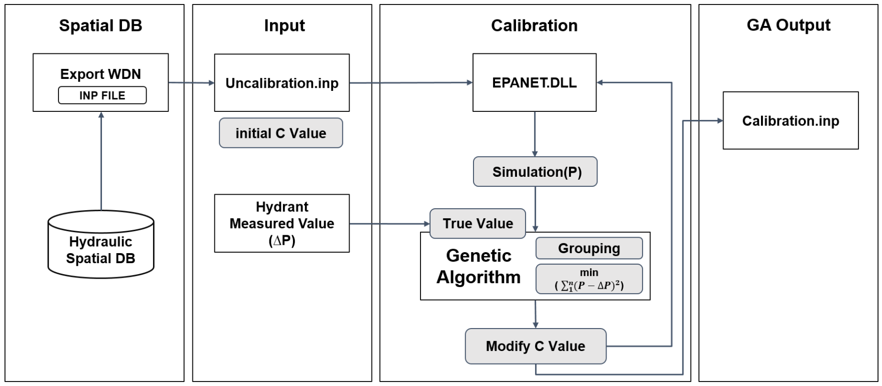


Figure 1: The proposed EPANET-GA model calibration work flow

The modified GA operation process

This research developed a modified GA operation, which consists of three stages as depicted in Figure 2: Data preparation, GA analysis, and Data output. These stages are further explained below:

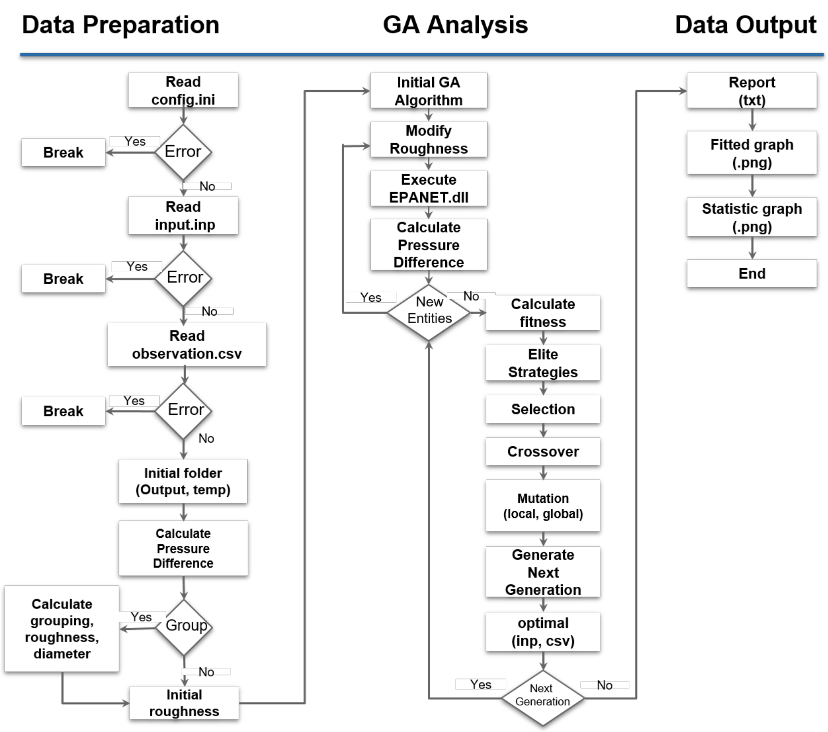


Figure 2: The proposed calibration procedures with GA and EPANET

Data Preparation

The first stage involves reading the config.ini file to retrieve the initial settings, followed by inputting the water distribution system (WDS) initialized model (input.inp) and water pressure measurements (observation.csv) data for the calculation process. The data is then checked for accuracy before proceeding to the next step.

If an error is detected, the calculation process is terminated. The INP file is then read to obtain information of the material types of the pipelines, pipeline diameters, pipeline roughness coefficient (C), and setting the group by diameter and roughness coefficient.

GA analysis

The GA is initialized, and the roughness coefficient (C) of the pipeline in the input.inp file is automatically imported to the EPANET.dll to perform the analysis. The percentage of pressure difference is then calculated. If new entities are presented, the process calculates fitness, performs selection, crossover, mutation, creates a new generation, and stores the optimized solution in the INP file.

Data Output

The results include three types: reports in TXT format, fitting curves in PNG format, and statistical charts in PNG format.

GA Graphic User Interface Design

To enhance the efficiency and ease of use of the calibration software, a graphic user interface (GUI) was developed using a GA, called WaterCali in this study. The interface is divided into six sections: the input area, GA parameter settings area, upper and lower limits of roughness, pipeline grouping settings area (with a focus on the spatial area), calibration result display area, and function key area. The WaterCali interface is illustrated in Figure 3 and offers a simple and intuitive user experience.

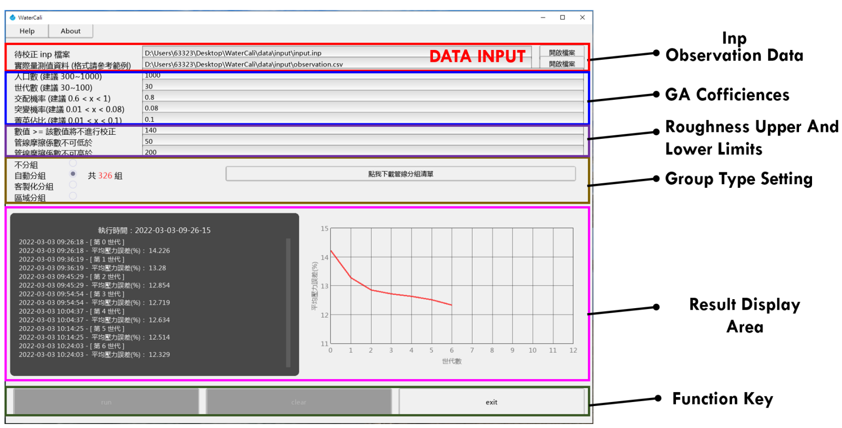


Figure 3: WaterCali graphic user interface (GUI)

This study proposes four group methods for setting groups in WaterCali, particularly in spatial groups. In Taipei, for example, the elevation ranges from 0 to 1177 meters. The user can input a GeoJSON file that contains area geometry to restrict the roughness coefficient (C).

Once the calibration process is finished, the outcomes are saved in the output folder located in the data directory, depicted in Figure 4. These outcomes encompass pressure data, illustrated in Figure 5, INP files for each generation, pipeline groups, and statistical charts and implementation reports presenting the results of each iteration.

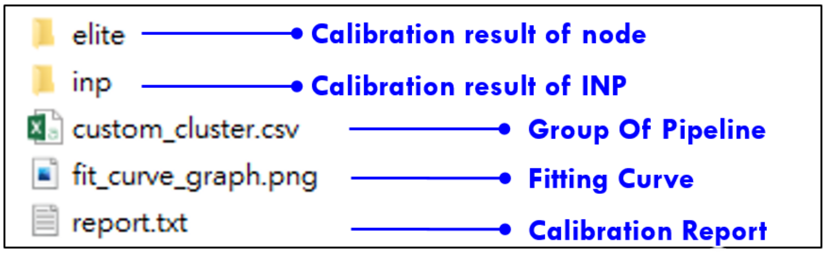
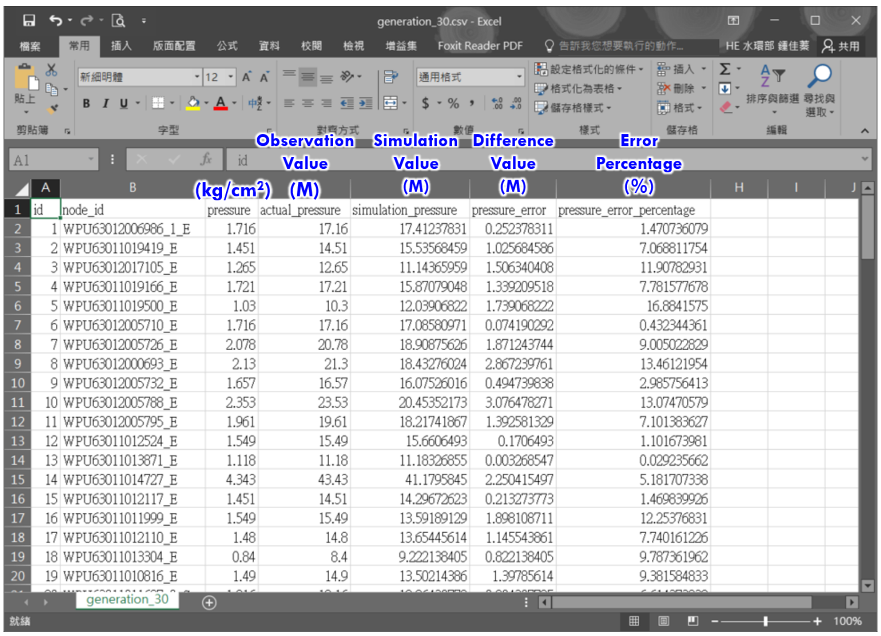


Figure 4: WaterCali output files



id	node_id	pressure	actual_pressure	simulation_pressure	pressure_error	pressure_error_percentage
1	WPU63012006986_1_E	1.716	17.16	17.41237831	0.252378311	1.470736079
2	WPU63011019419_E	1.451	14.51	15.53568459	1.025684586	7.068811754
3	WPU63012017105_E	1.265	12.65	11.14365959	1.506340408	11.90782931
4	WPU63011019166_E	1.721	17.21	15.87079048	1.339209518	7.781577678
5	WPU63011019500_E	1.03	10.3	12.03906822	1.739068222	16.8841575
6	WPU63012005710_E	1.716	17.16	17.08580971	0.074190292	0.432344361
7	WPU63012005726_E	2.078	20.78	18.90875626	1.871243744	9.005022829
8	WPU63012000693_E	2.13	21.3	18.43276024	2.867239761	13.46121954
9	WPU63012005732_E	1.657	16.57	16.07526016	0.494739838	2.985756413
10	WPU63012005788_E	2.353	23.53	20.45352173	3.076478271	13.07470579
11	WPU63012005795_E	1.961	19.61	18.21741867	1.392581329	7.101383627
12	WPU63011012524_E	1.549	15.49	15.6606493	0.1706493	1.101673981
13	WPU63011013871_E	1.118	11.18	11.18326855	0.003268547	0.029235662
14	WPU63011014727_E	4.343	43.43	41.1795845	2.250415497	5.181707338
15	WPU63011012117_E	1.451	14.51	14.29672623	0.213273773	1.469839926
16	WPU63011011999_E	1.549	15.49	13.59189129	1.898108711	12.25376831
17	WPU63011012110_E	1.48	14.8	13.65445614	1.145543861	7.740161226
18	WPU63011013304_E	0.84	8.4	9.222138405	0.822138405	9.787361962
19	WPU63011010816_E	1.49	14.9	13.50214386	1.39785614	9.381584833

Figure 5: WaterCali water pressure calculations in an output Excel file)

Introduction of case area

Introduction of case area

The case study was conducted at Taipei Water Department's Zhonghe and Yonghe Division. The Zhonghe Booster Station is the primary water supply facility for the Zhonghe District and Yonghe Division, where the northern side is a relatively low-pressure area, and the water source is derived from two branch lines of the Zhitan Water Treatment Plant, as illustrated in Figure 6. Table 1 provides some essential details of Taipei Water Department's Zhonghe and Yonghe Division.

Table 1: Scenerio settings for GA

Variable	Type I	Type II	Type III
Population	1,000	1,000	1,000
Generation	100	50	50
Rate Of Crossover	0.8	0.8	0.8
Rate Of Mutation	0.08	0.08	0.08
Proportion Of Optimal	0.1	0.1	0.1
Roughness Coefficient	$35 \leqslant C \leqslant 300$	$50 \leqslant C \leqslant 150$	$70 \leqslant C \leqslant 150$
Qualified Point	113	114	110

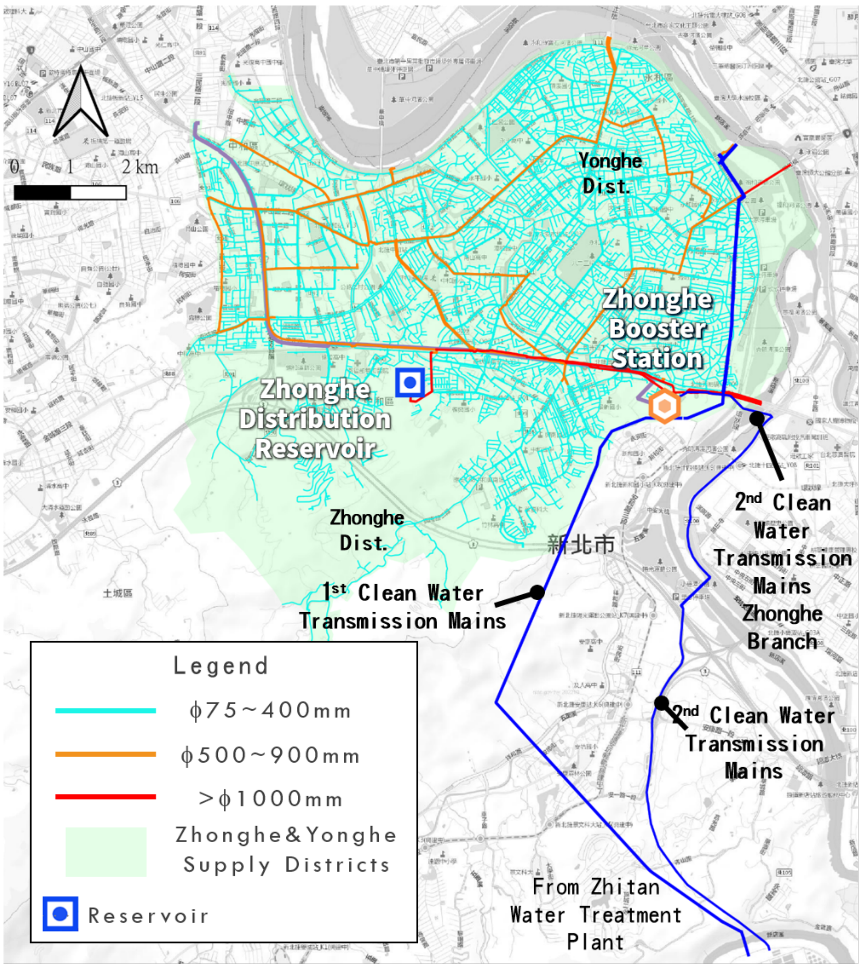


Figure 6: Water supply and pipeline distribution of the Zhonghe and Yonghe Division)

Model establishment

The WISE (Water Intelligent System of Enterprise) platform of the Taipei Water Department is currently in use, which allows users to select an area on the map and choose the water demand distribution model, then export the model for further analysis(Shiu & Chung, 2022). The resulting model can be opened in EPANET for analysis, as demonstrated in Figure 7. Following the aforementioned processing and calculations, the input parameter table for the selected area can be generated, resulting in an EPANET 2.X input file (*.inp). The INP file for the Zhonghe and Yonghe Division was used to compare the collected station and equipment data.

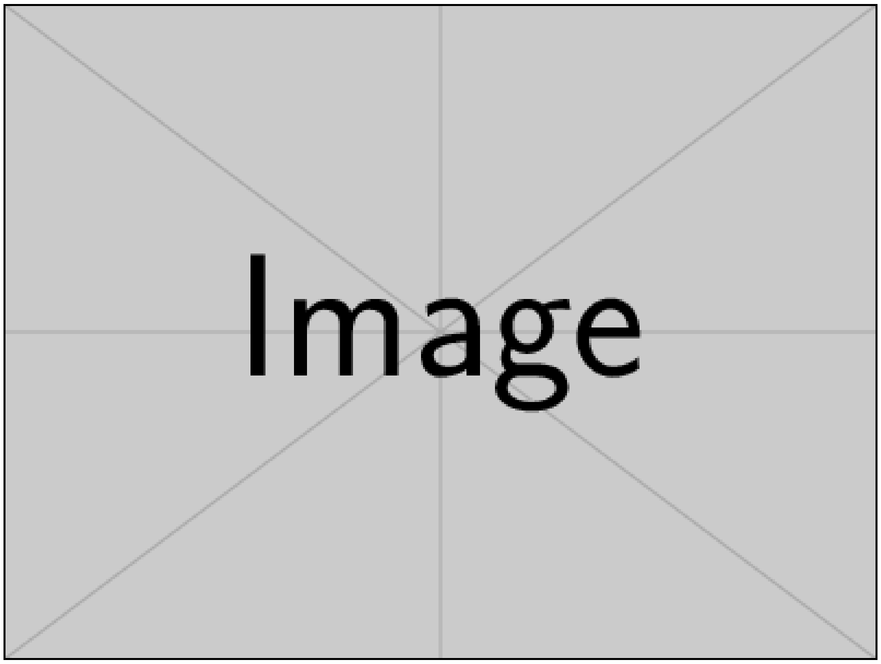


Figure 7: INP network of the Zhonghe and Yonghe Divisions)

SCADA data for pre-processing

Hydraulic model calibration is required to process a large amount of Supervisory Control and Data Acquisition (SCADA) data, including the pressure and flow measurements from field pump stations. The SCADA procedures in this study was organized as follows:

1. Collecting pump station data: collecting pump station data manually according to the target area for the calibration. To facilitate subsequent data selection and organization, the recommended data collection interval is once per minute.

2. Calculate the actual water requirement of the pipe network: using Microsoft Excel (Microsoft, Redmond, WA, USA) for data calculation and organization. The data required for organization and calculation are inputted into the EPANET to use its built-in formulas for calculation.

3. Determine the time slot of the maximum water requirement: From the previous calculation results, the maximum value of water amount is identified, then the corresponding time slot is used for EPANET at single time period simulation.

4. Obtain the data of all pump stations and monitoring points of the corresponding time slot: because the basis for single time period simulation has been identified and data of all pump stations can be established in the EPANET, including the inflows and outflows, and pressures. Thus, the pressure values of the monitoring

points at the corresponding time slot are listed for comparison and model modification, as shown in Figure 8.

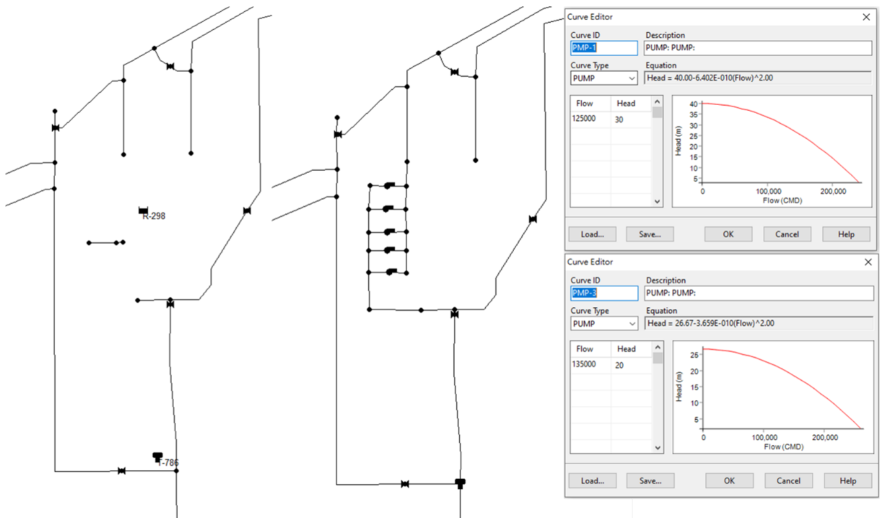


Figure 8: Setting Variables and links of Pump in EPANET)

Water Pressure Measurements

The total measured points(ΔN) of this study is set to 140 to satisfy the measured quantity which is at least 30% of the model length(km) as following Equation (3):

$$Pipe\ Length(km)\ of\ the\ Model\ *\ 0.3 \leqslant\ Measured\ Points(\Delta N) \tag{3}$$

In addition, the 140 measured points should be uniformly located in the water supply zone to understand the distribution of the water supply pressure. In order to prevent the measured error by unexpected valve closing, the measured points were randomly separated into two groups, red and green triangulars as shown in Figure 9. Each point was then installed with a pressure sensor to retrieve data more than 48 hours, the frequency of pressure measurement data recorded once per minute , as shown in Figure 10.

The time series display the pattern of two groups, as shown in Figure 11(A) and Figure 11(B). In this case study, the high peak of measured data was about 23:00 and the low peak is about 22:00. Measuring point No. 058 and 065 have a sharp drop in pressure at 2021/12/28 at 22:00, as shown in Figure 12, because of the large water consumption at the same time. It came back to normal suddenly. The water consumption recorded by the water meter at 22:00 on 2021/12/28 was 51-73% higher than the water consumption at 22:00 on 2021/12/29.

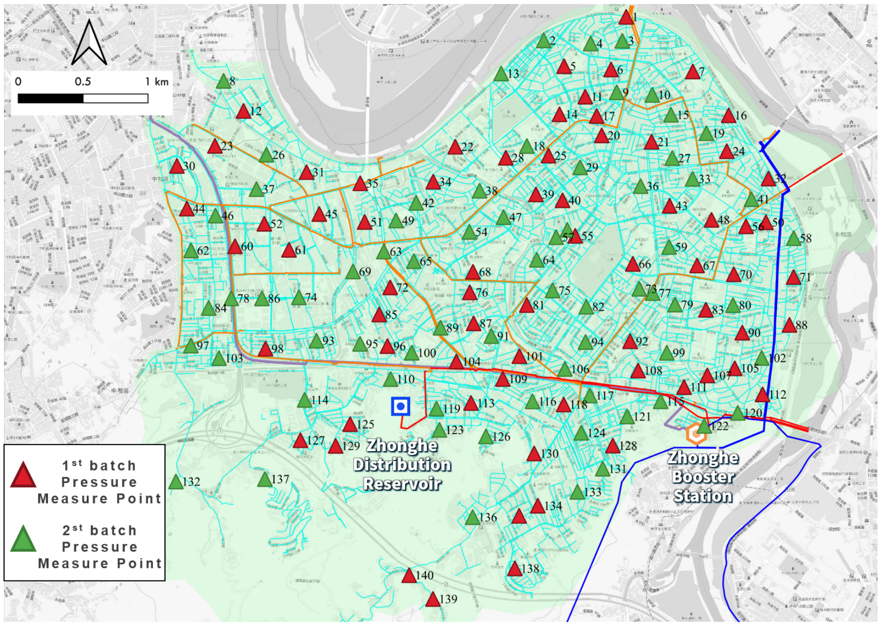


Figure 9: Distribution of measurement points in the Zhonghe and Yonghe Divisions)

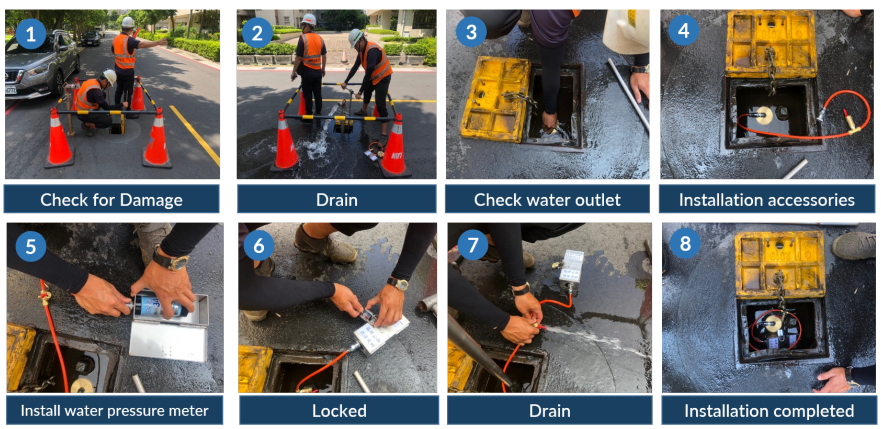


Figure 10: Work flow of installing a pressure sensor

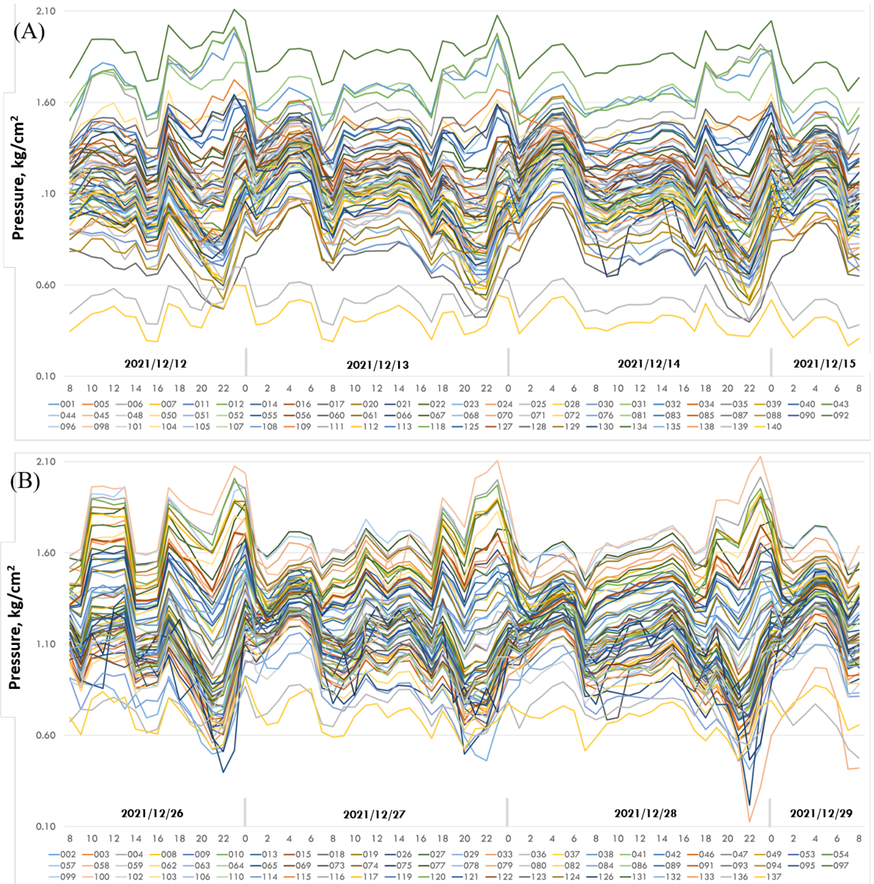


Figure 11: (A)1st Pressure measurement pattern and (B) 2nd Pressure measurement pattern

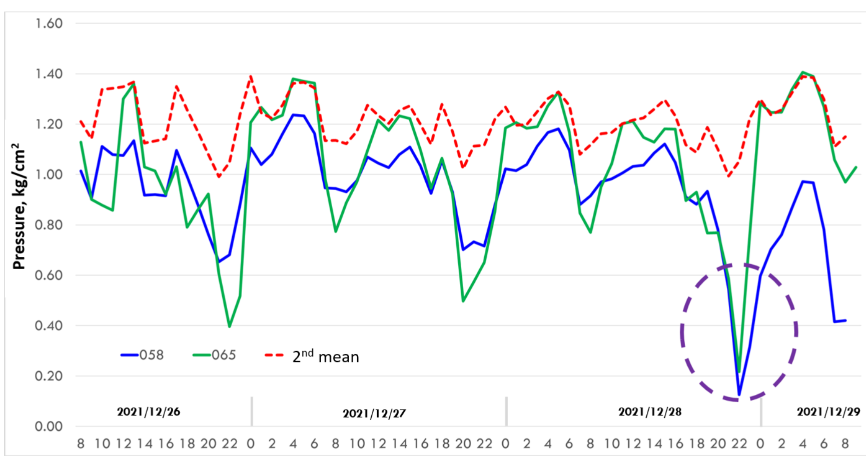


Figure 12: 2nd Obnormal point of pressure measurement.

Parametric results for GA

The validated paramters in GA are categorized into three types, as shown in Table 2 below. For the first type, the generation has been set as 100 and the Roughness Coefficient C as between 35 and 300 for testing the water head loss being reduced and reflected in C. In the second type, the generation was 50 and lies between 50 and 150 for testing the GA performance. In the third type, the generation is set 50 and C between 70 and 150 for imiting the value of C to get better results. Type I and II were used to compare the generation and GA performance, and Type II and III were used for a C comparison. It reflects that imiting the value of C can not get better results.

Figure 13 shows that Type I is fit in 45 generations and the mean error rate is about 11.759%. For Type II, the fitness is shown in 20 generations and the mean error rate is about 11.765%. In Type III, the result is also fit in 20 generations and the mean error rate is about 11.844%, as shown in Figure 13. The qualified point in Type I with 113, Type II with 114, and Type III with 110. After comparing with Type I and II, 50 generation is enough for using and comparing with Type II and III shows that the C between 50 and 150 is better.

Table 2: Scenerio settings for GA

Variable	Type I	Type II	Type III
Population	1,000	1,000	1,000
Generation	100	50	50
Rate Of Crossover	0.8	0.8	0.8
Rate Of Mutation	0.08	0.08	0.08
Proportion Of Optimal	0.1	0.1	0.1
Roughness Coefficient	$35 \leqslant C \leqslant 300$	$50 \leqslant C \leqslant 150$	$70 \leqslant C \leqslant 150$
Qualified Point	113	114	110

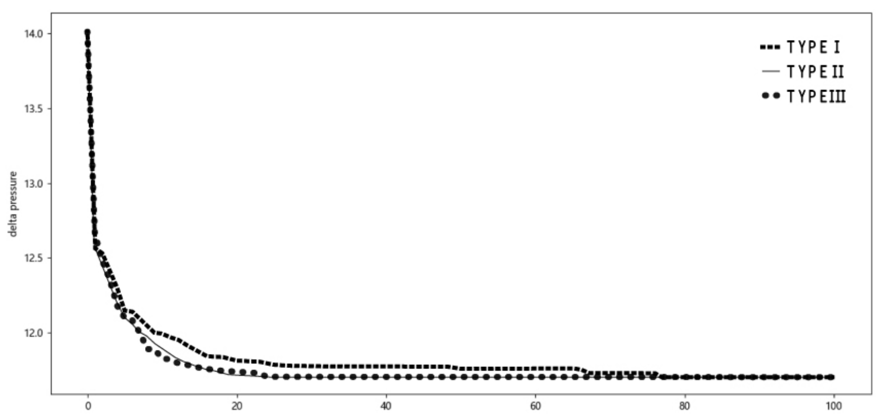


Figure 13: The Fitting Curve With Different GA Types

Results

Simulation Results before GA Roughness Optimization

Figure 14 shows the distribution of the simulated water pressure with the previous SCADA pre-processing before the Roughness Coefficient C optimization. According to the statistical results shown in Table 3, out of the 140 water pressure measurement points in the Zhonghe and Yonghe Divisions, 64 points have a pressure difference of less than 0.1 kg/cm^2, 44 points have a difference between 0.1-0.2 kg/cm^2, 18 points are between 0.2-0.3 kg/cm^2, 8 points are between 0.3-0.4 kg/cm^2, and 6 points have a difference greater than 0.4 kg/cm^2. Out of the total, 108 points have a pressure error within ±20%, which accounts for 77.1% of the total. The area with the largest difference from the actual measured pressure is primarily located at the end of the pipeline, as shown in Figure 15. The pressure at the end of the pipeline is typically lower than in other areas, which causes an obvious difference error.

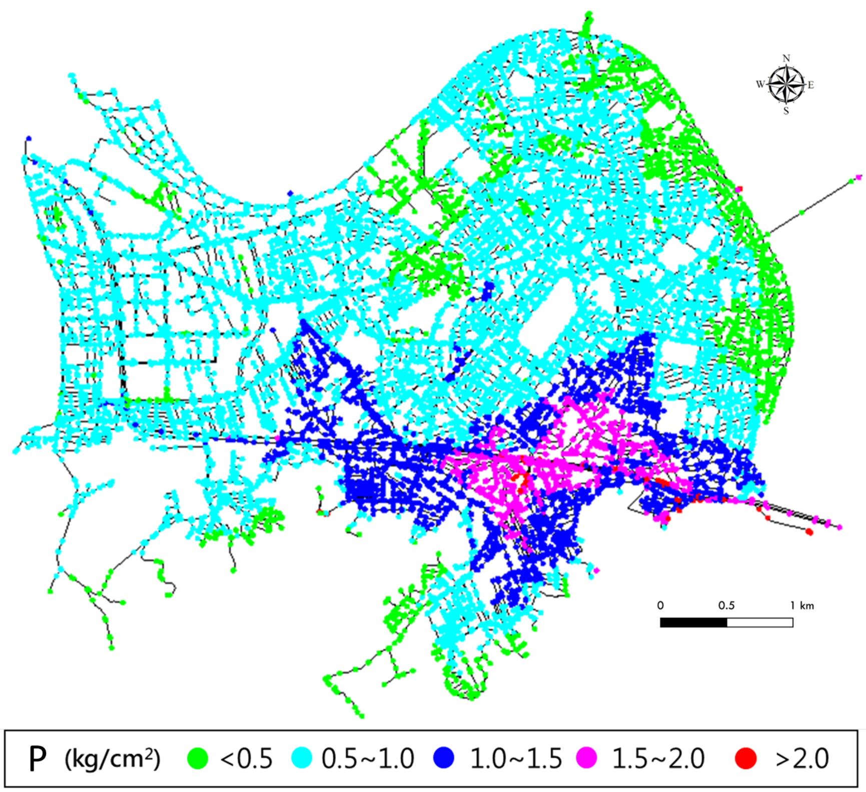


Figure 14: Simulated pressure distribution map before roughness optimization

Table 3: Comparison of prediction errors of WaterGEMs and EPANET-GA

WaterGEMs			EPANET-GA		
Error(%)	Count	Percentage(%)	Error(%)	Count	Percentage(%)
< 10	64	45.7	< 10	70	50
10-20	48	34.3	$10 - 20$	44	31.4
> 20	28	20.0	> 20	26	18.6

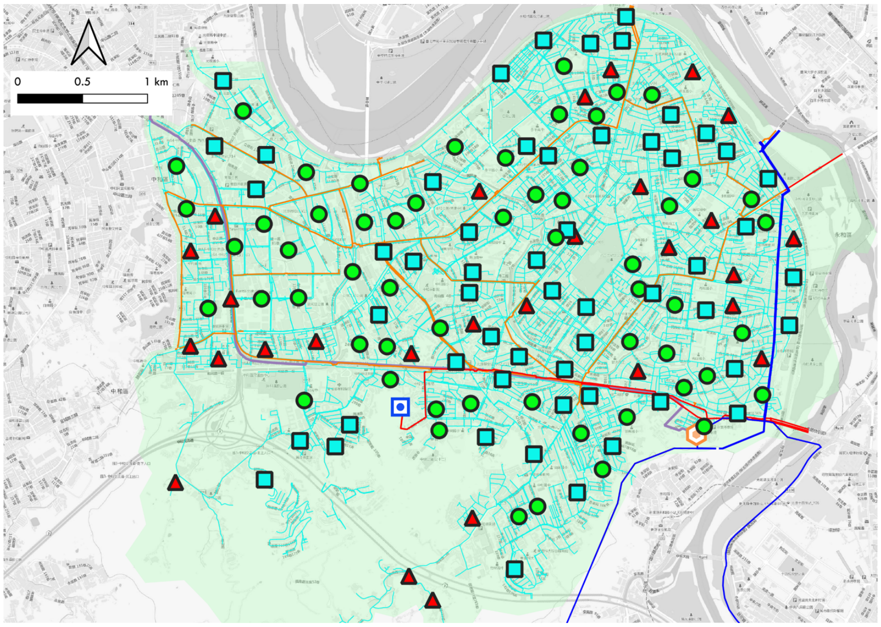


Figure 15: Pressure difference distribution before roughness optimization

Simulation Results after Roughness Optimization

Table 4 displays the simulation results roughness optimization. Among the 140 water pressure measurement points, 75 points have a pressure difference of less than 0.1 kg/cm^2, 39 points are between 0.1-0.2 kg/cm^2, 18 points are between 0.2-0.3 kg/cm^2, 1 point is between 0.3-0.4 kg/cm^2, and 7 points are above 0.4 kg/cm^2.

Table 4: Comparison of prediction errors of WaterGEMs and EPANET-GA

WaterGEMs			EPANET-GA		
Error(%)	Count	Percentage(%)	Error(%)	Count	Percentage(%)
< 10	64	45.7	< 10	70	50
10-20	48	34.3	$10 - 20$	44	31.4
> 20	28	20.0	> 20	26	18.6

The error within 20% is observed in 114 points, accounting for 81.4% of the total, and the error of less than 10% increased from 51 points to 70 points improving 37.3%, which suggests a significant improvement in overall pressure difference, as shown in Figure 15. The points with a larger error are primarily located at the end of the pipeline and are lower pressure in WDS.

The absolute value of the pressure difference and the error at each point are closer to the lower range. The calculated correlation coefficient between the mean value observed and the simulated pressure was 0.9, which is considered good compared to the research by Kepa (2021)(Kepa, 2021). Based on the calibration, the developed EPANET-GA model was deemed acceptable and represented a reliable representation of the tested water supply network.

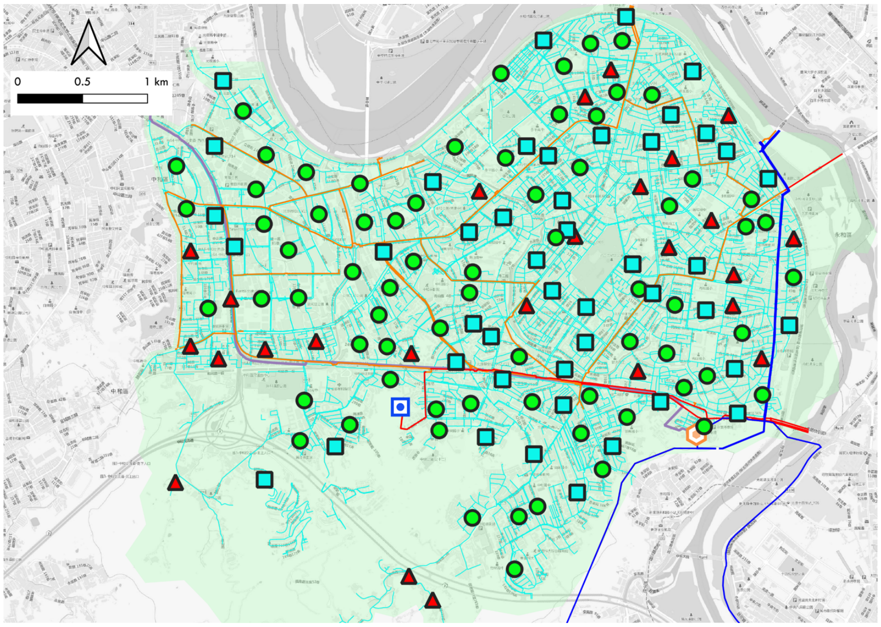


Figure 16: Pressure difference distribution after roughness optimization

Comparison with WaterGEMs

To assess the reliability and effectiveness of the proposed method, this study used both the EPANET-GA and WaterGEMs simulation results with those obtained from actual measured water pressures. WaterGEMs is a comprehensive and user-friendly decision-support tool for water distribution networks provided by Bentley. WaterGEMs contains another algorithm of calibration called Darwin Calibrator.

This commercial software is well known to improve the operational strategies of decision makers, enhance the model-building process, and effectively manage local models(Z.Y. et al., 2004). Table 5 shows the pressure difference between EPANET-GA after calibration and WaterGEMs. The results indicate that 112 points have an error within 20%, which accounts for 80% of the total, and 57 points have an error less than 10%. EPANET-GA outperformed WaterGEMs in terms of accuracy.

Table 5: Comparison of prediction errors of WaterGEMs and EPANET-GA

WaterGEMs			EPANET-GA		
Error(%)	Count	Percentage(%)	Error(%)	Count	Percentage(%)
< 10	64	45.7	< 10	70	50
10-20	48	34.3	$10 - 20$	44	31.4
> 20	28	20.0	> 20	26	18.6

Result Validation

Based on the previous section's analysis, it was found that the areas with significant pressure differences before model calibration were mainly located at the end of the pipeline, as indicated in Figure 17. To assess the reliability of the EPANET-GA model for long-term simulation, the simulation results were compared with the monitoring points using 24-hour data, as shown in Figure 18 and Table 6. The EPANET-GA model's mean error rate after calibration for all monitoring points in 24 hours was 8.93%.

Figure 19 shows a comparison of the pressure difference between EPANET-GA after calibration with WaterGEMs, with 10 monitoring points used for comparison. The results indicate that the EPANET-GA method has slightly better performance with an error rate of 8.93%, compared to WaterGEMs with an error rate of 9.00%. When the monitoring points are near the Pump Station, they tend to yield better simulation results with an error rate of less than 10. However, larger error values can still be observed at the end of the pipe network.

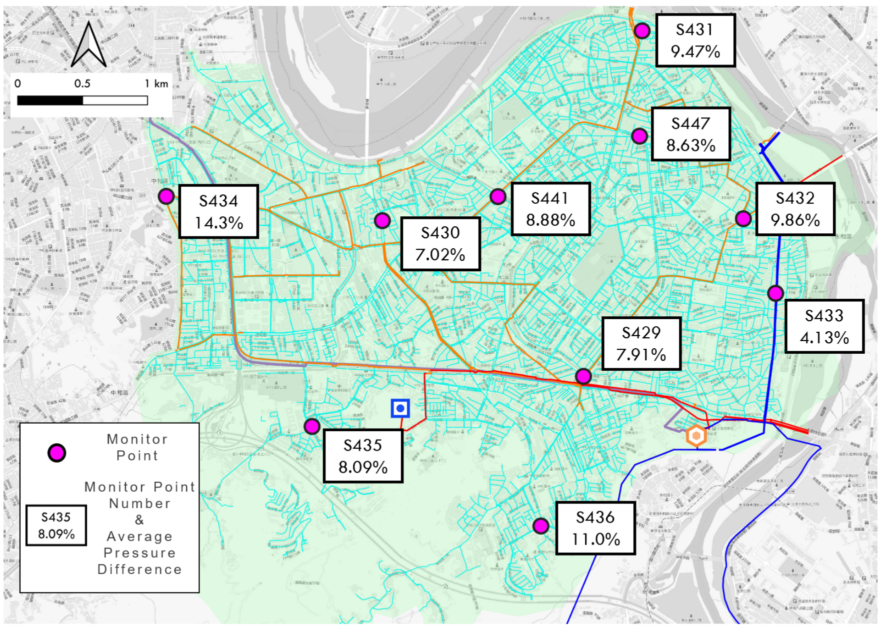


Figure 17: Specified monitoring points located at the end of the pipeline

Figure 18: 24-hours pressure comparison between monitoring points and EPANET-GA simulations.

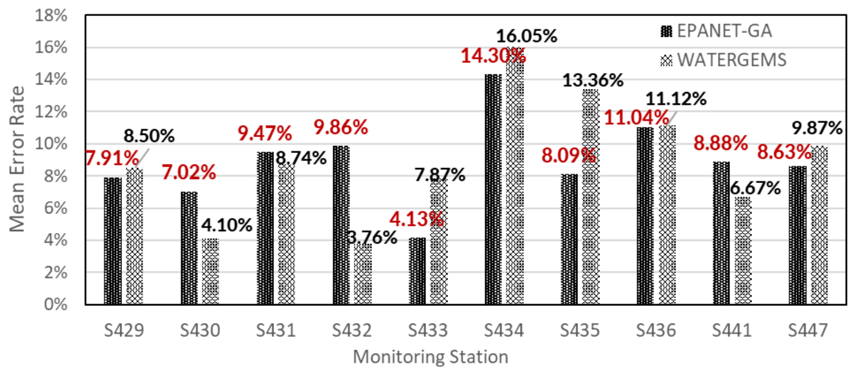


Figure 19: Comparison bewteen WaterGEMs and EPANET-GA

Validation of 24 HR simulation

	S429	S430	S431	S432	S433	S434	S435	S436	S441	S
0	8.713	4.230	2.355	4.052	6.719	7.011	17.099	15.344	1.227	13
1	4.787	4.227	8.656	14.012	7.026	5.207	6.149	9.538	13.861	2
2	8.348	1.246	0.148	7.176	6.638	0.957	8.161	12.531	9.331	5
3	16.265	8.241	11.382	3.152	3.797	10.812	15.504	19.581	1.173	14
4	15.187	8.187	10.623	2.976	2.656	11.015	16.351	18.623	0.813	13
5	11.371	4.216	3.964	3.314	2.576	4.197	13.379	14.168	4.769	7
6	8.658	0.059	1.628	7.642	6.362	1.184	11.504	11.478	8.806	4
7	12.039	5.996	7.010	2.931	2.351	4.392	16.412	17.183	2.814	15
8	5.378	4.789	4.507	10.859	3.097	10.582	9.405	11.184	12.843	7
9	4.650	9.779	6.887	11.501	3.487	14.420	8.280	10.979	12.049	5
10	5.992	4.817	5.116	10.175	2.048	14.976	8.643	12.644	11.555	6
11	5.678	4.523	3.536	8.752	0.246	18.214	9.442	13.748	10.641	7
12	5.456	7.985	6.177	9.545	2.172	17.056	7.391	12.034	13.226	4
13	4.398	8.119	7.832	10.778	3.307	17.509	7.163	14.094	14.643	3
14	5.572	6.274	4.179	8.101	1.975	17.007	5.240	11.006	11.836	5
15	4.822	6.159	4.386	7.017	2.606	19.220	3.421	13.212	11.940	4
16	4.544	5.806	5.117	6.708	2.140	16.537	0.165	13.253	11.163	5
17	4.955	7.143	3.788	6.350	1.689	22.748	3.908	12.740	11.149	8
18	3.783	11.353	13.533	13.884	0.243	29.479	6.143	0.426	12.518	5
19	0.706	7.650	11.932	12.255	1.874	17.128	2.647	0.649	8.390	10
20	11.130	18.675	28.120	27.370	6.236	31.030	8.099	7.364	16.829	6
21	14.662	10.847	27.463	18.293	8.753	22.538	0.452	4.473	5.118	16
22	13.347	8.434	24.563	15.480	13.013	14.313	5.876	4.829	0.930	19
23	9.519	9.636	24.268	14.366	8.222	15.783	3.383	3.964	5.426	11
AVG	7.915	7.016 7	9.465	9.862	4.135	14.305	8.092	11.044	8.877	8

Discussion

This technical article presents three primary topics of discussion. Firstly, EPANET-GA highlights the importance of adjusting the valve setting for calibrating the water distribution network model. It is crucial to match the local settings and measurement conditions obtained from SCADA before initiating GA optimization to achieve optimal simulation results and streamline the model checking process. Failure to do so may lead to significant effort being expended to identify problems in the simulation, resulting in mismatched outcomes.

Secondly, measurement points should be randomly selected in a normal distribution within the pipe network and divided into at least two groups to mitigate the impact of the pipe network's operations, as previously mentioned. The measurement duration must be at least 48 consecutive hours.

Thirdly, the GA process varies between WaterCali and WaterGEMs. While WaterCali employs random crossover and mutation techniques, WaterGEMs limits user control of the random variable and transforms it using Fast Messy Genetic Algorithm. WaterCali also incorporates the spatial factor in the calibration process, making it better suited for real-world scenarios and simulations.

Conclusions and Suggestions

The proposed methodology involves combining the genetic algorithm (GA) with the EPANET.dll water analysis library to create EPANET-GA, which enables identification of the optimal solution that aligns with measured data. The roughness coefficient is adjusted by the GA through iterations of selection, crossover, and constant mutation. To validate the efficiency of the pipeline network model and calibration process, results were compared with SCADA monitoring points at Zhonghe and Yonghe Division. The hydraulic model's preliminary analysis results indicate a reasonable distribution of water pressure calculated by the Zhonghe and Yonghe Division model. The results demonstrate a strong correlation coefficient of 0.9 between the simulated and measured data, a mean error rate of only 8.93% compared to 24-hour monitoring data, and superior performance compared to WaterGEMs. EPANET-GA can rapidly identify a range of solutions, not just a single optimal solution.

The case of the water pressure calculated by EPANET-GA in Zhonghe and Yonghe Division model indicates that the analysis model could be used in future work programs, such as Taipei Water Department's Shilin and Beitou Division, aiding engineers in decision-making and providing cost-effective solutions. However, the traditional EPANET software currently lacks model calibration functions, and a plug-in solver is required for operation, which is inconvenient for ordinary users. Given that commercial software can be expensive, this study provide WaterCali plugin to share with interested parties requiring reliable water distribution network calibration. Users can refer to the proposed processes and procedures to quickly construct a preliminary hydraulic analysis model and adjust parameters as required for future models.

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References

Calibration procedure for water distribution systems: comparison among hydraulic models. (2020). *Water*, *12(5)*, 1421. https://doi.org/doi.org/10.3390/w12051421

Using complex network analysis for optimization of water distribution networks. (2020). *Water Resources Research*, *56*, e2020WR027929. https://doi.org/doi.org/ 10.1029/2020WR027929

Quo vadis water distribution model calibration?. (209AD). *Urban Water Journal*, *6*, 3–22. https://doi.org/10.1080/15730620802613380

Parameter tuning for simulation models of water distribution networks. (1980). *In: Institution of Civil Engineers*, *69*, 751–762.

A technique for calibrating network models. (1983). *Journal of Water Resources Planning and Management*, *109*(4), 360–372.

Case study: pipe network model calibration issues. (1986). *Journal of Water Resources Planning and Management*, *112*(2), 238–249.

Calibrating water distribution network models. (1988). *Journal of Environmental Engineering*, *114*(1), 120–136.

Model calibration data: the good, the bad, and the useless. (2000). *Journal-American Water Works Association*, *92*(1), 94–99.

(2002).

Calibration of Water Distribution System Using Topological Analysis. (2010). *Water Distribution Systems Analysis 2010*, 1664–1681.

Optimal design and operation of water distribution systems. (1974). *Water Resources Research*, *10*(1), 27–36.

Parameter estimation for water distribution networks. (1991). *Journal of Water Resources Planning and Management*, *117*(1), 126–144.

(1996). *Journal of Water Resources Planning and Management*, *122*(3), 157–164.

Inverse transient analysis in pipe networks. (1994). *Journal of Hydraulic Engineering*, *120*(8), 934–955.

Implicit network calibration. (1989). *Journal of Water Resources Planning and Management*, *115*(2), 243–257.

New approach to water distribution network calibration. (1999). *Journal of Hydraulic Engineering*, *125*(8), 849–854.

Using a kalman filter approach for looped water distribution network calibration. (1999).

Leak analysis in pipeline systems by means of optimal valve regulation. (1999). *Journal of Hydraulic Engineering*, *125*(3), 277–285.

Genetic Algorithm Techniques for Calibrating Network Models. (1995).

(1996). *Water Resources Research*, *32*(2), 449–458.

Calibration and Leak Detection in Pipe Networks Using Inverse Transient Analysis And Genetic Algorithms. (1997).

(2000). *Journal of Water Resources Planning and Management*, *126*(4), 262–265.

Inverse transient calibration of water distribution systems using genetic algorithms. (1999).

Calibration of Water Distribution System Hydraulic Models. (2002).

Optimal Network Calibration Model Based on Genetic Algorithms. (1998).

Calibration Model for Water Distribution Network Using Pressures Estimated by Artificial Neural Networks. (2017). *Water Resource Management*, *31*, 4339–4351. https://doi.org/doi.org/10.1007/s11269-017-1750-2

A genetic algorithm for demand pattern and leakage estimation in a water distribution network. (2014). *Journal of Water Supply: Research and Technology-Aqua*, *64(1)*, 35–46. https://doi.org/doi.org/10.2166/aqua.2014.004

A model to simulate leakage through joints in water distribution systems. (2015). *Journal of Water Supply: Research and Technology-Aqua*, *15*, 852–863. https://doi.org/10.2166/ws.2015.043

Calibration of water demand multipliers in water distribution systems using genetic algorithms. (2016). *Journal of Water Resources Planning and Management*, *142*, 04016044. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000691

Frictional head loss relation between Hazen-Williams and Darcy-Weisbach equations for various water supply pipe materials. (2019). *International Journal of Water*, *13*, 333–347. https://doi.org/10.1504/IJW.2019.10027784

Effect of Pipe Size and Location on Water-Main Head Loss in Water Distribution Systems. (2020). *Journal of Water Resources Planning and Management*, *146*, 06020006. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001222

Darwin Calibrator Improving Project Producivity and Model Quality for Large Water Systems. (2004). *Journal-American Water Works Association*, *146*, 27–34. https://doi.org/doi.org/10.1002/j.1551-8833.2004.tb10715.x

A Modified Hydrologic Model Algorithm Based on Integrating Graph Theory and GIS Database. (2022). *Water*, *14*, 3000. https://doi.org/doi.org/10.3390/w14193000

The genetic algorithm and its application to calibrating conceptual rainfall-runoff models. (1991). *Water Resources Research*, *27*(9), 2467–2471.

Calibrating hydrodynamic models by means of simulated evolution. (1994). 193–200.

Optimizing Pump Operations in Water Supply Networks Through Genetic Algorithms. (2016). *Journal (American Water Works Association)*, *108*(2), E119–E125.

Hydraulic tables: the elements of gagings and the friction of water flowing in pipes, aqueducts, sewers, etc. as determined by the Hazen and Williams formula and the flow of water over sharp-edged and irregular weirs, and the quantity discharged, as determined by Bazin's formula and experimental investigations upon large models. (1909). J. Wiley and sons.

Hazen-Williams Coefficients. (2012).

Use of the hydraulic model for the operational analysis of the water supply network: a case Study. (2021). *Water*, *13*, 326. https://doi.org/doi.org/10.3390/w13030326