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Improved EPANET Hydraulic Model with Optimized Roughness Coefficient using Genetic Algorithm

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Key Points:

- The study proposed the integration of GA Algorithm with EPANET hydraulic model.
- The roughness can be optimized by considering pipe's material and spatial distributions.
- Simulation with the optimized roughness was highly correlated (0.9) with the field data.

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.

Keyword: water distribution systems (WDS); Genetic Algorithm (GA); EPANET hydraulic model; roughness coefficient

1 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) and Sitzenfrei et al. (2020). The calibration of water distribution models involves adjusting network parameters, such as pipe roughness and nodal demand (Savic et al., 2009), 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, 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., 2009). However, this method requires a

75 large quantity of observation data to accurately estimate calibration parameters (Walski, 2000).
76 Nevertheless, simplifications of the model should be made to find a reasonable solution.

77   The third category of calibration methods involves implicit models that are generally
78 based on optimization techniques. The calibration variables for these models encompass a broad
79 range of parameters, such as nodal demand and pipe roughness (Wu et al., 2002), or valve status
80 and leak parameters (Laucelli et al., 2011). A variety of optimization methods have been
81 employed to address the relevant calibration problem, including the general reduced gradient
82 method (Shamir, 1974; Lansey & Basnet, 1991), the Gauss-Newton method (Reddy et al., 1996),
83 the Levenberg-Marquardt method (Liggett & Chen, 1994), the extended complex method of box
84 (Ormsbee, 1989), linear and non-linear programming (Greco & Del Giudice, 1999), the Kalman
85 filtering method (Todini, 1999), and the simulated annealing method (Tucciarelli et al., 1999).
86 However, there are trade-offs and no general guidance exists regarding which optimization
87 technique is preferable for a specific calibration problem.

88   Various optimization techniques have been proposed for model calibration utilizing
89 genetic algorithms (GAs) (Dandy et al., 1996; Savic & Walters, 1995; Vítkovský & Simpson,
90 1997; Tang et al., 1999; Kapelan, 2002; Vítkovský et al., 2000, 2003; Lingireddy & Ormsbee,
91 1998; Meirelles et al., 2017; Zanfei et al., 2020). GAs have been shown to be efficient in
92 assessing sensitivities, managing extensive calibrations, and integrating additional calibration
93 parameter types and constraints into the optimization process. Recently, researchers have
94 explored the use of evolutionary computer techniques to calibrate hydraulic models, with a focus
95 on leakage estimation (Di Nardo et al., 2014; Covelli et al., 2015) and water demand (Do et al.,
96 2016).

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

104   Regarding the previous requirements and limitations, this study proposes an enhanced
105 method that employs Genetic Algorithm to optimize the roughness coefficient while
106 incorporating the spatial factor and actual junction demand in the EPANET hydraulic model.
107 Notably, EPANET is a freely available software that models the water quality and hydraulic
108 behavior of water distribution piping systems (Nallanathel et al., 2018). Furthermore, a case
109 analysis is carried out in the study to illustrate how the proposed technique can enhance the
110 operational effectiveness by minimizing the difference between the simulated and observed
111 values. The proposed method is further compared to WaterGEMs to provides a reliable reference
112 for the design and routing scenario of WDS.

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2 Materials and Methods

2.1 Overall concept

This study aims to collaborate with an EPANET-based hydraulic model algorithm (Shiu et al., 2022), 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 (Di Nardo et al., 2014; Do et al., 2016; Mambretti, S. & E. Orsi, 2016; Meirelles et al., 2017; Zanfei et al., 2020). 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 et al., 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:

$$V = k \, C \, R^{0.63} S^{0.54} \tag{1}$$

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 (Williams et al., 1909).

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:

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

The objective function, F(x), is defined as the minimized sum of nth water pressure difference squared, where ΔP represents the actual measured value and P 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.

2.2 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:

1. 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.

2. 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.

3. Data Output:

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

2.3 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.

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) to the same area as follows.

"{ "type": "FeatureCollection",
        "name": "A",
        "crs": { "type": "name", "properties": { "name": "urn:ogc:def:crs:EPSG::3826" } },
        "features": [
        { "type": "Feature", "properties": { "id": 0, "area": 131874.60656700001, "perimeter": 1367.29384 }, "geometry": { "type": "Polygon", "coordinates": [[[300076.488, 2773317.927], [299863.84, 2773330.234], [299770.886, 2773347.906], [299716.224, 2773429.392], [299843.986, 2773650.023], [300018.272, 2773651.079], [300122.724, 2773642.446], [300163.252, 2773613.56699999981], [300200.169, 2773517.413], [300207.555, 2773403.838], [300185.121, 2773370.367], [300076.488, 2773317.927]]] } }]
} "

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.

3 Introduction of case area

3.1 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. Basic information of study area

Division	Pipe Length (Km)		Valve	Hydrant	Meter	Booster Station	Tank Volume(t)	Monitoring Point
	Water-Distribution	Water-Service						
Zhonghe	256	156	3,690	2,542	20,943	1	30,222	5
Yonghe	143	108	2,552	1,421	15,554			5

3.2   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. 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.

3.3   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 measuremens 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.

3.4 Water Pressure Measurements

According to suggestion of Shiu et al. (2022), the total measured points 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):

$$Pipe\ length(km)\ of\ the\ Model * 0.3 \leq Measured\ Points\ (\Delta P) \qquad (3)$$

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

266	prevent the measured error by unexpected valve closing, the measured points were
267	randomly separated into two groups, red and green triangulars as shown in Figure 9.
268	Each point was then installed with a pressure sensor to retrieve data more than 48 hours,
269	the frequency of pressure measurement data recorded once per minute , as shown in
270	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.

3.5 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	$35 \leq C \leq 300$	$50 \leq C \leq 150$	$70 \leq C \leq 150$
Qualified Point	113	114	110

* If the initial Roughness Coefficient (C) > 140, it will not be modify in GA model.

297 **4 Results**

298 4.1 Simulation Results before GA Roughness Optimization

299 Figure 14 shows the distribution of the simulated water pressure with the
300 previous SCADA pre-processing before the Roughness Coefficient C optimization.
301 According to the statistical results shown in Table 3, out of the 140 water pressure
302 measurement points in the Zhonghe and Yonghe Divisions, 64 points have a pressure
303 difference of less than 0.1 kg/cm^2, 44 points have a difference between 0.1 to 0.2
304 kg/cm^2, 18 points are between 0.2 to 0.3 kg/cm^2, 8 points are between 0.3 to 0.4 kg/cm^2,
305 and 6 points have a difference greater than 0.4 kg/cm^2.

306 Out of the total, 112 points have a pressure error within ±20%, which accounts
307 for 80% of the total. The area with the largest difference from the actual measured
308 pressure is primarily located at the end of the pipeline, as shown in Figure 15. The
309 pressure at the end of the pipeline is typically lower than in other areas, which causes an
310 obvious difference error.

311 **Table 3.** Statistics of pressure difference before calibration

Water pressure Difference (kg/cm^2)	Count	Percentage (%)	Error (%)	Count	Percentage (%)
< 0.1	64	45.7	10	57	40.7
0.1~0.2	44	31.4	10-20	55	39.3
0.2~0.3	18	12.9	More than 20	28	20.0
0.3~0.4	8	5.7			
More than 0.4	6	4.3			

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313 4.2 Simulation Results after Roughness Optimization

314 Table 4 displays the simulation results roughness optimization. Among the 140
315 water pressure measurement points, 75 points have a pressure difference of less than 0.1
316 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
317 point is between 0.3~0.4 kg/cm^2, and 7 points are above 0.4 kg/cm^2.

318 The error within 20% is observed in 114 points, accounting for 81.4% of the
319 total, and the error of less than 10% increased from 57 points to 70 points, which
320 suggests a significant improvement in overall pressure difference, as shown in Figure 15.
321 The points with a larger error are primarily located at the end of the pipeline.

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

Table 4. Statistics of pressure difference after roughness optimization

Water pressure Difference (kg/cm^2)	Count	Percentage (%)	Error (%)	Count	Percentage (%)
< 0.1	75	53.6	10	70	50
0.1 ~ 0.2	39	27.9	10-20	44	31.4
0.2 ~ 0.3	18	12.8	More than 20	26	81.4
0.3 ~ 0.4	1	0.7			
> 0.4	7	5.0			

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4.3 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. This commercial software is well known to improve the operational strategies of decision makers, enhance the model-building process, and effectively manage local models (Wu 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	71	50.0
10~20	48	34.3	10~20	45	31.4
> 20	28	20.0	> 20	24	18.6

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4.4 Assessment of longterm simulation

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. 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.

5 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.

6 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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523

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

Spatial DB	Input	Calibration	GA Output

Spatial DB

Export WDN
INP FILE

Hydraulic Spatial DB

Input

Uncalibration.inp

initial C Value

Hydrant Measured Value (ΔP)

Calibration

EPANET.DLL

Simulation(P)

True Value

Genetic Algorithm

Grouping

$$\text{min} \left(\sum_1^n (P - \Delta P)^2 \right)$$

Modify C Value

GA Output
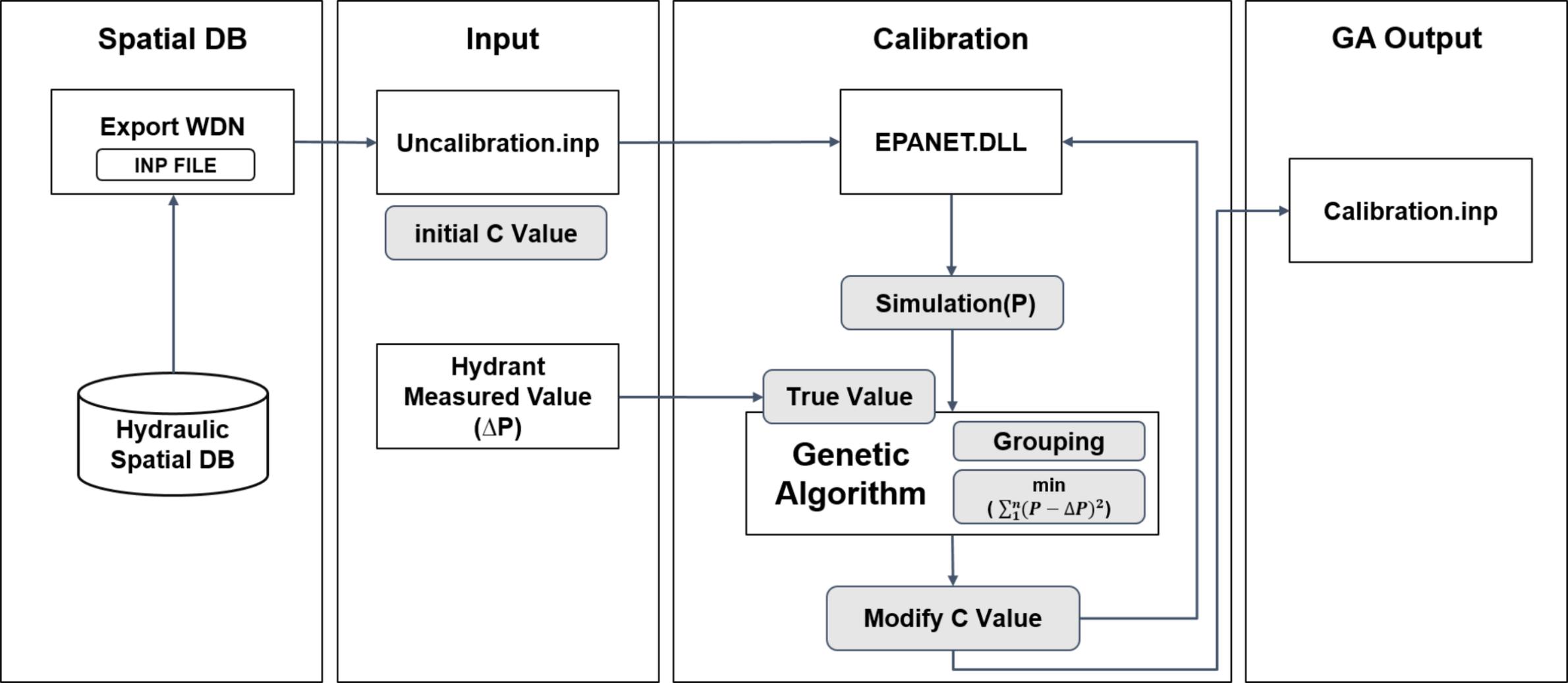
Calibration.inp

Figure 2. The proposed calibration procedures with GA and EPANET.

Data Preparation

Read config.ini

Error — Yes → **Break**

No

Read input.inp

Error — Yes → **Break**

No

Read observation.csv

Error — Yes → **Break**

No

Initial folder (Output, temp)

Calculate Pressure Difference

Group — Yes → **Calculate grouping, roughness, diameter**

No

Initial roughness

GA Analysis

Initial GA Algorithm

Modify Roughness

Execute EPANET.dll

Calculate Pressure Difference

New Entities — Yes / No

Calculate fitness

Elite Strategies

Selection

Crossover

Mutation (local, global)

Generate Next Generation

optimal (inp, csv)

Next Generation — Yes / No

Data Output

Report (txt)

Fitted graph (.png)

Statistic graph (.png)

End

Figure 3. WaterCali graphic user interface (GUI).

WaterCali

Help   About

待校正 inp 檔案   D:\Users\63323\Desktop\WaterCali\data\input\input.inp   **DATA INPUT**   開啟檔案
實際量測值資料 (格式請參考範例)   D:\Users\63323\Desktop\WaterCali\data\input\observation.csv   開啟檔案

● Inp
● Observation Data

人口數 (建議 300~1000)   1000
世代數 (建議 30~100)   30
交配機率 (建議 0.6 < x < 1)   0.8
突變機率(建議 0.01 < x < 0.08)   0.08
菁英佔比 (建議 0.01 < x < 0.1)   0.1

● GA Cofficiences

數值 >= 該數值將不進行校正   140
管線摩擦係數不可低於   50
管線摩擦係數不可高於   200

● Roughness Upper And Lower Limits

不分組   ○
自動分組   ●   共 326 組   點我下載管線分組清單
客製化分組   ○
區域分組   ○

● Group Type Setting

執行時間：2022-03-03-09-26-15

2022-03-03 09:26:18 - [第 0 世代]
2022-03-03 09:26:18 - 平均壓力誤差(%)：14.226
2022-03-03 09:36:19 - [第 1 世代]
2022-03-03 09:36:19 - 平均壓力誤差(%)：13.28
2022-03-03 09:45:29 - [第 2 世代]
2022-03-03 09:45:29 - 平均壓力誤差(%)：12.854
2022-03-03 09:54:54 - [第 3 世代]
2022-03-03 09:54:54 - 平均壓力誤差(%)：12.719
2022-03-03 10:04:37 - [第 4 世代]
2022-03-03 10:04:37 - 平均壓力誤差(%)：12.634
2022-03-03 10:14:25 - [第 5 世代]
2022-03-03 10:14:25 - 平均壓力誤差(%)：12.514
2022-03-03 10:24:03 - [第 6 世代]
2022-03-03 10:24:03 - 平均壓力誤差(%)：12.329

(plot: y-axis 平均壓力誤差(%) from 11 to 15, x-axis 世代數 from 0 to 12)

● Result Display Area

run   clear   exit

● Function Key

Figure 4. WaterCali output files.

📁 elite	━━━━━━━━━━▶	**Calibration result of node**
📁 inp	━━━━━━━━━━▶	**Calibration result of INP**
📊 custom_cluster.csv	━━━━━━━━━━▶	**Group Of Pipeline**
🖼 fit_curve_graph.png	━━━━━━━━━━▶	**Fitting Curve**
📄 report.txt	━━━━━━━━━━▶	**Calibration Report**

Figure 5. WaterCali water pressure calculations in an output Excel file.

id	node_id	pressure (Observation Value (kg/cm²))	actual_pressure (M)	simulation_pressure (Simulation Value (M))	pressure_error (Difference Value (M))	pressure_error_percentage (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 6. Water supply and pipeline distribution of the Zhonghe and Yonghe Divisions.
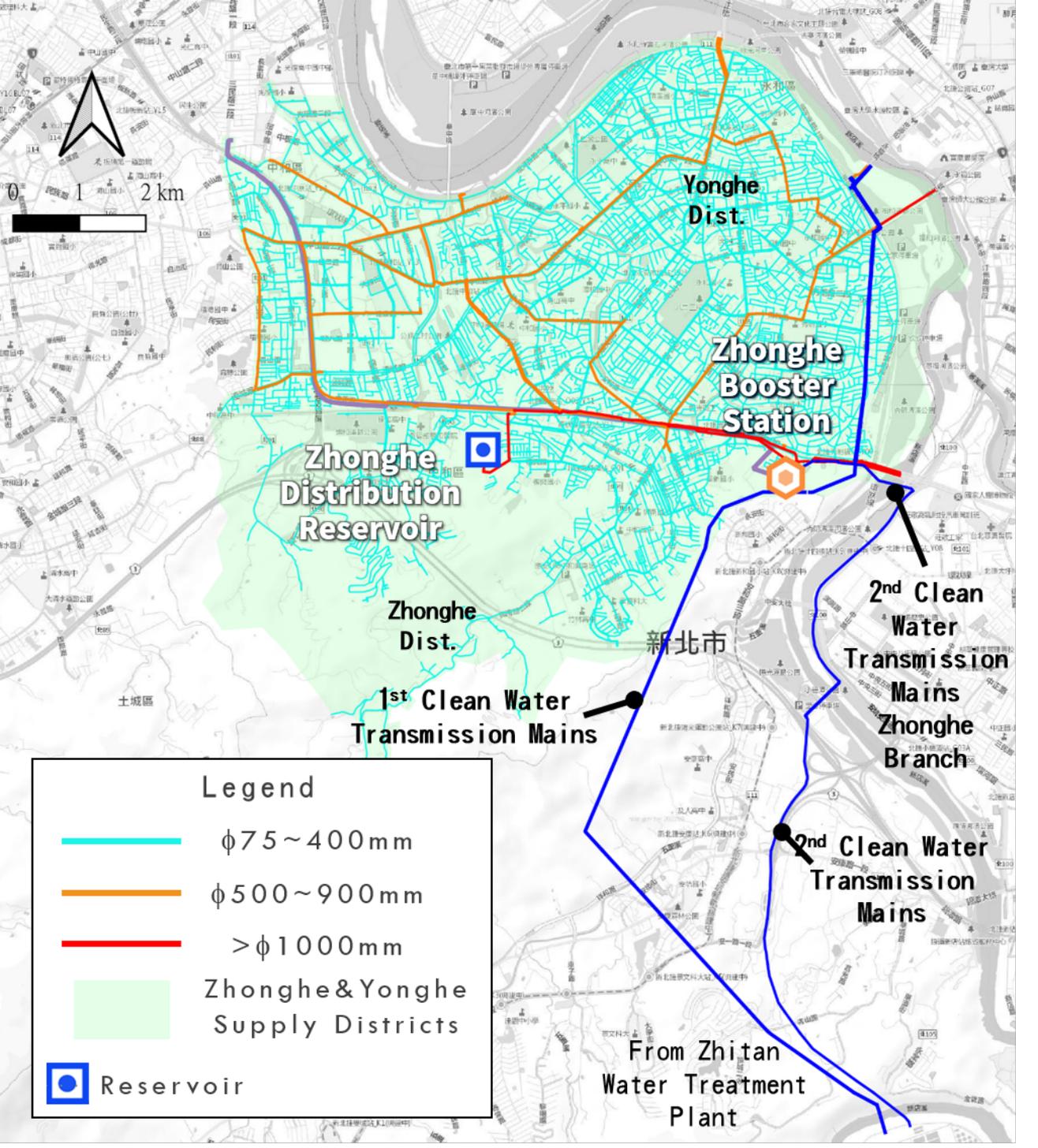
Legend

▬▬	φ75~400mm
▬▬	φ500~900mm
▬▬	>φ1000mm
	Zhonghe&Yonghe Supply Districts
◧	Reservoir

Yonghe Dist.

Zhonghe Booster Station

Zhonghe Distribution Reservoir

Zhonghe Dist.

新北市

1st Clean Water Transmission Mains

2nd Clean Water Transmission Mains Zhonghe Branch

2nd Clean Water Transmission Mains

From Zhitan Water Treatment Plant

Figure 7. INP network of the Zhonghe and Yonghe Divisions.

Figure 8. Setting Variables and links of Pump in EPANET.

Curve Editor

Curve ID: PMP-1
Description: PUMP: PUMP:
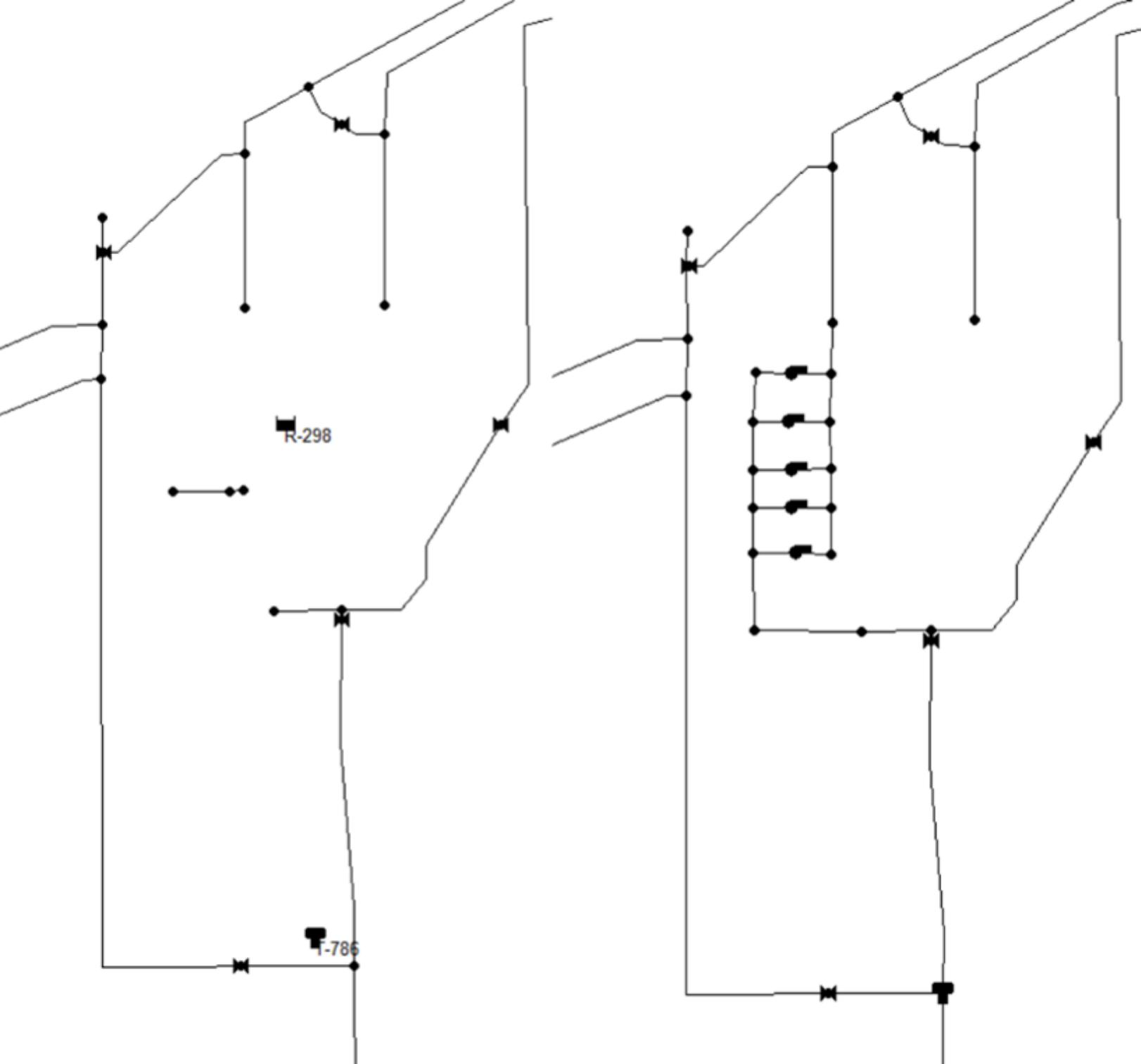
Curve Type: PUMP
Equation: Head = 40.00-6.402E-010(Flow)^2.00

Flow	Head
125000	30

Load... | Save... | OK | Cancel | Help

Curve Editor

Curve ID: PMP-3
Description: PUMP: PUMP:

Curve Type: PUMP
Equation: Head = 26.67-3.659E-010(Flow)^2.00

Flow	Head
135000	20

Load... | Save... | OK | Cancel | Help

R-298

T-786

Figure 9. Distribution of measurement points in the Zhonghe and Yonghe Divisions.
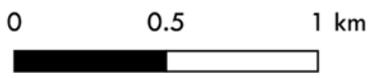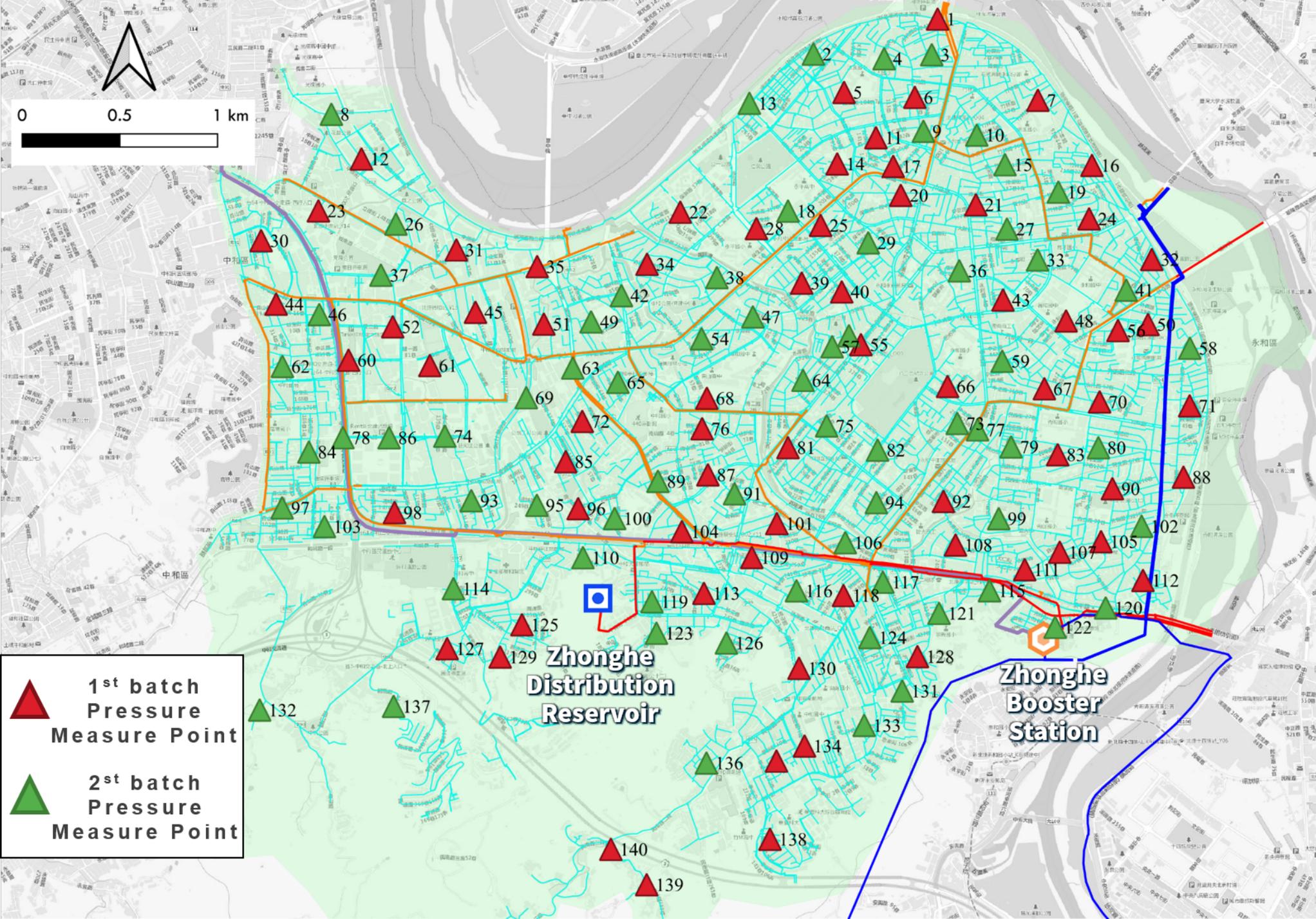
Legend:
- 1st batch Pressure Measure Point (red triangle)
- 2nd batch Pressure Measure Point (green triangle)

Zhonghe Distribution Reservoir

Zhonghe Booster Station

Figure 10. Work flow of installing a pressure sensor.

1 — Check for Damage

2 — Drain

3 — Check water outlet
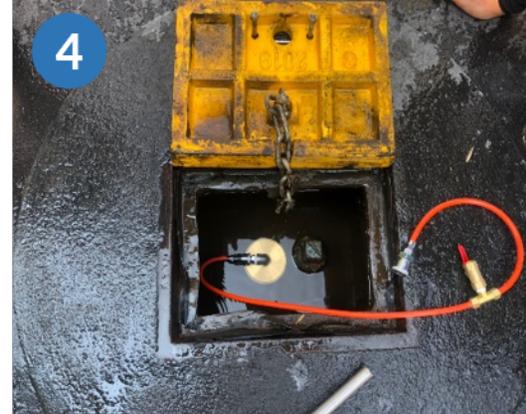
4 — Installation accessories

5 — Install water pressure meter

6 — Locked
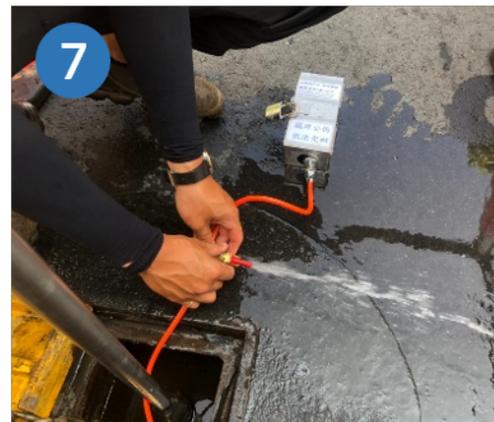
7 — Drain

8 — Installation completed

Figure 11. (A)1st Pressure measurement pattern and (B) 2nd Pressure measurement pattern.
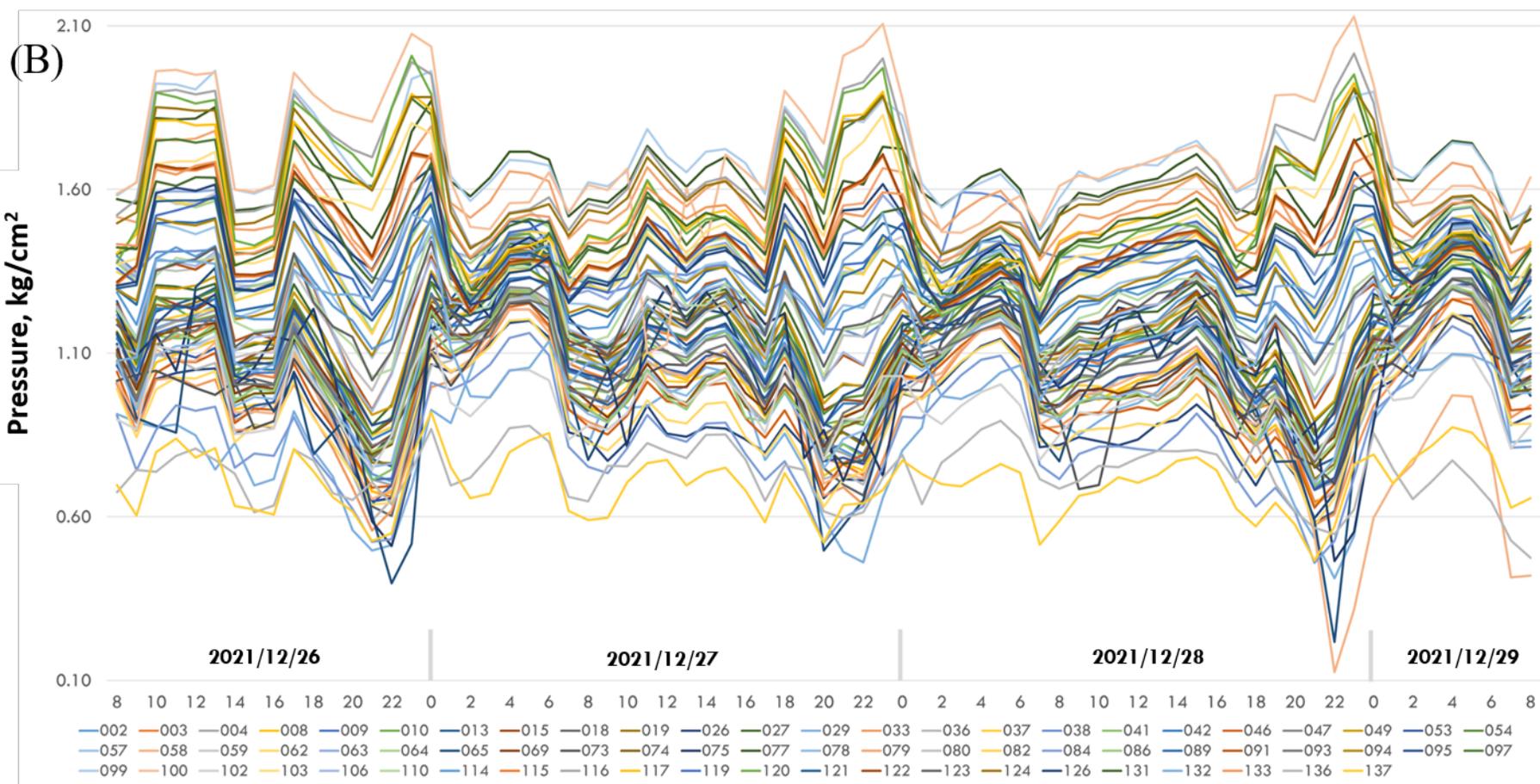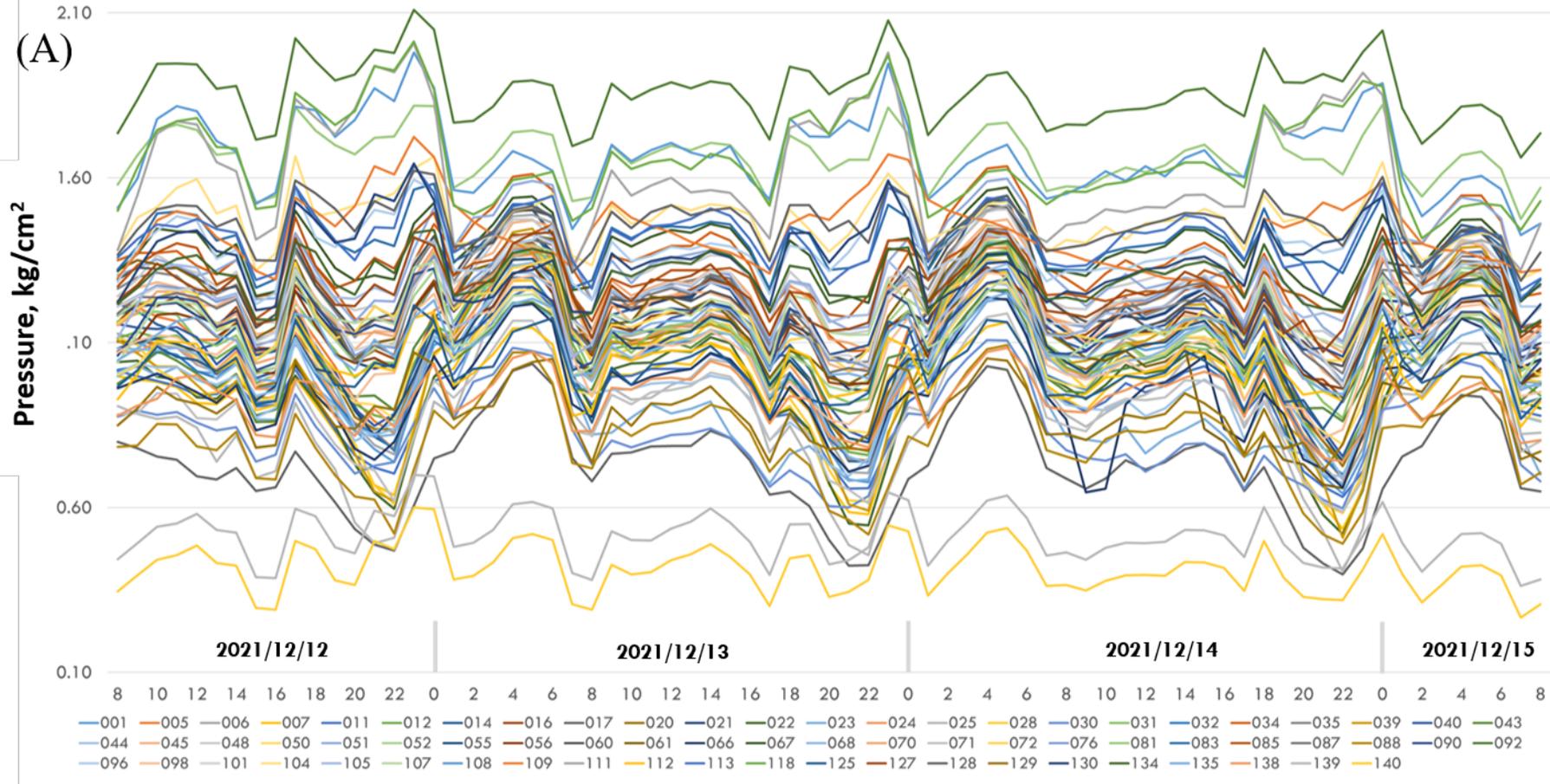
Figure 12. 2nd Obnormal point of pressure measurement.
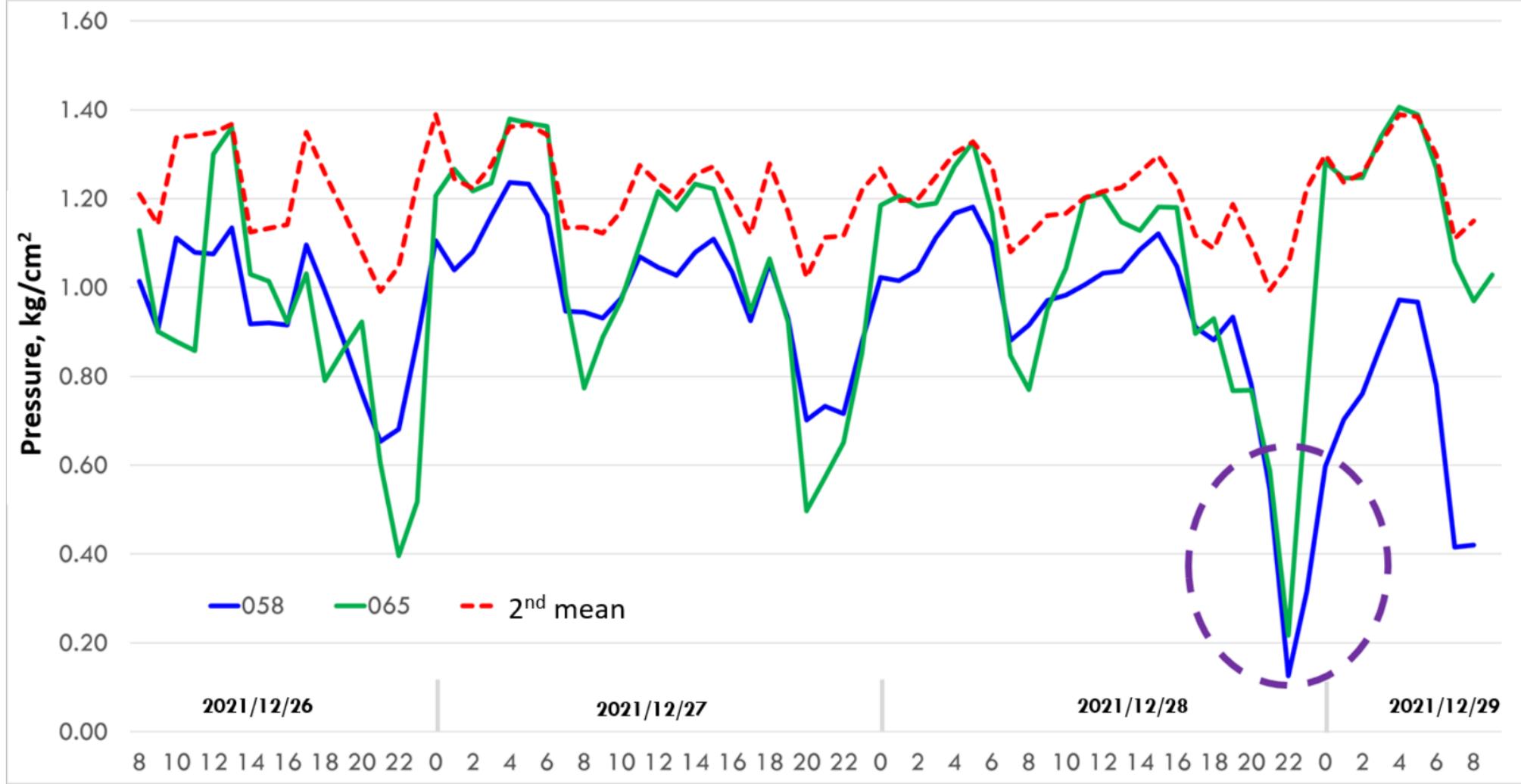
Figure 13. The Fitting Curve With Different GA Types.
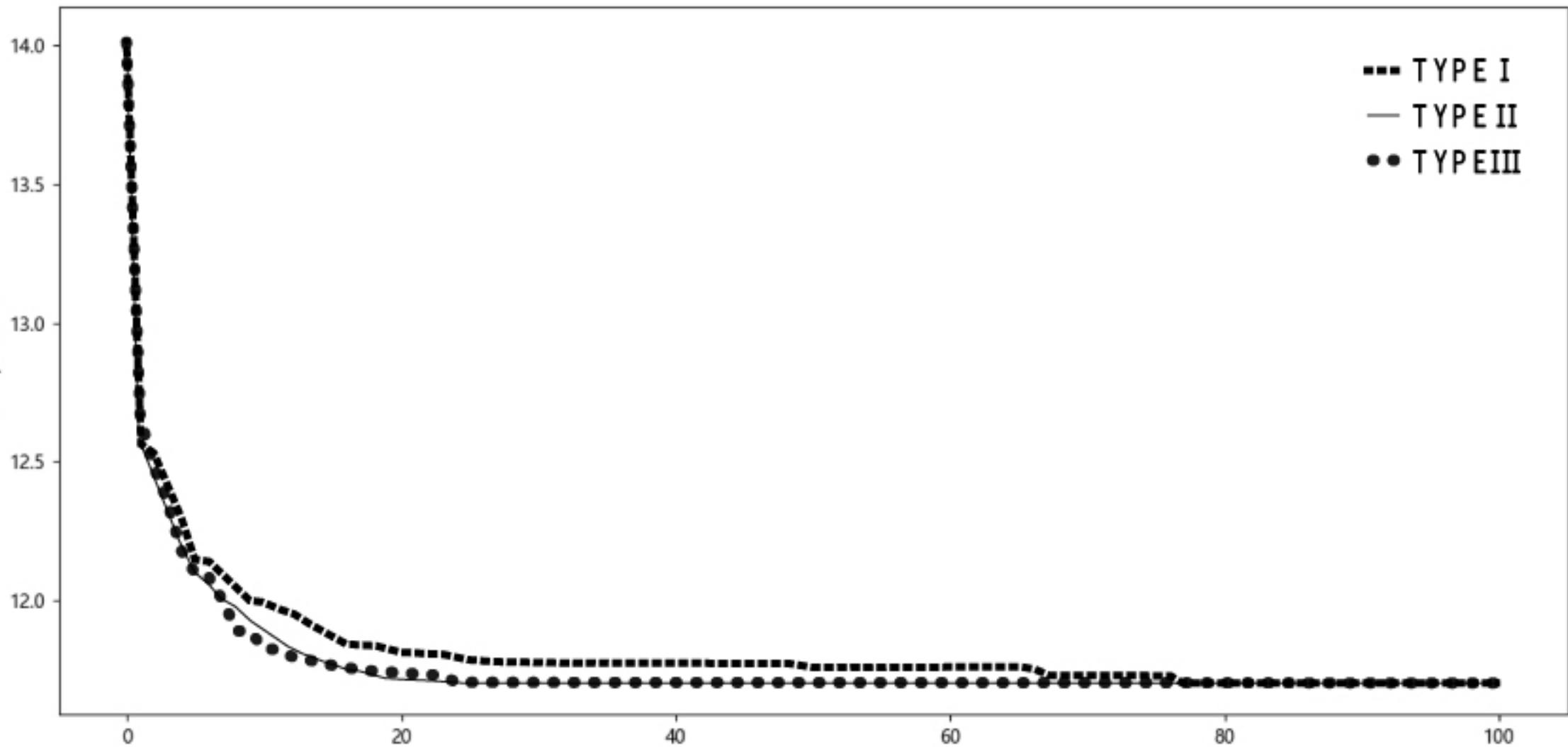
Figure 14. Simulated pressure distribution map before roughness optimization.
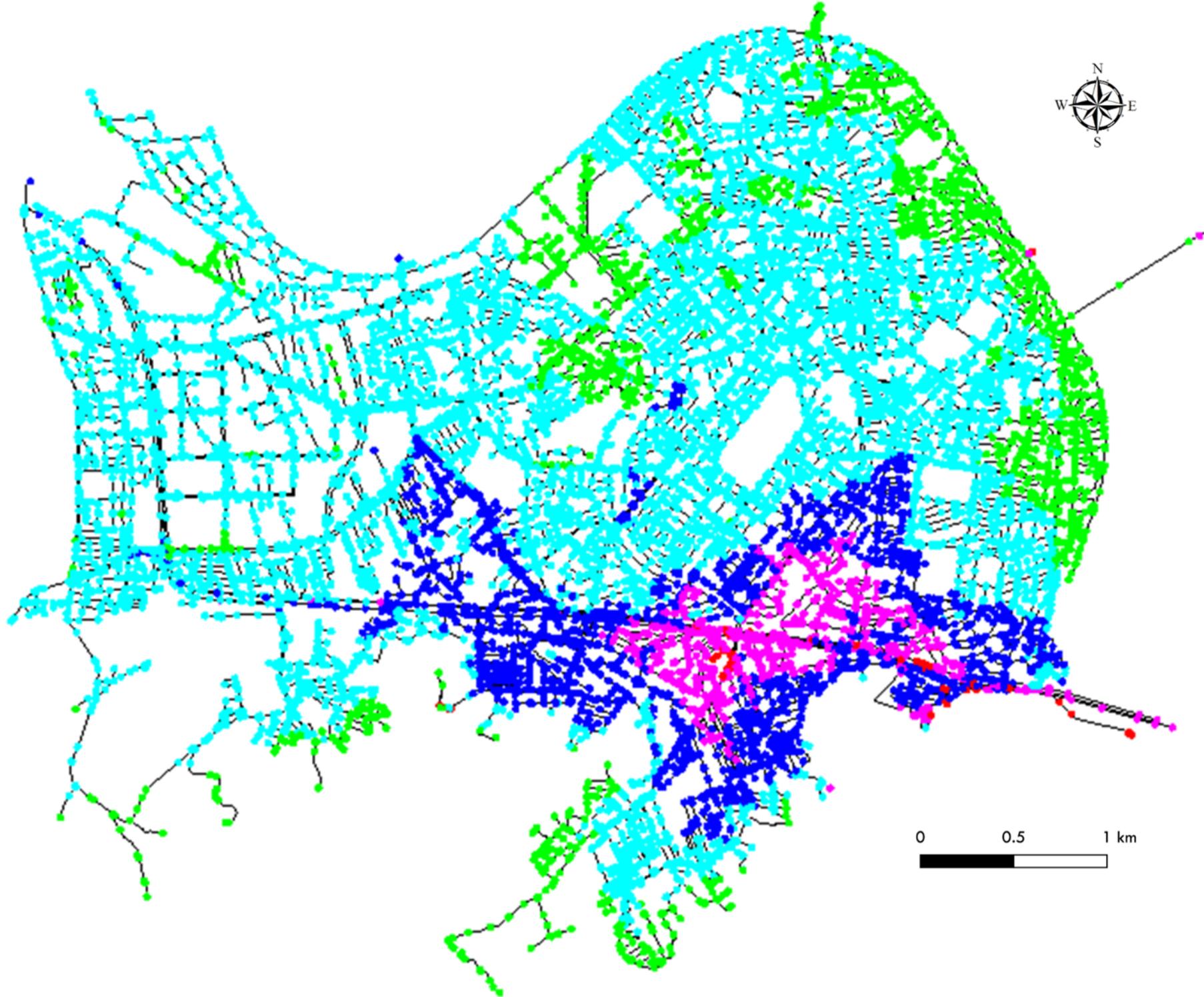
| P (kg/cm²) | ● <0.5 | ● 0.5~1.0 | ● 1.0~1.5 | ● 1.5~2.0 | ● >2.0 |

Figure 15. Pressure difference distribution before roughness optimization.
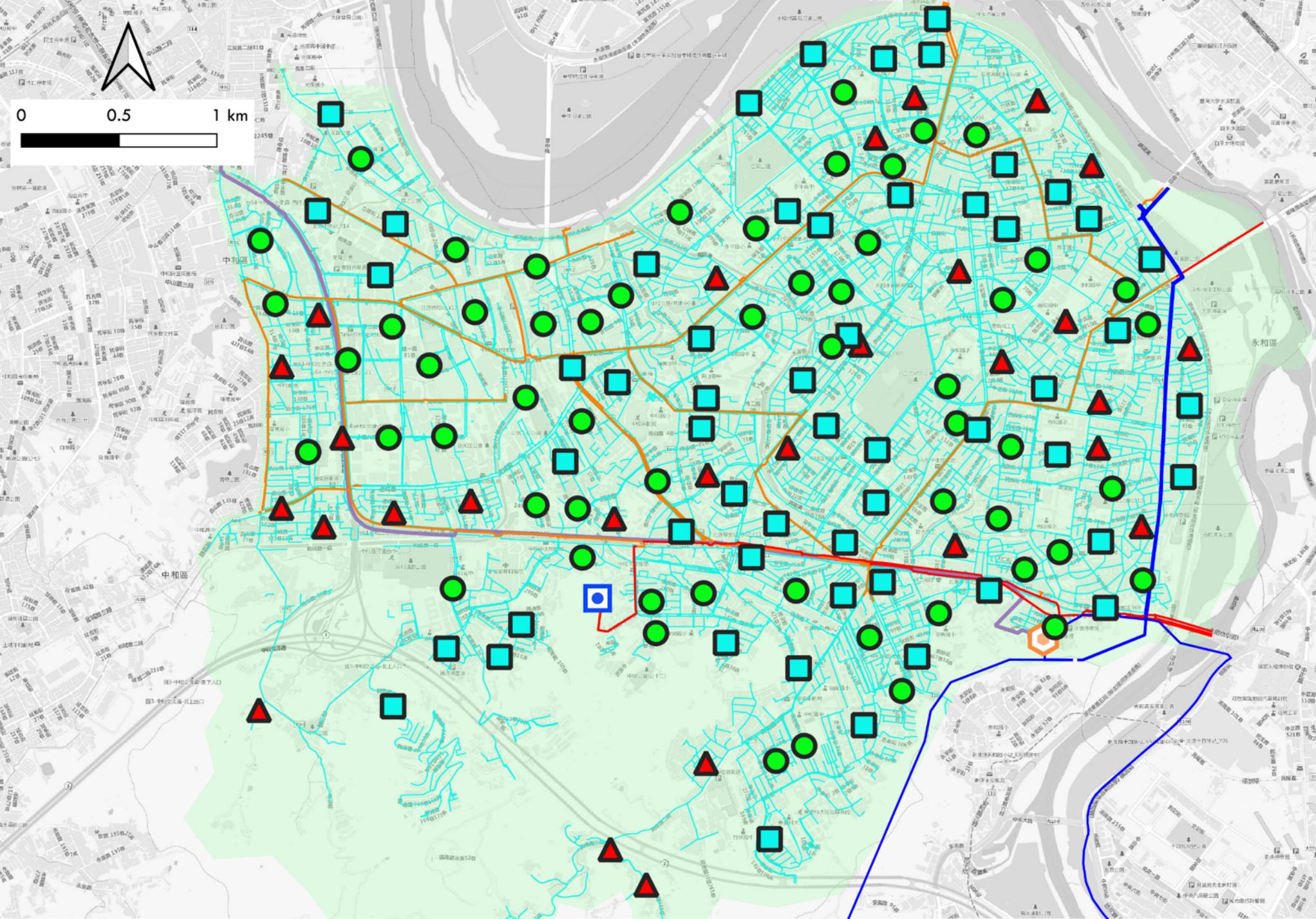
Figure 16. Pressure difference distribution after roughness optimization.
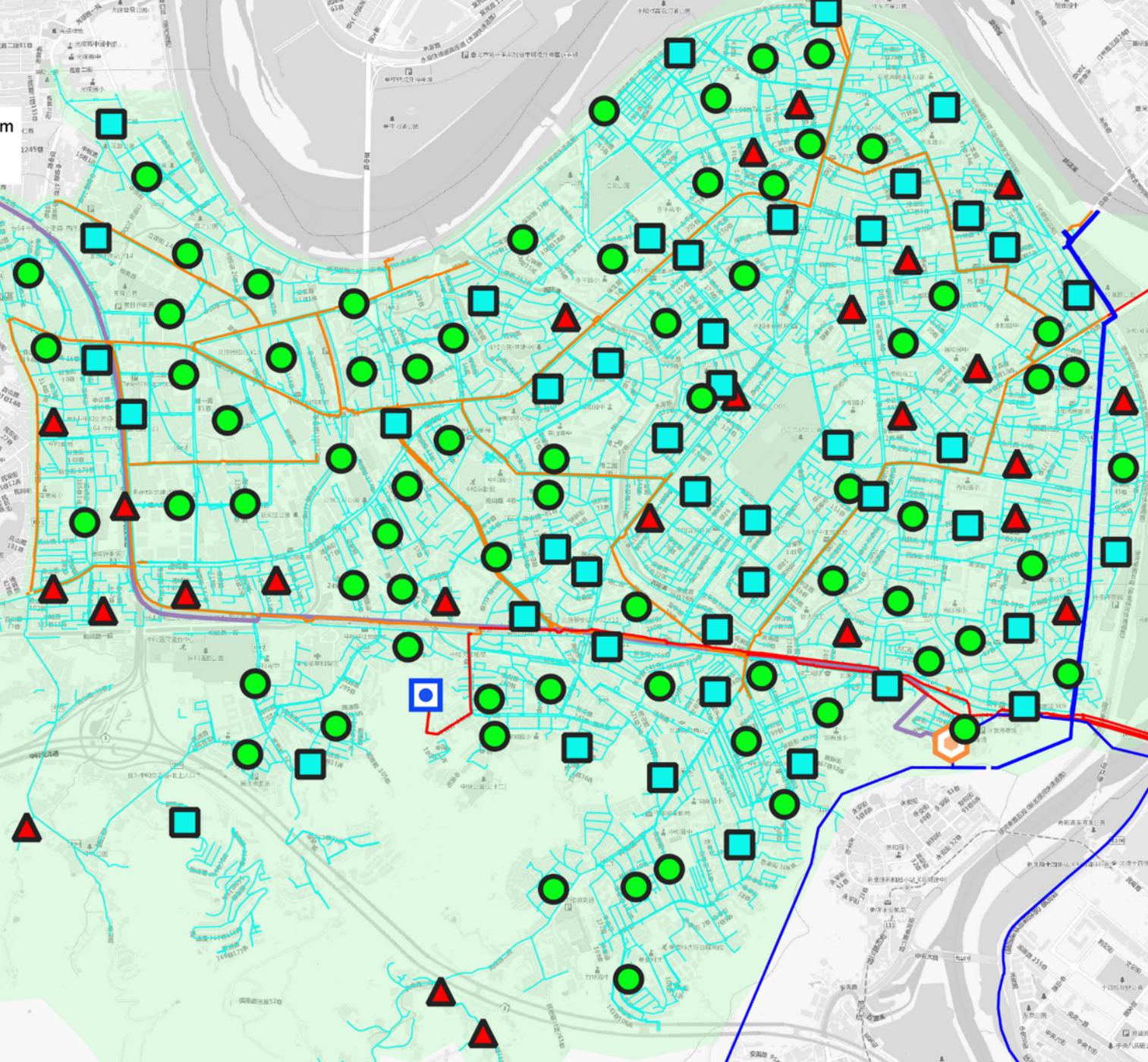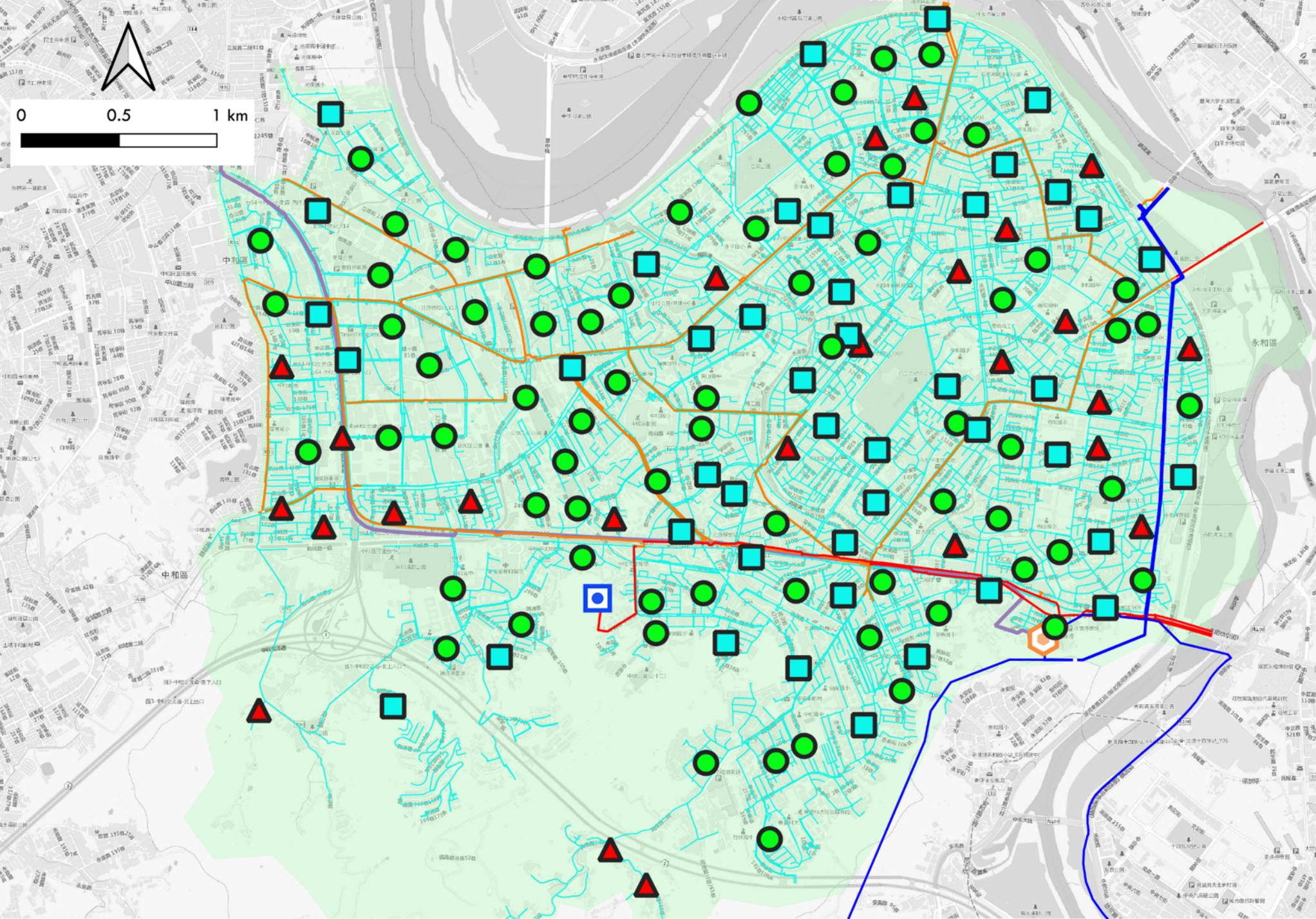
Figure 17. Specified monitoring points located at the end of the pipeline.
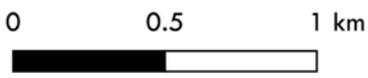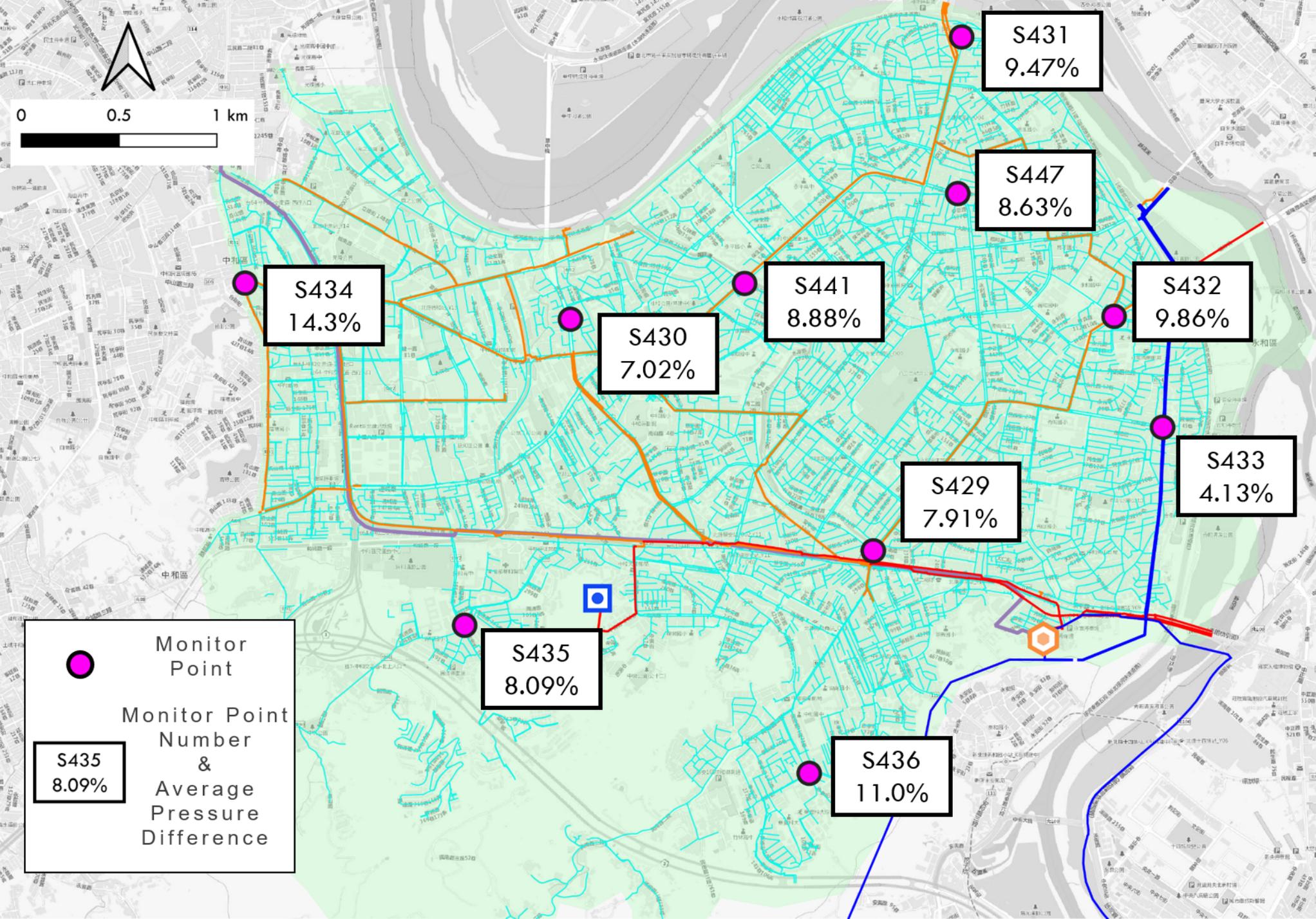
S431
9.47%

S447
8.63%

S434
14.3%

S441
8.88%

S432
9.86%

S430
7.02%

S433
4.13%

S429
7.91%

S435
8.09%

S436
11.0%

Monitor
Point

Monitor Point
Number
&
Average
Pressure
Difference

S435
8.09%

0   0.5   1 km

Figure 18. 24-hours pressure comparison between monitoring points and EPANET-GA simulations.
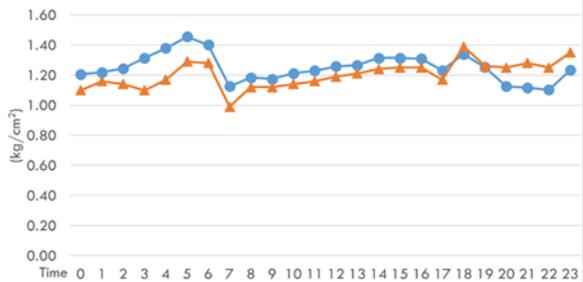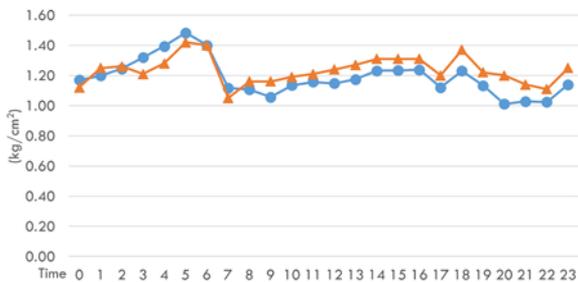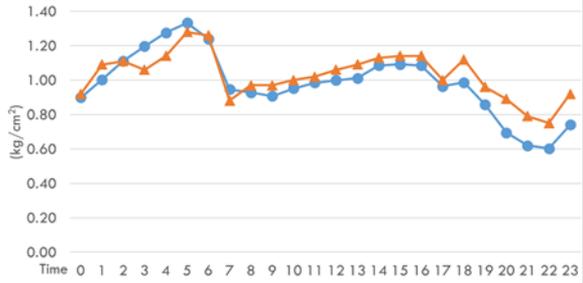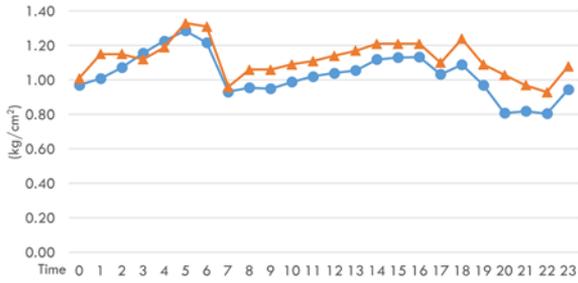
S429 · S430 · S431 · S432 · S433 · S434 · S435 · S436 · S441 · S447
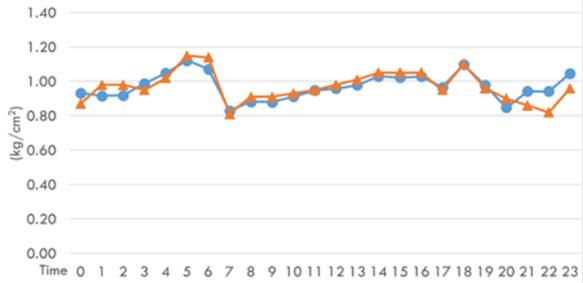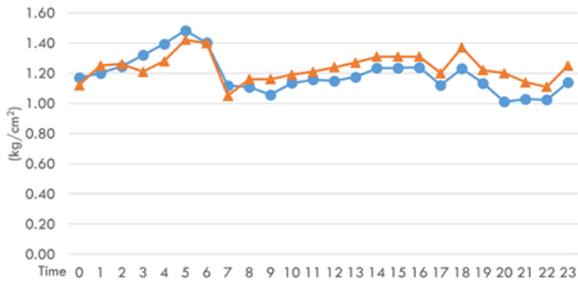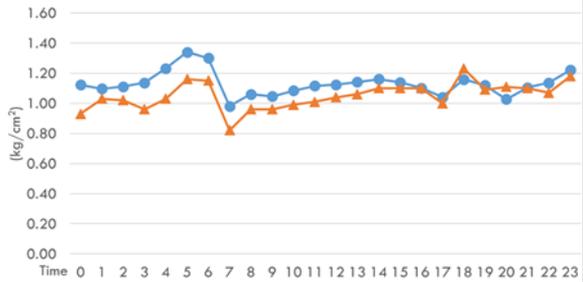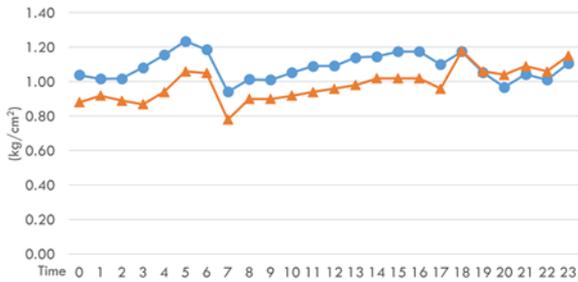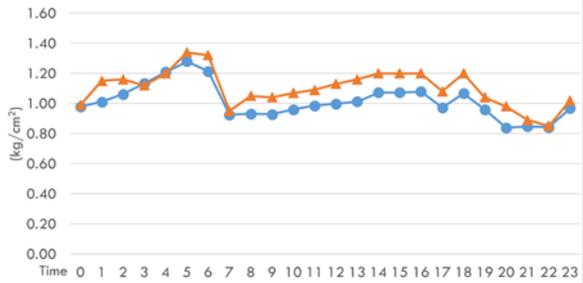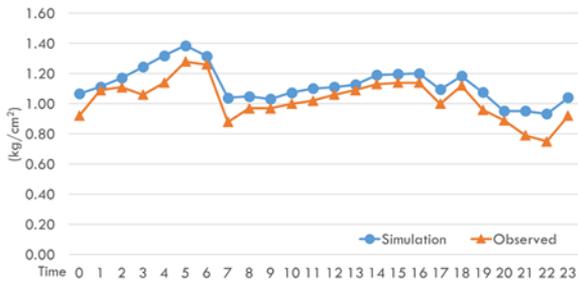
Simulation — Observed

Figure 19. Comparison bewteen WaterGEMs and EPANET-GA.