Comparison between single and multi-objective strategies for urban drainage model optimization using genetic algorithms : A case study of Badalona Urban drainage network

INTRODUCTION

Recent floods in Badalona highlight vulnerabilities in its drainage systems. The city relies on combined sewer networks, necessitating efficient calibration methods. This study compares single and multi-objective genetic algorithm (GA) optimization strategies to enhance decision-making and model performance. Multi-objective strategies can balance resilience, environmental impact, and costs, but their efficiency needs evaluation.

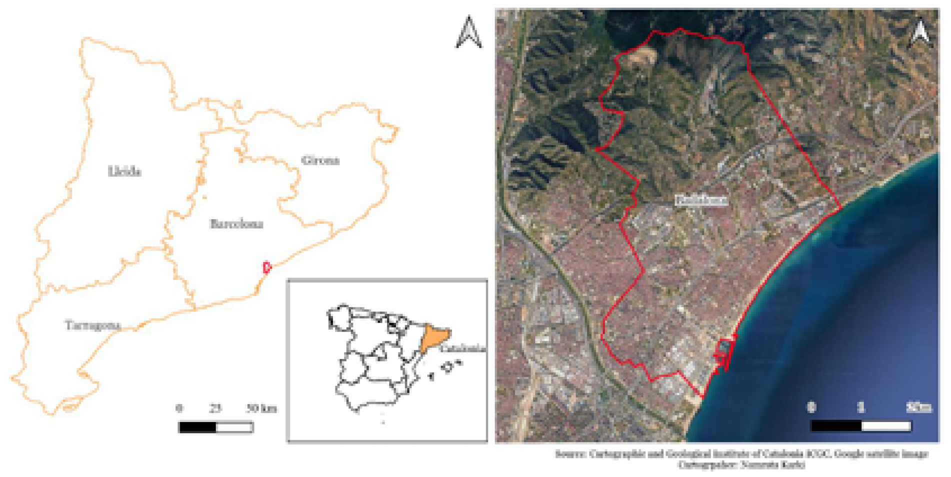

Figure 1: Badalona Municipality Area Location

METHODOLOGY

This research combines the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) with SWMM to optimize six parameters: Manning's roughness coefficients (pervious, impervious areas, conduits), curve number, depression storage, and impervious area percentage. Data was pre-processed using rating curve analysis to assess rainfall quality from three stations, followed by sensitivity analysis with Morris's method, highlighting the need for a global search approach like GA.

The model was optimized through iterative random adjustment and sampling using NSGA-II and SWMM in Python (nsga and pyswmm libraries). Single-objective optimization maximized Nash-Sutcliffe Efficiency (NSE), while multi-objective optimization targeted minimizing peak discharge (E1), maximizing NSE (E2), and minimizing runoff volume error (E3), with constraints to maintain satisfactory NSE levels. Simulations covered various rainfall events, both high-intensity/short-duration and low-intensity/long-duration, and were validated at multiple outfall points. A total of 200 simulations (10 generations × 20 population size) were used for automatic calibration. Further details on rainfall events, nodes, objective functions, and validation are provided below.

Table 1. Optimization Strategy

	Single Objective Function Strategy	Multi-Objective Function Strategy	Hybrid Optimization Strategy
No. of Rainfall Events	1	1	2
No. of Node	1	1	3
Objective Function	E2	E1, E2, E3	E1, E2, E3
Validation	For rest of the objection function	All objective functions for remaining nodes	All objective functions for remaining nodes

CASE STUDY

Badalona, a city in the Barcelona metropolitan area with 21.2 km2 area with more than 200 thousand inhabitants was chosen for this study. The vulnerability of the city to urban flash floods as observed in the past decades, combined with the availability of the drainage network data and rainfall event records made it an excellent choice to progress with this study.

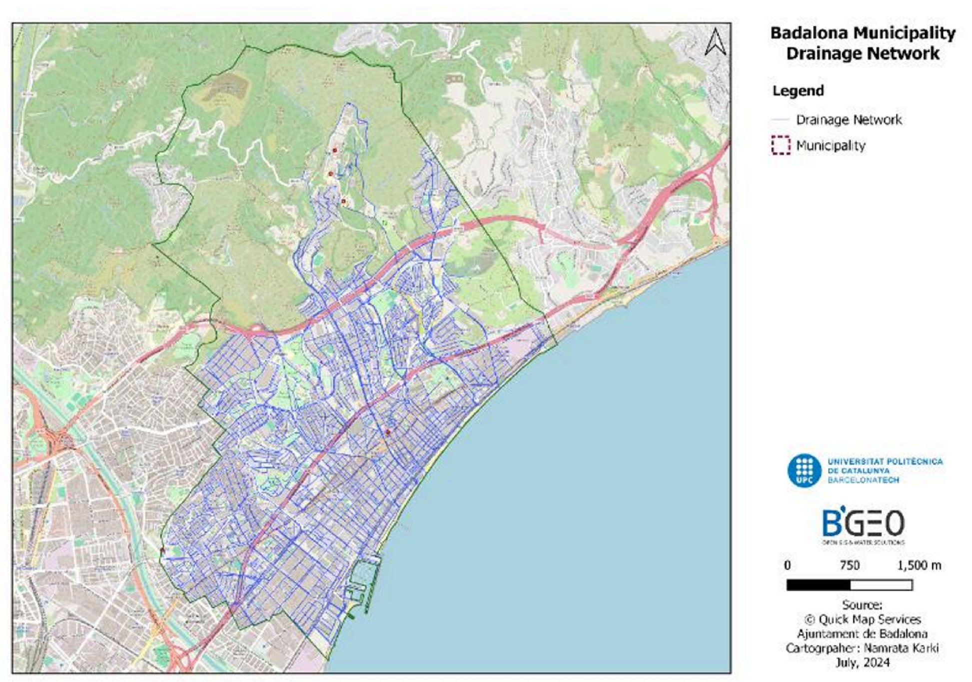

Figure 2: Drainage Network of Badalona

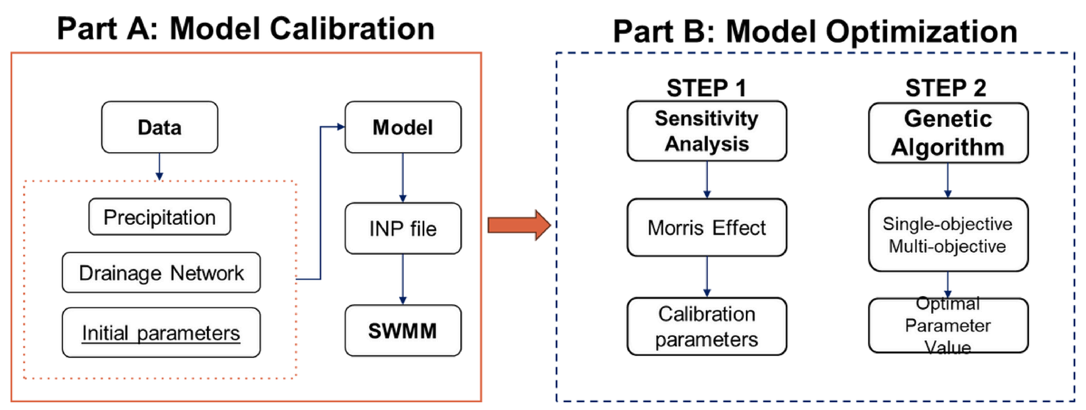

Figure 3: Methodology

Table 2 . Objective function values

	Single Objective Function Strategy	Multi-Objective Function Strategy
E1	0.5	0.27
E2	0.44	0.45
E3	2.6	2.6

RESULTS AND DISCUSSION

Results of this study demonstrates that single objective strategy may be sufficient while optimizing for simple models focusing solely on the model's accuracy as depicted by the NSE value 0.56 (>0.5), showcasing a satisfactory level of performance (Moriasi et al., 2015). However, it lacks the ability to provide a holistic approach with balanced inclusivity of all the necessary objectives which includes model's performance along with flood preventions, and water quality. A pareto plot (Figure 4) was also observed to see the nature of the GA under the optimization strategy. The decrease in the error value of E1 from 0.50 as obtained from single objective strategy to 0.27 with the implication of multiobjective strategy, along with a satisfactory model's performance (NSE = 0.55), indicates that more robust and versatile models can be produced through a proper balance between the goals. Furthermore, through the hybrid optimization strategy achieved by combining multi-objective strategy with multiple rainfall events and objective functions at multiple outfall points resulted in better overall balanced outcomes compared to other strategy as shown in Table 3 below.

Table 3. NSE and RMS values at nodes obtained from all strategies

	Single Objective Function Strategy		Multi-Objective Function Strategy		Hybrid Optimization Strategy	
Nodes	NSE	RMSE	NSE	RMSE	NSE	RMSE
26787	0.56	0.49	0.55	0.49	0.51	0.51
7093	-0.66	0.14	-0.81	0.14	-0.44	0.13
26187	-3.4	0.51	-4.35	0.51	-2.15	0.37

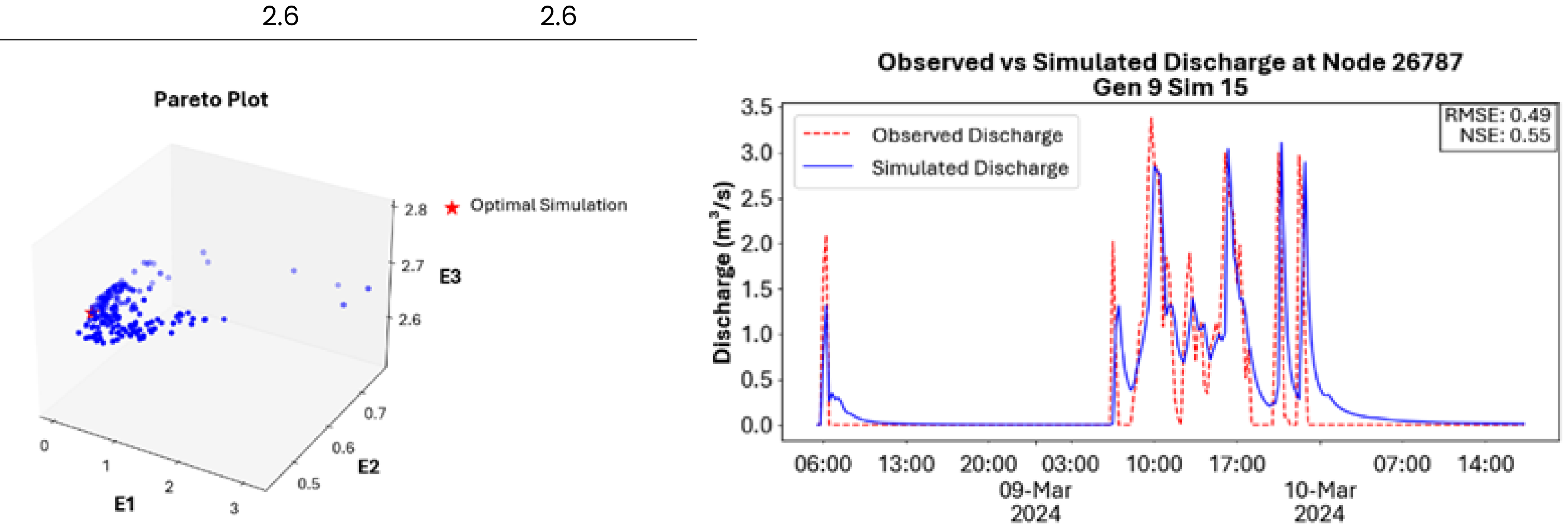

Figure 4: Pareto plot corresponding to multi-objective function strategy optimization (left) and hydrograph outlet 26787 after optimization (right).

CONCLUSION AND FUTURE WORK

In conclusion, the study indicates that the multi-objective GA optimization provides robust solutions to parameter balancing all the objectives which is a vital key in holistic approach of water resource management for flood prevention, water quality and runoff control, and model accuracy. While it is worth mentioning that for a simple drainage network with less complexities and objectives, singleobjective function strategy may suffice. The use of the open-source integration of QGIS - Giswater (for SWMM inp file) - Python (GA) enhances the accessibility of optimization of such drainage network by any user, even with data scarcity, although greater the amount of data is preferred for better outputs. To address the limitations occurred due to high-computational time and lack of inclusivity of the decision of the stakeholders, further works can be done such as opting for better simulation processing extension other than SWMM, simplifying the network focusing only on the major CSO points and including objective functions based on the effective decision-making strategy leading better pareto solution selection.

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Martínez-Gomariz, E., Locatelli, L., Guerrero, M., Russo, B., & Martínez, M. (2019). Socio Economic Potential Impacts Due to Urban Pluvial Floods in Badalona (Spain) in a Context of Climate Change. Water, 11(12), 2658. https://doi.org/10.3390/w11122658 Moriasi et al. (2015). Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria Transactions of the ASAB E, 58(6), 1763–1785. https://doi.org/10.13031/trans.58.10715 N. (2024). Comparison between single and multi-objective strategies for urban drainage model optimization using genetic algorithms: A case study of Badalona urban drainage network (master's thesis, Technische Universität Dresden & IHE Delft Institute for Water Education). UPCommons. https://www.upcommons.upc.edu Michalewicz, Z. (1996). Genetic Algorithms + Data Structures = Evolution Programs | SpringerLink. https://link.springer.com/book/10.1007/978-3-662-03315-9 Barreto, W., Vojinovic, Z., Price, R., & Solomatine, D. (2010). Multiobjective Evolutionary Approach to Rehabilitation of Urban Drainage Systems. Journal of Water Resources Planning and Management, 136(5), 547–554. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000070 Del Giudice, G., & Padulano, R. (2016). Sensitivity Analysis and Calibration of a Rainfall Runoff Model with the Combined Use of EPA-SWMM and Genetic Algorithm. Acta Geophysica, 64(5), 1755–1778. https://doi.org/10.1515/acgeo2016-0062

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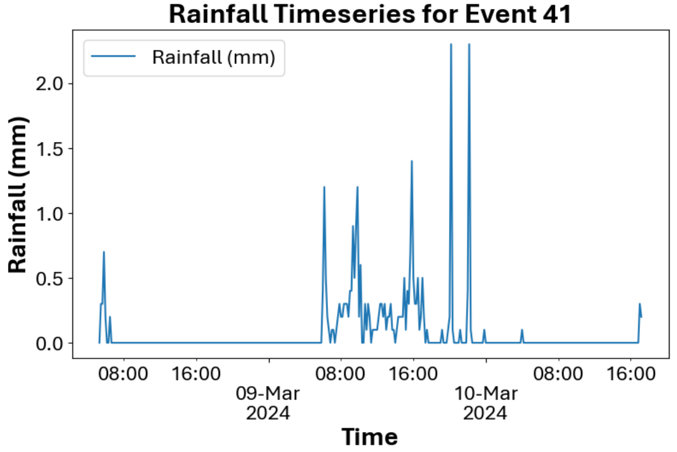
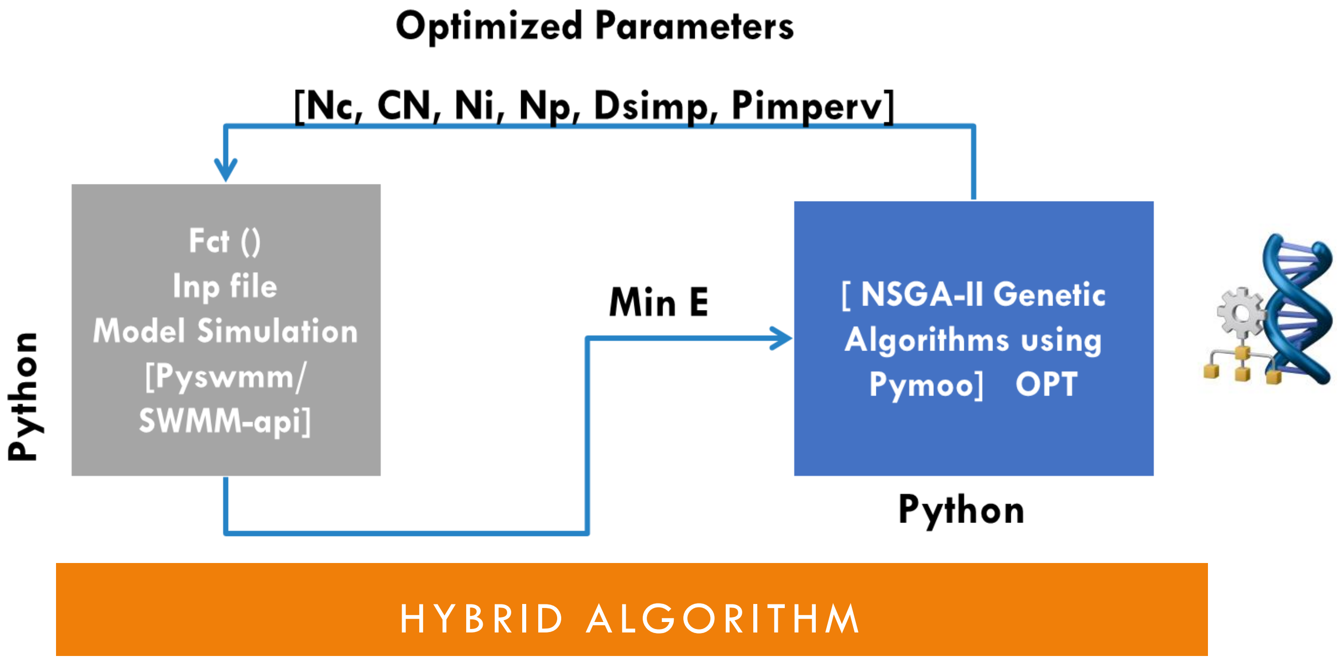
Rainfall Data



Objective Functions

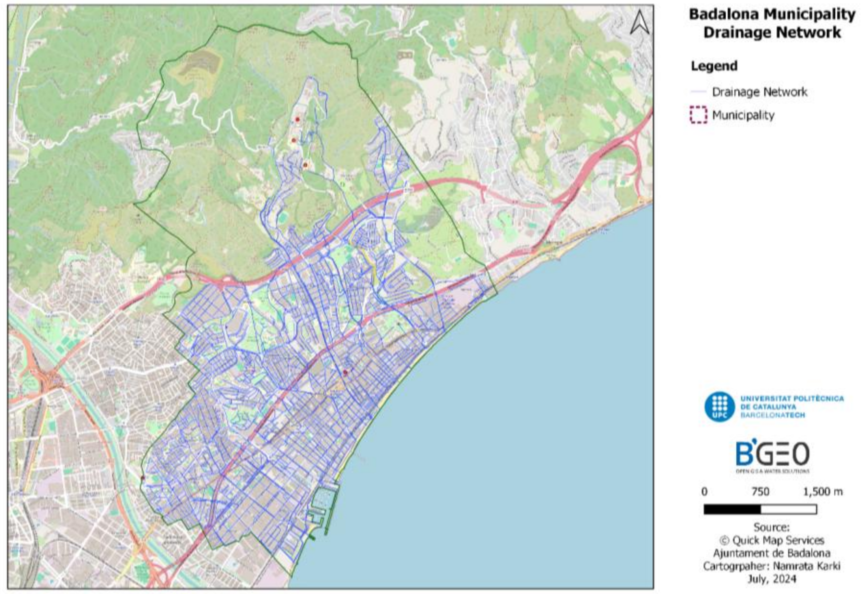
- Minimisation of Peak Error
- Maximisation of Model Performance
- Minimisation of Volume Error



Parameters Selected for Optimization

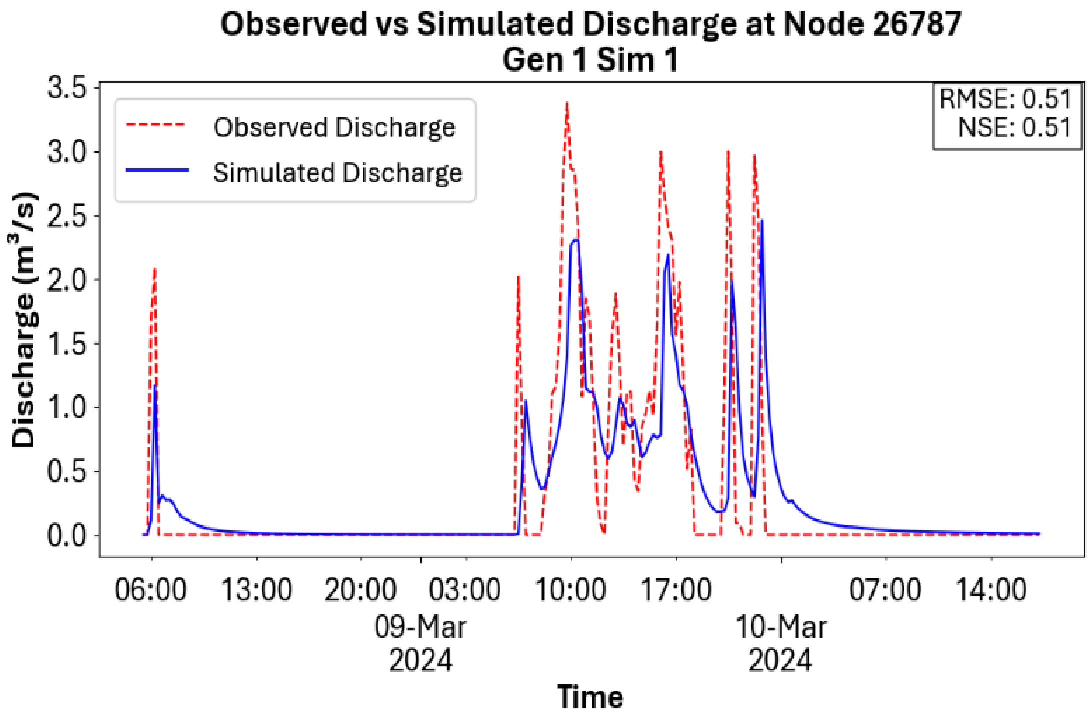
Manning's n (imperv/perv/conduits)
Depression storage
Curve Number (CN)
% Impervious area

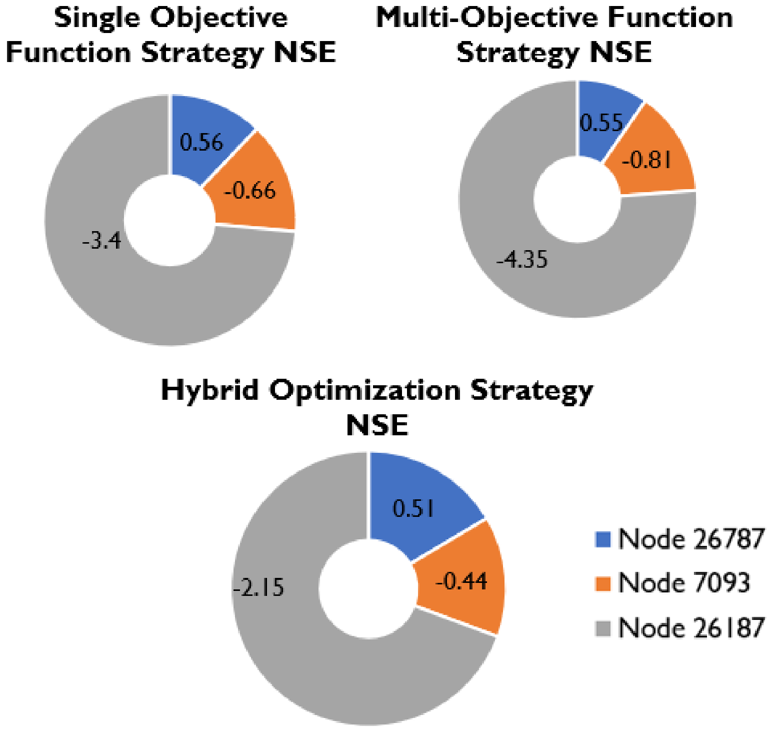
Case Study Area



Drainage Network INP FILE

Optimization Results





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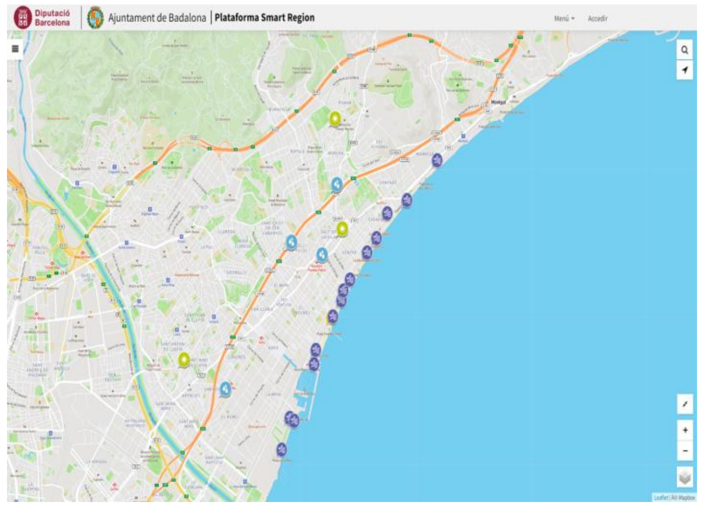
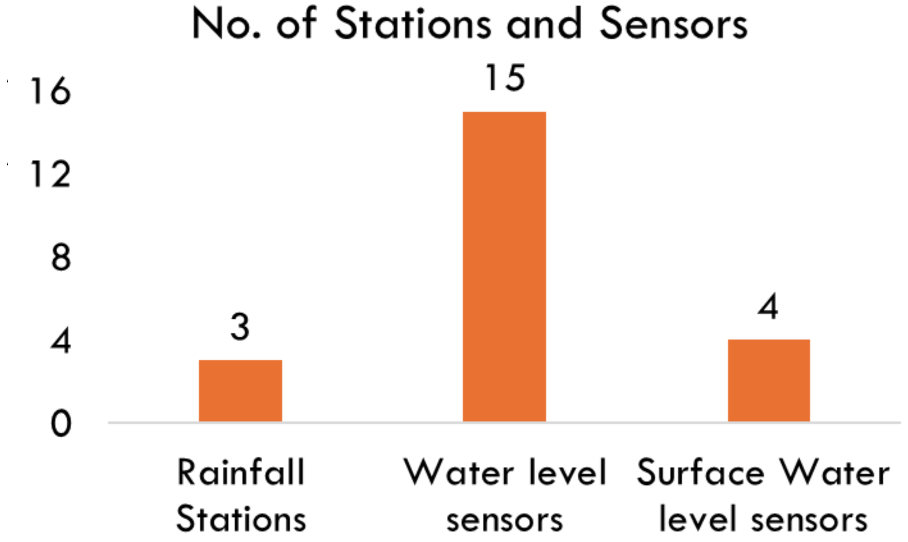


Figure : SENTILO Platform for DATA



Obtained: **SENTILO**
2 years (2022- April 2024) Rainfall Daily Accumulated

10 min interval

Converted :
Rainfall Daily Timeseries

10 min interval

Events defined :
With gap of no rain for more than 24 hour

47

Events selected :
Rainfall accumulated >1mm and screened and compared amongst all stations

Table. Selected Rainfall events for optimization

Event	Date	Total Accumulated Rainfall(mm)	Maximum Intensity (mm/h)	Time step (min)	Duration (hours)
6	31 August 2022	38.2	101.0	10	11.3
26	26 August 2023	50.1	67.2	10	25.5
41	08 March 2024	31.0	24.0	10	59.7
46	28 April 2024	65.0	30.0	10	48.8

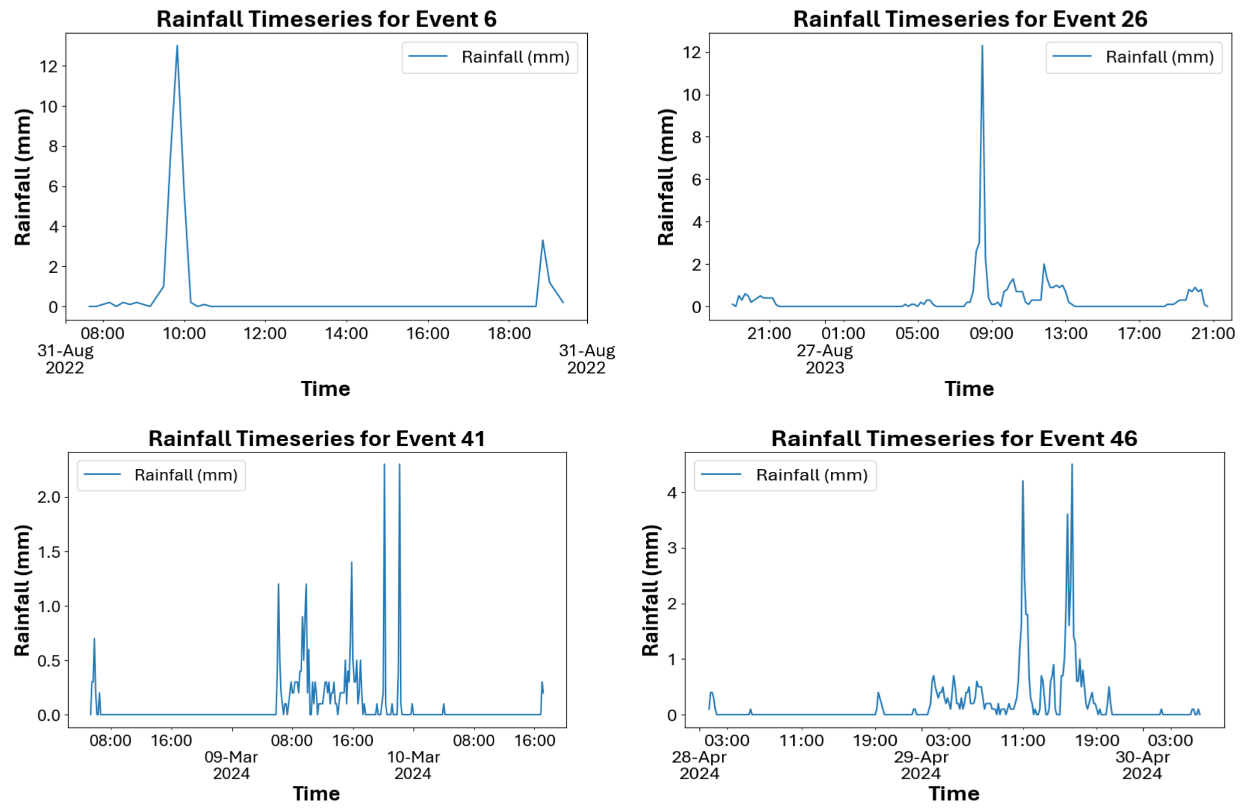


Figure : Rainfall Timeseries for different Events

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SCREENING OF WATER LEVEL SENSORS DATA BY RATING CURVE

Figure : Water level sensors in network system

RATING CURVE ANALYSIS was done in order to understand the data quality

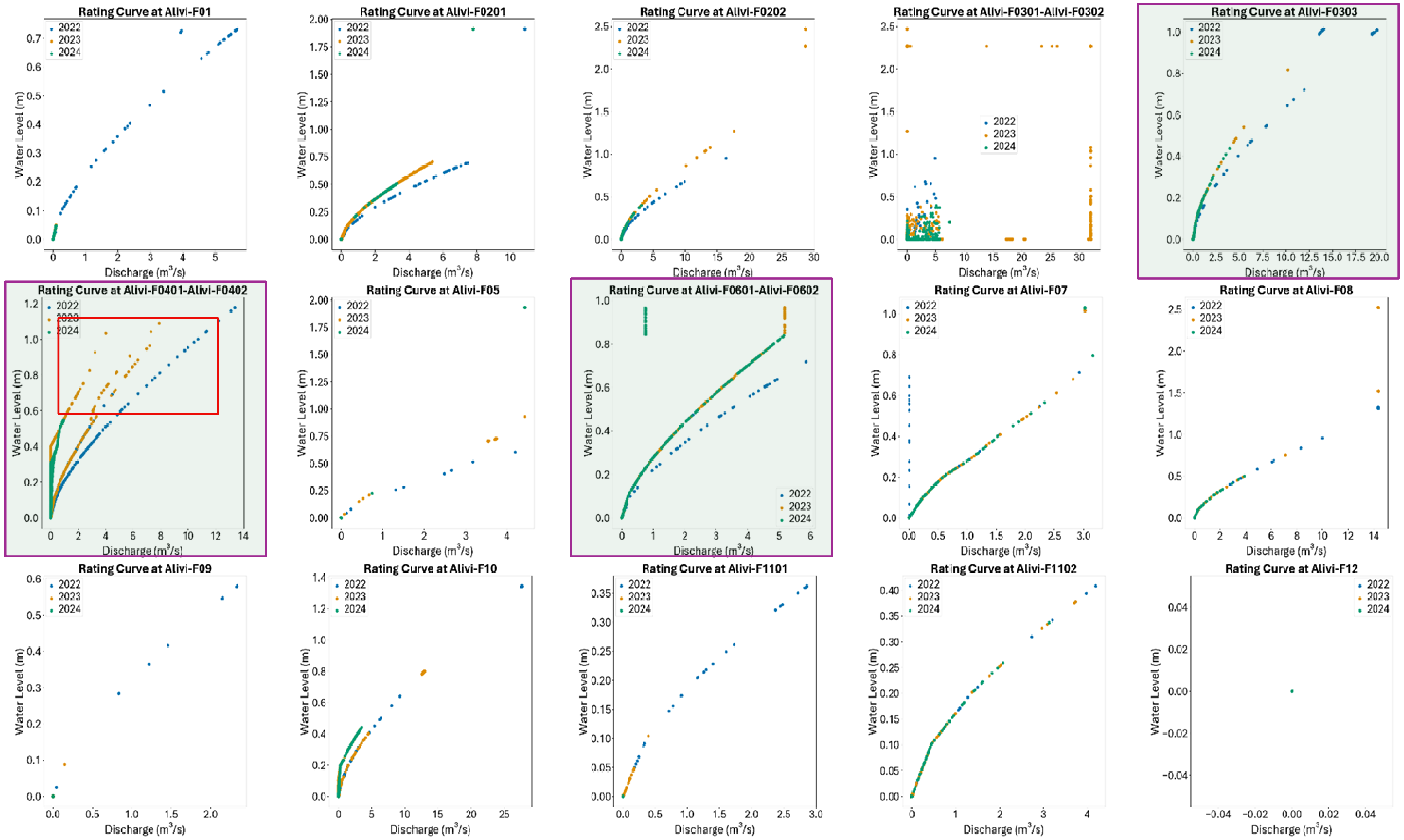

Figure : Rating Curves at various water level sensors

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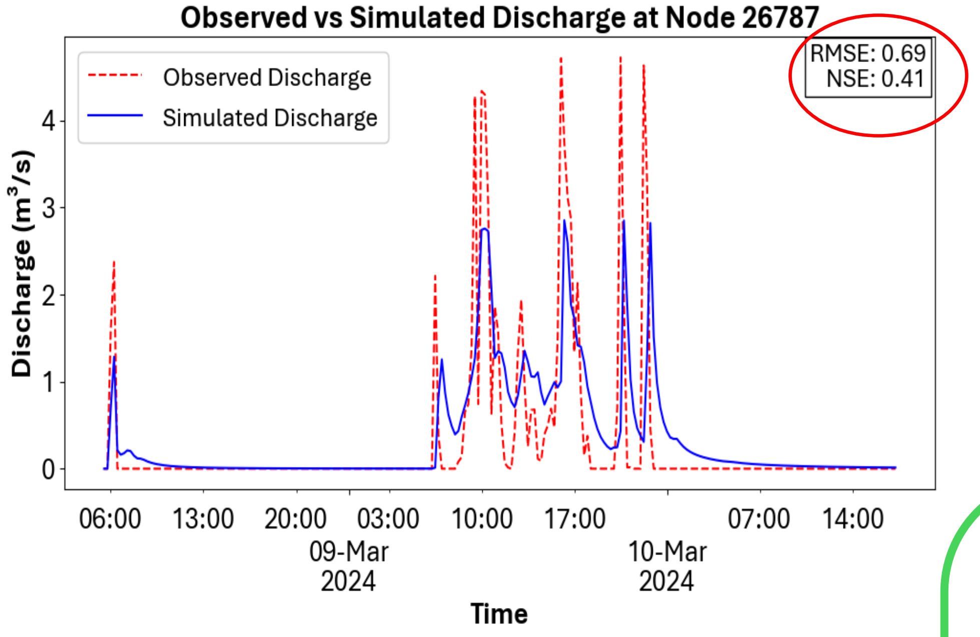
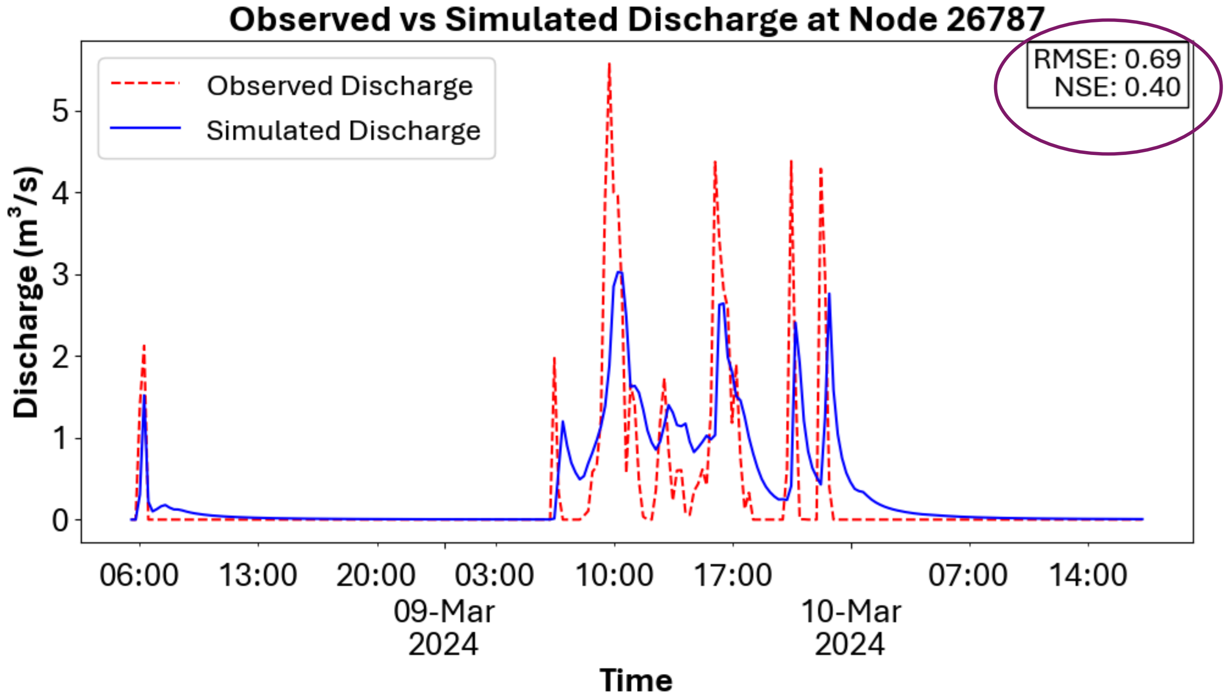
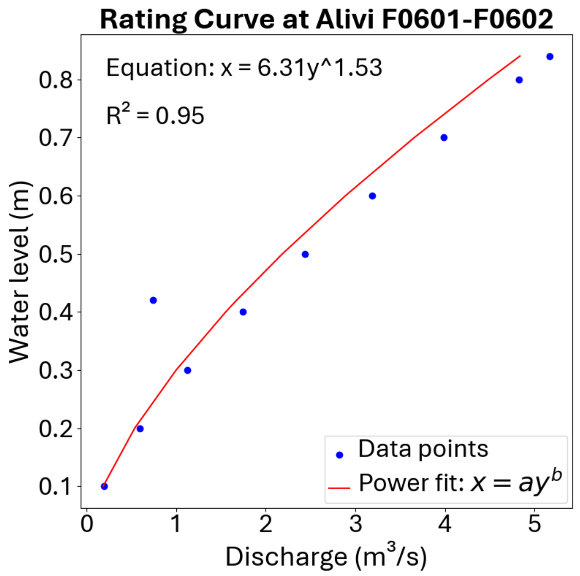
RATING CURVE ANALYSIS

Case A.

Using original discharge values



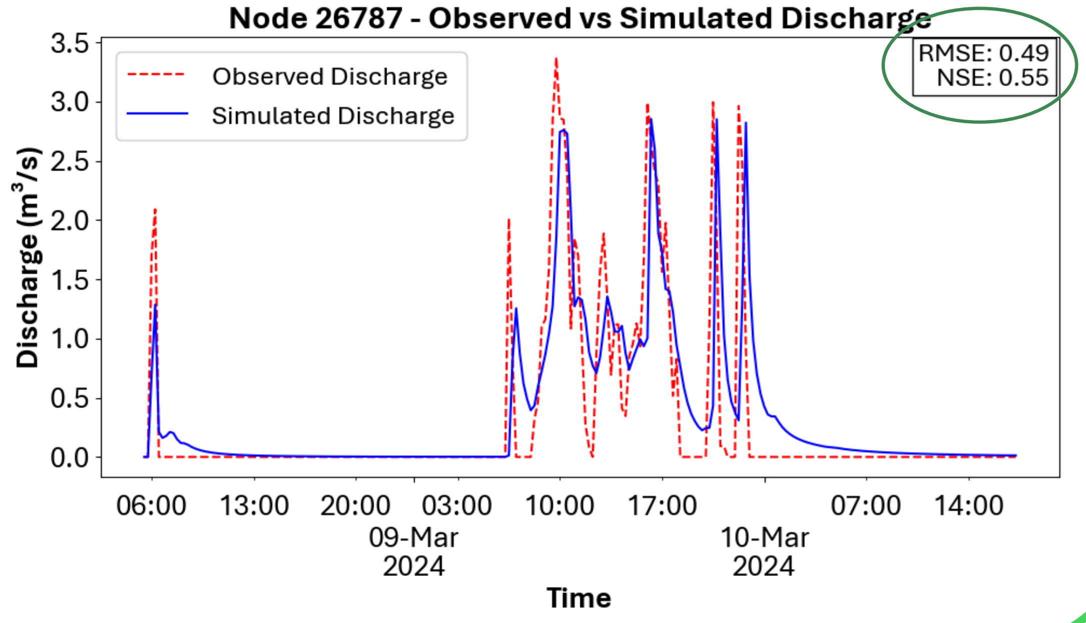


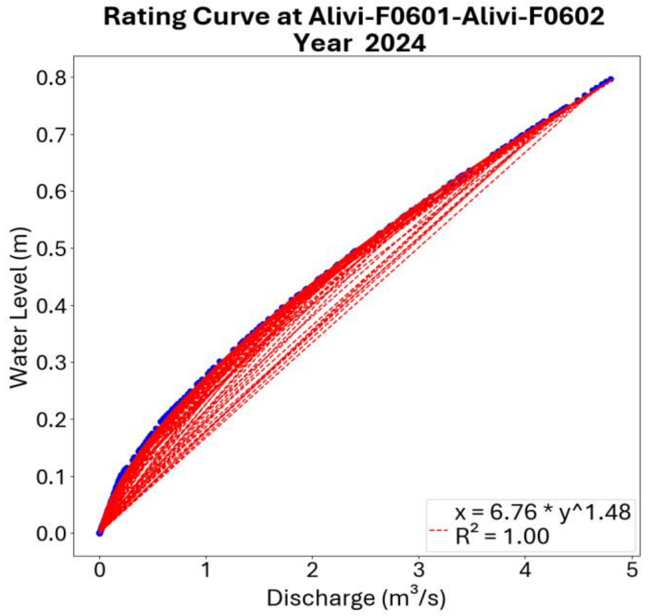


Case B.

Developing a new rating curve and obtaining discharge values

Proceeded with the one yielding highest NSE value





Case C.

Creating a rating curve using recent year data (2024) and obtaining discharge values

To the SENSOR DATA

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Figure . Calibration using different cases of the rating curve analysis

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Sensitivity Analysis for Parameter Selection

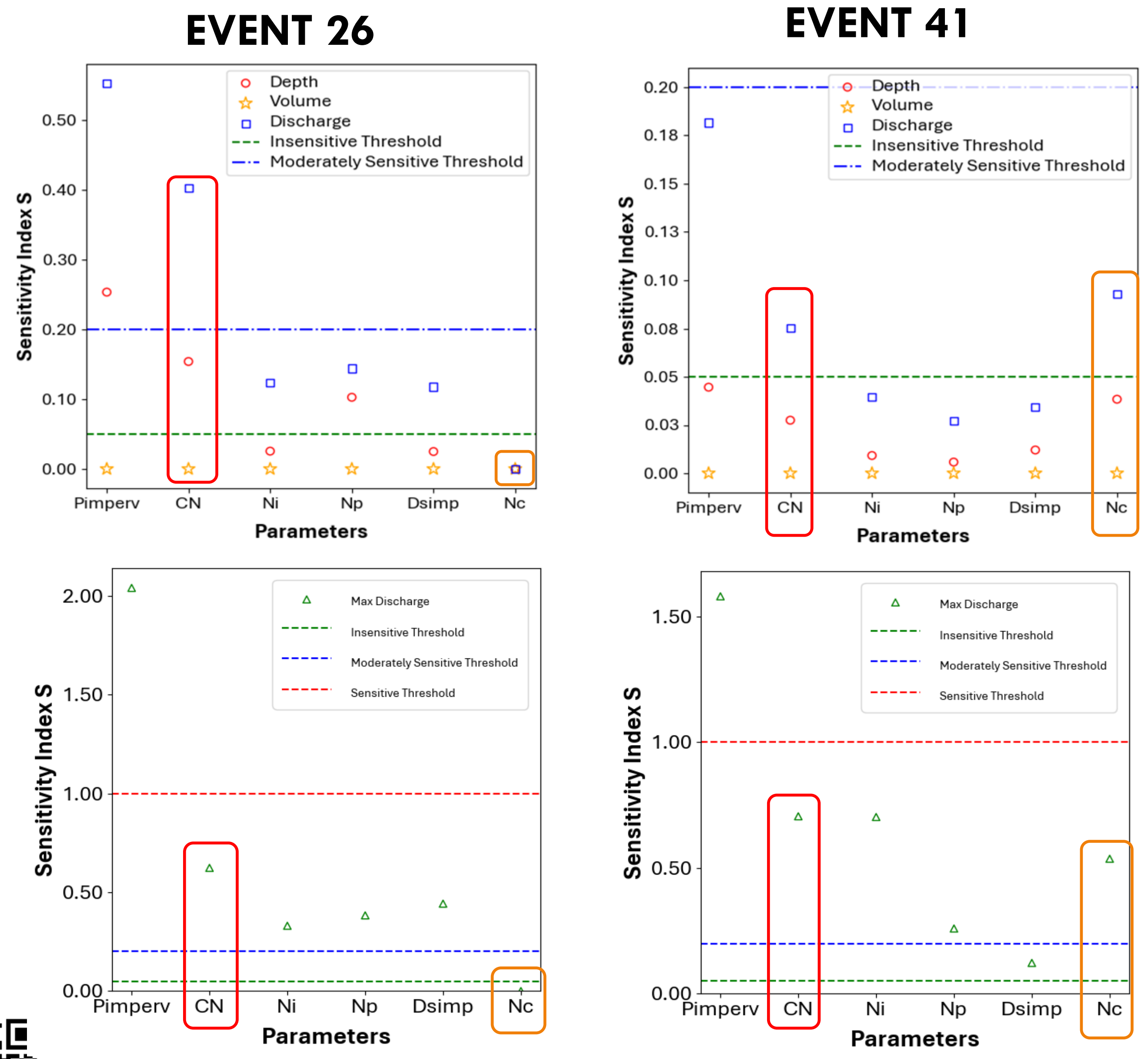

Figure : Sensitivity Analysis

How?

- Morris screening method used (one-at-a-time sensitivity).
- Parameters varied: CN, Pimperv, Ni, Np, Dsimp, Nc.
- NSE used to compare observed vs. simulated discharge.

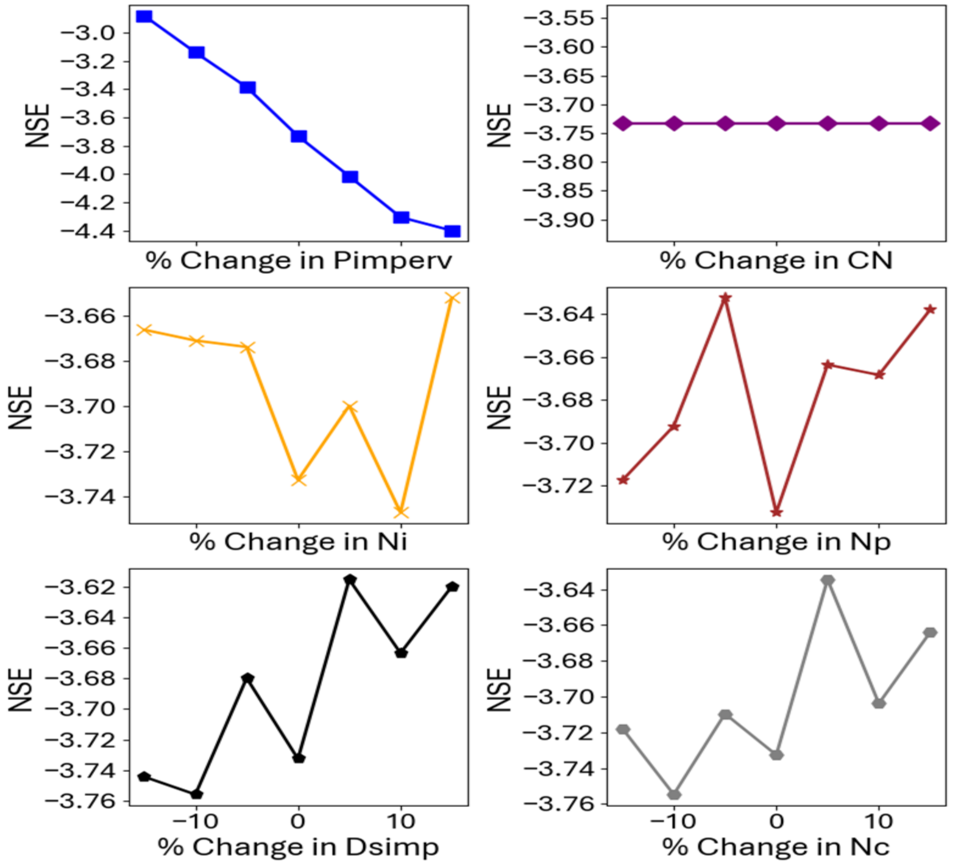

Figure : Sensitivity Analysis Using NSE for Event 26

What's the Result?

- Sensitivity varies with rainfall intensity.
- Pimperv, CN most influential.
- Complex response to NSE → Genetic Algorithms recommended for better optimization.

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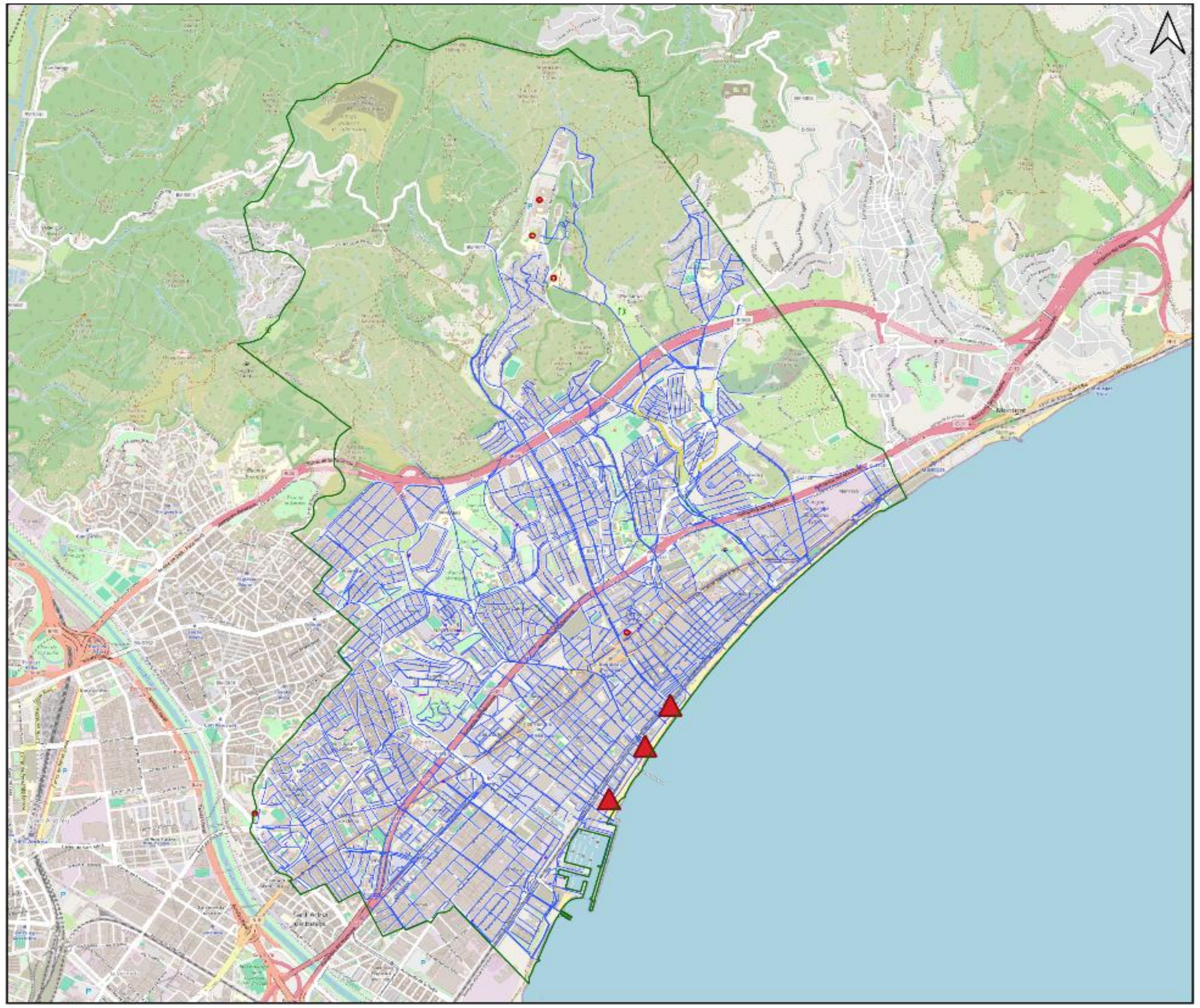
CASE STUDY AREA

Catchment Area : 21.13 km^2

Combined Drainage Network

Junctions	: 11,384
Conduits	: 11,717
Outfalls	: 53
Storage	: 132
Gully	:1024



Badalona Municipality Drainage Network

Legend

- Rainfall Stations
- Calibration Node Outlets
- Municipality

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0 750 1,500 m

Source:
© Quick Map Services
Ajuntament de Badalona
Cartogrpaher: Namrata Karki
July, 2024

Figure: Drainage Network of Badalona

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WHY?

Traditional Model Calibration → Hit and Trial → Educated Guess → Subjective, Time consuming, Could miss the optimum parameter set

HOW

Part A: Model Calibration

Data → Precipitation, Drainage Network, Initial parameters → Model → INP file → SWMM

Part B: Model Optimization

STEP 1: Sensitivity Analysis → Morris Effect → Calibration parameters

STEP 2: Genetic Algorithm → Single-objective / Multi-objective → Optimal Parameter Value

Single-objective function

$$E_1(min) = |Q_{ps} - Q_{po}|$$

$$E_2(min) = 1 - \left[1 - \frac{\sum_{i=0}^{n} \left(Q_{o(i)} - Q_{s(i)}\right)^2}{\left(Q_{o(i)} - \overline{Q_{o(i)}}\right)^2}\right]$$

$$E_3(min) = |V_s - V_o|$$

Multi-Objective functions

$$G_1 = E_2 - 0.5, \text{ if } E_2 > 0.5 \text{ else } 0$$

$$G_2 = 0.5 - E_2, \text{ if } E_2 < 0.5 \text{ else } 0$$

Constraints

Where,

Q_{ps} : Peak Simulated flow

Q_{po} : Peak Observed flow

$Q_{o(i)}$: Observed flow value at moment i

$Q_{s(i)}$: Simulated flow value at moment i

V_s : Simulated total runoff volume

V_o : Observed total runoff volume

USING GENETIC ALGORITHM

Optimized Parameters

[Nc, CN, Ni, Np, Dsimp, Pimperv]

Python: Fct () Inp file Model Simulation [Pyswmm/ SWMM-api]

Min E

[NSGA-II Genetic Algorithms using Pymoo] OPT

Python

HYBRID ALGORITHM

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Parameters and INP file

Calibrations and input data files

Drainage_network.inp
Timeseries.dat
Discharge.csv
Volume.csv

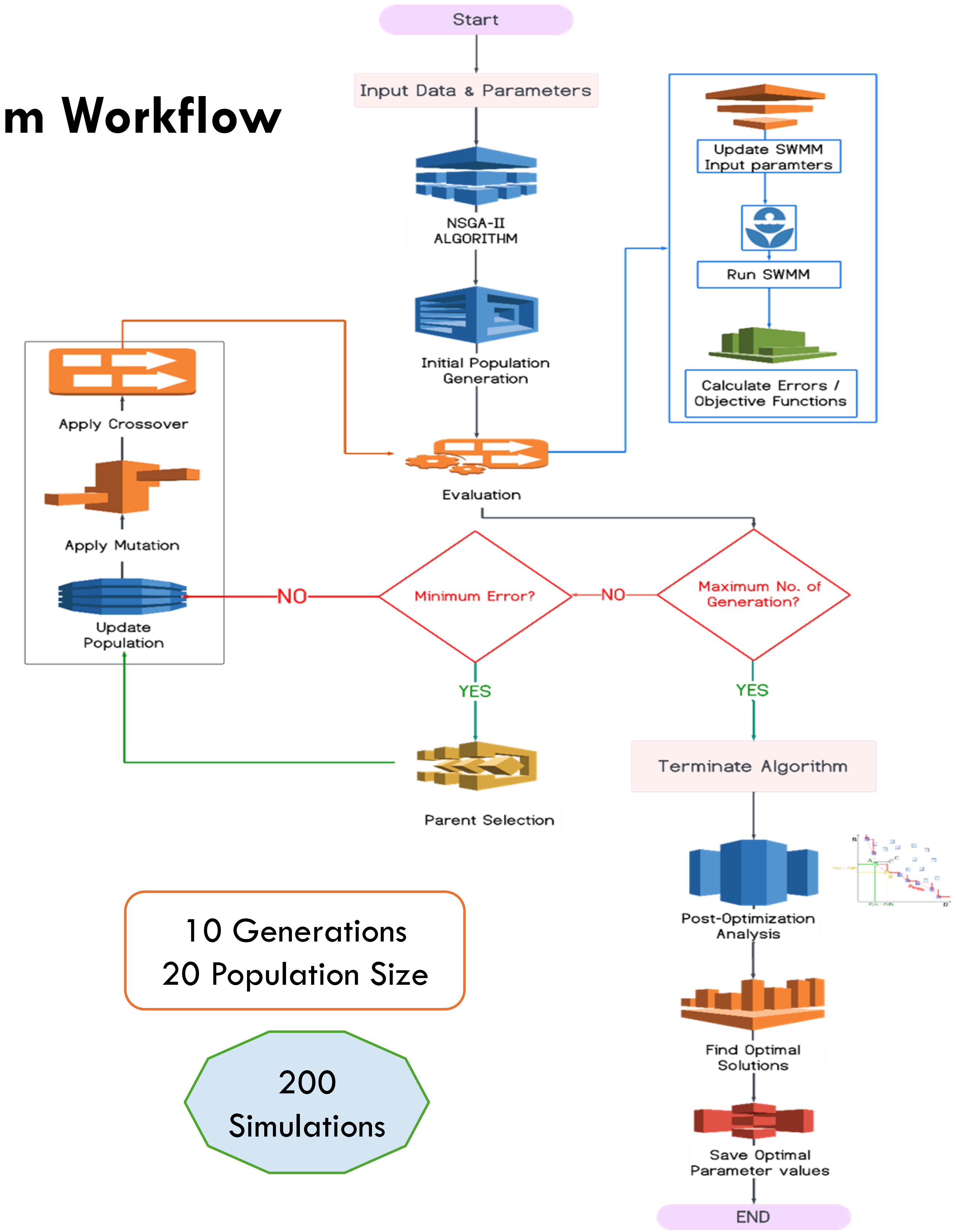
SWMM Model and GA

python

Visual Studio Code

RESULTS

Algorithm Workflow



10 Generations
20 Population Size

200
Simulations

OPTIMIZATION STRATEGY

	Single Objective Function Strategy	Multi-Objective Function Strategy	Hybrid Optimization Strategy
No. of Rainfall Events	1	1	2
No. of Node	1	1	3
Objective Function	E_2	E_1, E_2, E_3	E_1, E_2, E_3
Validation	For rest of the objection function	All objective functions for remaining nodes	All objective functions for remaining nodes for all rainfall events

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Table 1 . NSE and RMS values at nodes obtained from all strategies

	Single Objective Function Strategy		Multi-Objective Function Strategy		Hybrid Optimization Strategy	
Nodes	**NSE**	**RMSE**	**NSE**	**RMSE**	**NSE**	**RMSE**
26787	**0.56**	**0.49**	**0.55**	**0.49**	**0.51**	**0.51**
7093	-0.66	0.14	-0.81	0.14	**- 0.44**	**0.13**
26187	-3.40	0.51	-4.35	0.51	**-2.15**	**0.37**

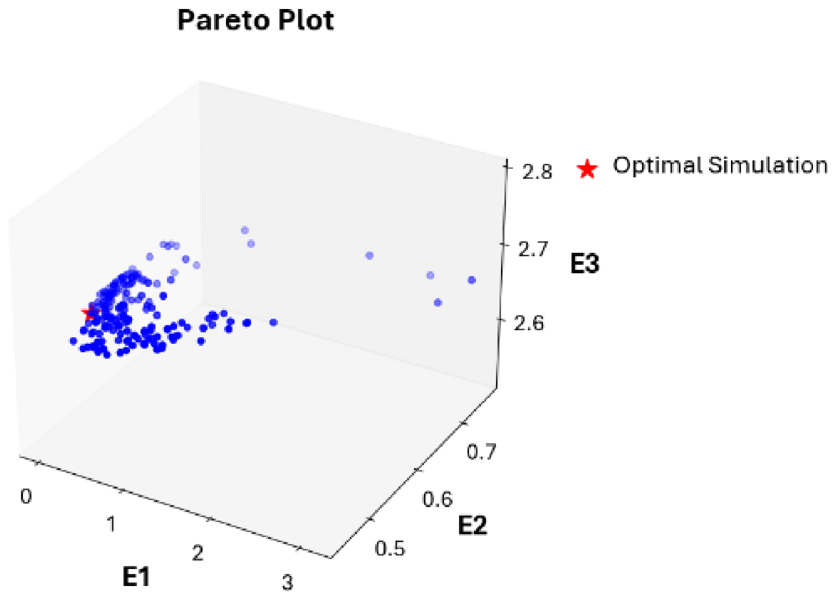
Table 2. Objective function values obtained from single and multi-objective strategies at a node

	Single Objective Function Strategy	Multi-Objective Function Strategy
E1	0.50	0.27
E2	0.44	0.45
E3	2.60	2.60

CONCLUSIONS

- **Effective Optimization:** NSGA-II with SWMM optimizes drainage networks.
- **Multi-objective strategy** performs better than **Single-objective strategy** balancing all objectives
- **Single-objective** may **be enough for one objective** for simple models but **lacks balanced inclusivity** of all objectives required for holistic understanding of drainage network.
- **Limitations of GAs :** Computational ability and data quality
- **Contribution:** Enhanced algorithm for Badalona drainage network

Additional Plots ?



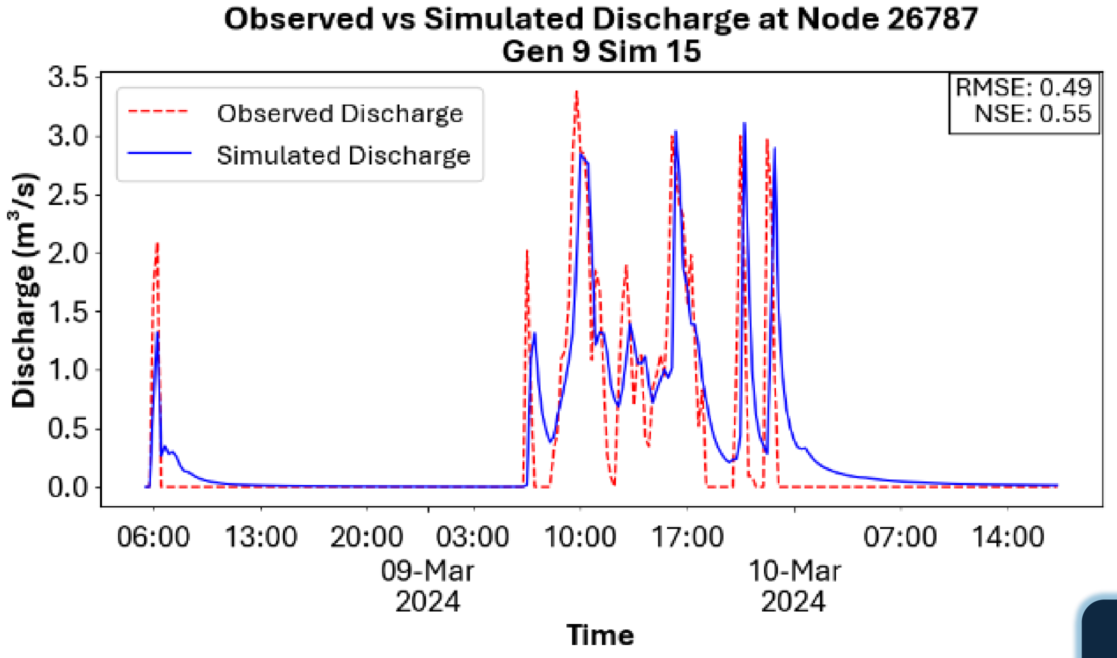


Figure . Pareto plot corresponding to multi-objective function strategy optimization (left) and hydrograph at outlet 26787 after optimization (right).

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Additional Plots

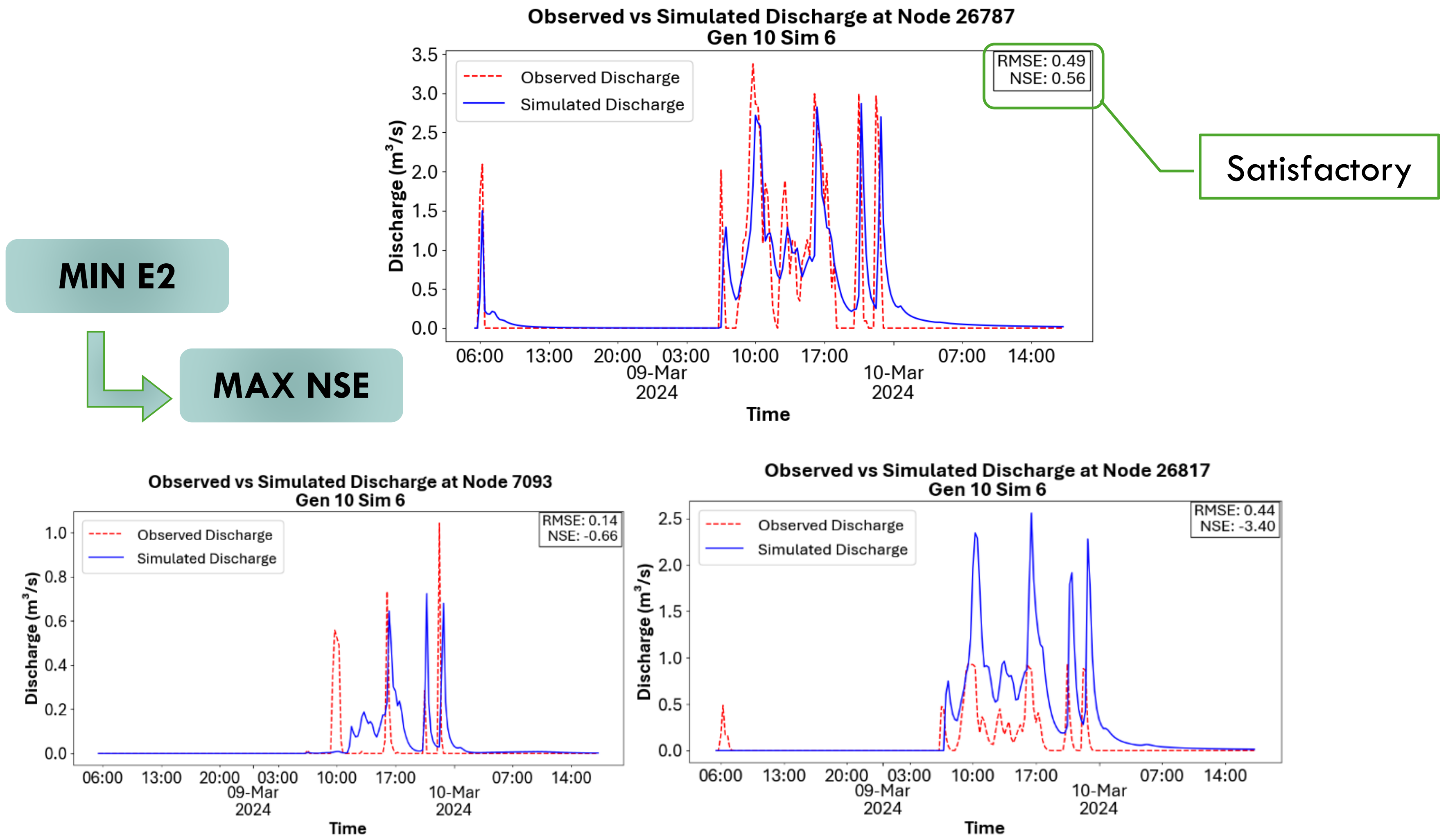

Figure. Single Objective Function Optimization Strategy Outputs

Process – Single Objective Optimization Strategy

- Focused on optimizing one objective function (minimizing model error/ maximizing NSE).
- Used Genetic Algorithms to calibrate parameters of the urban drainage model.
- Simple setup: one performance criterion guided the entire search process.

Analysis – How It Worked

- Efficient convergence toward solutions improving the targeted objective.
- Genetic operations (selection, crossover, mutation) evolved better parameter sets.
- Focused search reduced complexity compared to multi-objective approaches.

Result – Outcome and Observations

- Achieved high performance for the selected objective.
- However, limited flexibility: other important aspects of the model performance were not optimized.
- Highlighted the trade-off between simplicity and comprehensive model robustness.

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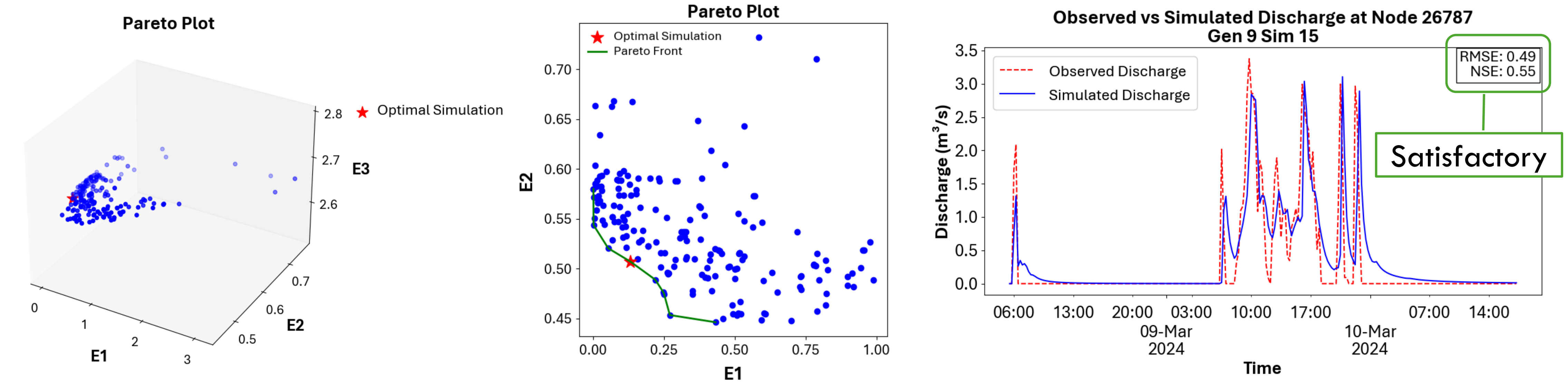

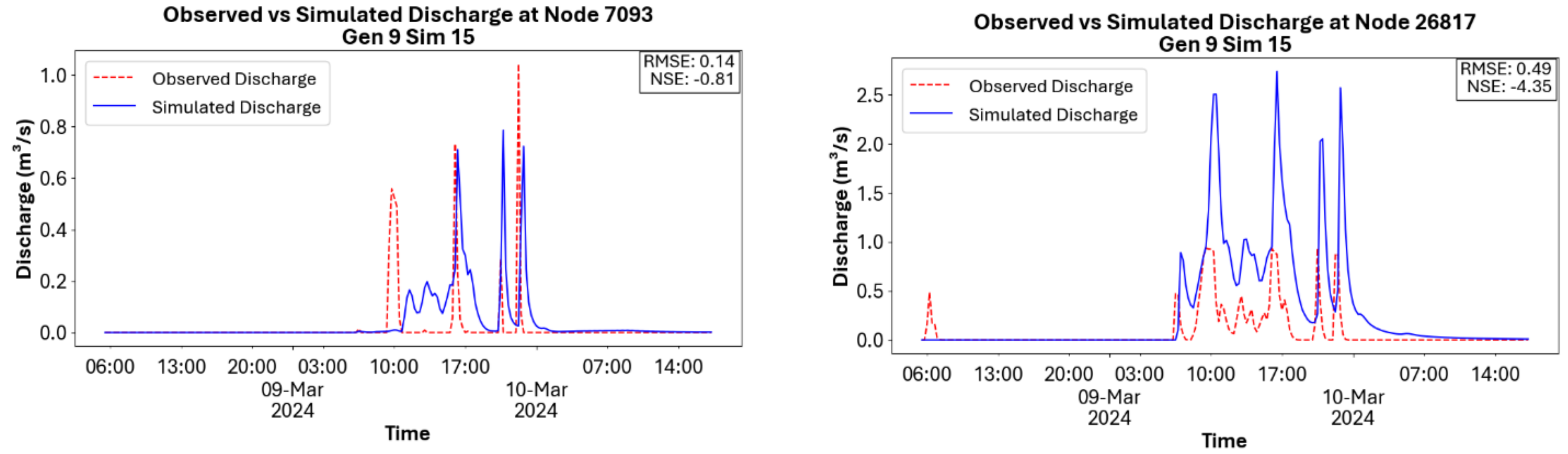

Figure. Multi Objective Function Optimization Strategy Outputs

Process – Multi-Objective Optimization Strategy

- Focused on optimizing multiple conflicting objectives simultaneously (peak discharge error, model accuracy NSE, and runoff volume error).
- Used NSGA-II (Non-dominated Sorting Genetic Algorithm) for a balanced, multi-objective search.
- Allowed exploration of trade-offs between objectives instead of focusing on just one performance metric.

Analysis – How It Worked

- Efficient generation of a Pareto front showing trade-offs between objectives.
- Genetic operations (selection, crossover, mutation) evolved diverse, high-quality solutions.
- Knee-point selection technique identified the best compromise solution balancing model accuracy, flood control, and runoff management.

Result – Outcome and Observations

- Produced a more robust, flexible, and versatile model performance across all objectives.
- Outperformed the single-objective strategy by better addressing multiple aspects of urban drainage behavior.
- Highlighted the strength of a holistic approach over a narrowly focused optimization.

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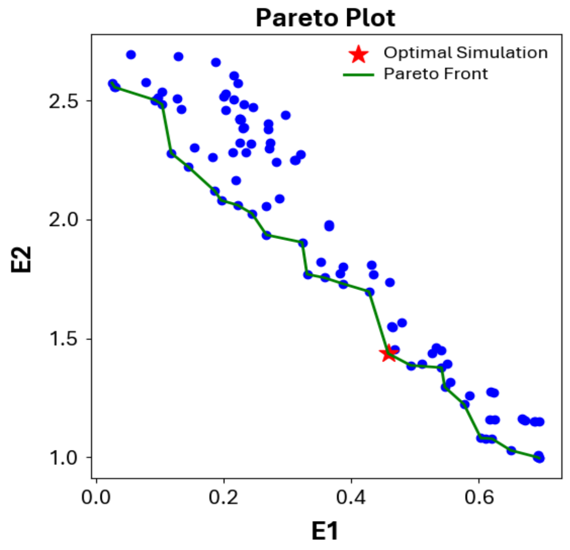
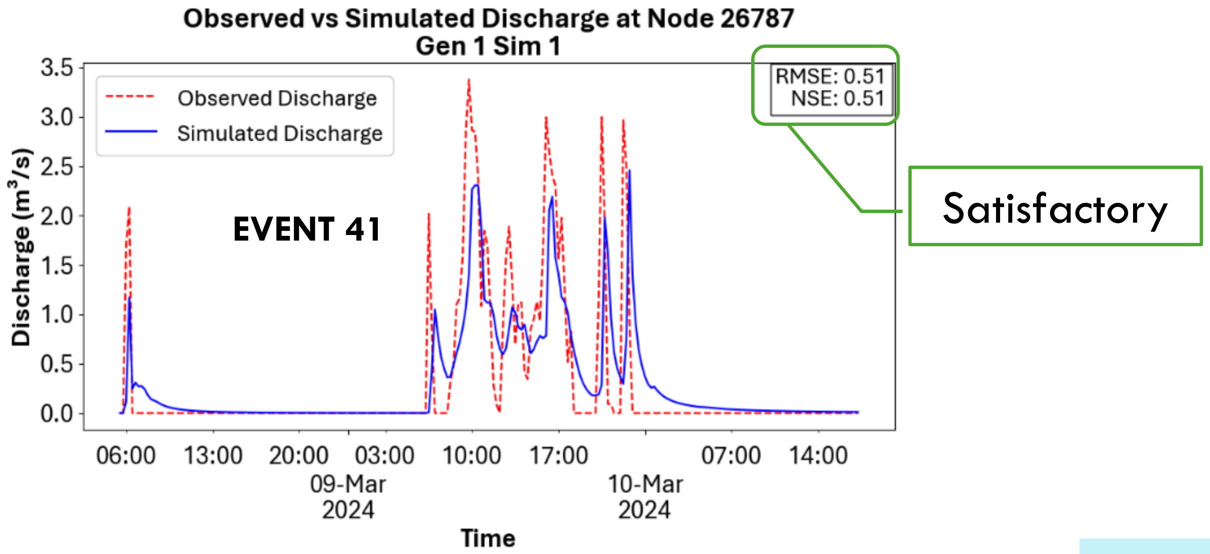
COMPARISON BETWEEN SINGLE AND MULTI-OBJECTIVE STRATEGIES FOR URBAN DRAINAGE MODEL OPTIMIZATION USING GENETIC ALGORITHMS:

A case study of Badalona urban drainage network





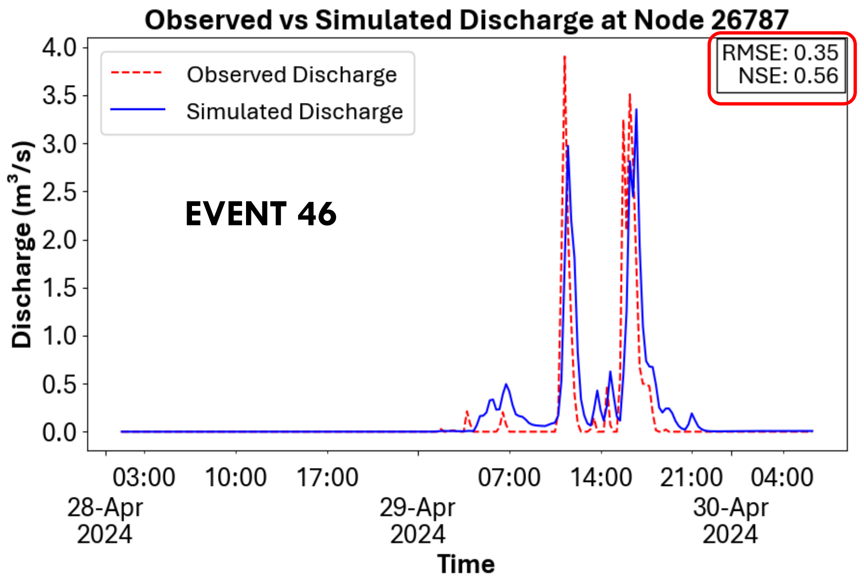


Figure. Hybrid Optimization Strategy Outputs for different events

Process – Hybrid Optimization Strategy

- Combined the strengths of both single and multi-objective approaches.
- Initially optimized with multi-objective NSGA-II to balance multiple performance criteria (E1, E2, E3).
- Followed by a targeted refinement phase using the best compromise (knee-point) solution to fine-tune individual objectives.

Analysis – How It Worked

- Multi-objective optimization generated a diverse Pareto front offering a range of trade-off solutions.
- Knee-point solution selection provided a balanced initial parameter set.
- Further localized search enhanced the selected solution, improving model precision without sacrificing robustness.

Result – Outcome and Observations

- Delivered the most balanced and reliable model performance among all strategies.
- Achieved strong performance across all key objectives — model accuracy, flood peak reduction, and runoff management.
- Demonstrated that a hybrid approach can effectively combine flexibility, precision, and comprehensive system understanding.

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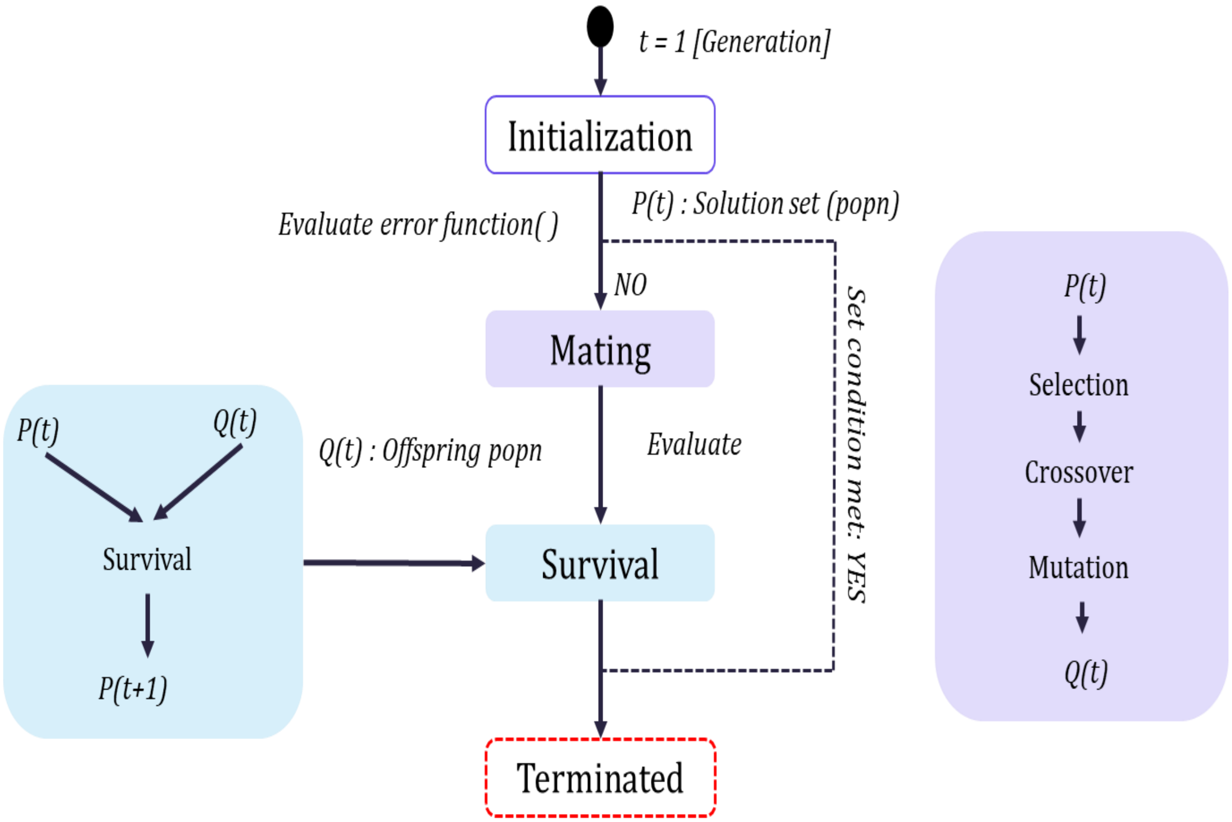
Formulas

$$S = \frac{\sum_{i=0}^{n-1} \frac{(Y_{i+1} - Y_i)/Y_0}{P_{i+1} - P_i}}{n - 1}$$

S	:	Parameter sensitivity index
Y_i	:	Output value of the ith run of the model
Y_{i+1}	:	Output value of the i +1th run of the model
Y_0	:	Initial value of the calculated result after the parameter calibration
P_i	:	Percentage change in the ith model operation compared to the parameter value after calibration
P_{i+1}	:	Percentage change in the i +1th model operation compared to the parameter value after calibration
n	:	Number of model runs

$\lvert S \rvert < 0.05$	:	Insensitive parameter
$0.05 < \lvert S \rvert < 0.2$	:	Moderately sensitive parameter
$0.2 < \lvert S \rvert < 1.0$	:	Sensitive parameter
$\lvert S \rvert > 1.0$	:	Overly sensitive parameter

Genetic Algorithm



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Comparison between single and multi-objective strategies for urban drainage model optimization using genetic algorithms: A case study of Badalona Urban drainage network

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Abstract

Urban drainage networks are critical to address the exacerbated flooding in the cities due to climate change and rapid urbanization. Badalona, a city in Spain has been facing recurrent pluvial flooding due to high-intensity and short-duration rainfall events driven by the Mediterranean climate. Although the city has its combined sewer networks modelled in SWMM, MOUSE, and Info works, it is supported through manual calibration methods. This approach is highly time-consuming for such a large network, and is subjective, depending on the modeler which can lead to suboptimal parameter selection. This research aims to address this limitation, by configuring a hybrid algorithm leveraging Non-Dominated Sorting Genetic Algorithm (NSGA-II) and SWMM to automatize the calibration process comparing single and multi-objective optimization strategies. Results demonstrate that the multi-objective optimization strategy offers a more holistic approach with a balance between various objective criteria effectively. With this methodology integrated into urban drainage management, an effective and comprehensive framework can be provided for sustainable water infrastructure that helps in achieving improved water quality, model performance, system resilience, and flood prevention.

Highlights

- Integration of Genetic Algorithms (NSGA-II) with SWMM for automated calibration of drainage networks for robust solutions.
- Multi-objective optimization strategy produces better results compared to single objective providing a balanced trade-off amongst all objectives.

Introduction

Recent pluvial floods in Badalona's drainage networks have identified its vulnerability to extreme rainfall events. The city's combined sewer network to accommodate both drainage and stormwater are critical to the proper functioning of the drainage network under exceptional cases of pluvial and flash floods. The use of traditional approaches still prevails while modelling the network, highlighting the need of automated method of calibration to make it more efficient and robust. This study develops and compare the single and multi-objective genetic algorithm (GA) optimization strategies to support the decision-making by enhancing the model's performance. Research have shown that the multi-objective strategy balances the conflicting factors such as resilience, environmental impact and the cost providing more robust solutions. However, it is necessary to understand whether these are efficient in terms of application and evaluation. This research aims to identify the key parameters in an urban drainage network to optimize, automatize the calibration of drainage model by coupling SWMM with NSGA-II, and evaluate and explore the efficiency of these GA and calibration strategies. This study offers a systematic approach to drainage model calibration using real-time data.

Methodology

The methodology of this research integrates the Non-Dominated Sorting Genetic Algorithm-II (NSGA II), a genetic algorithm, with SWMM, optimizing six key parameters: Manning's roughness coefficient for pervious and impervious areas, and the conduits, Curve number, depression storage and the percentage of the impervious areas using single or multiple objective functions. The optimization was done after a rigorous pre-processing of the data through rating curve analysis to understand the rainfall data quality obtained from the 3 rainfall stations. In addition to this, sensitivity analysis was performed using Morris's effect revealing the heuristic nature of the influence of the aforementioned parameters on the desired outputs (discharge, depth and volume). This indicated a need for a global search method, a key characteristic of the GA. With an initial simulation set-up, the model was optimized by automated iterative process of random adjustment and sampling of the parameter values. This process aimed to minimize error or objective function values through the hybrid algorithm created leveraging both NSGA-II and SWMM in python environment utilizing the nsga and pyswmm libraries respectively. While single objective optimization focused solely on the performance of the model i.e. maximizing Nash- Sutcliffe Efficiency (NSE), the multi-objective optimization was done using three functions: minimizing the peak discharge (E_1), maximizing NSE (E_2) and minimizing runoff volume error (E_3). The function to maximize the model's accuracy (E_2) was provided with constraints ensuring the NSE value to be of satisfactory level for each progressive simulation. The simulation was run for multiple rainfall events screened out considering both high-intensity short duration and low-intensity long duration events and validated at multiple outfall points of the drainage network. A comparative analysis was performed for 10 generation and 20 population size totalling to 200 simulations for the automatic calibration. Details of number of rainfall events, number of nodes, objective functions and validation approach used in the analysis is listed below:

Table 1. Optimization strategy

	Single Objective Function Strategy	**Multi-Objective Function Strategy**	**Hybrid Optimization Strategy**
No. of Rainfall Events	1	1	2
No. of Node	1	1	3
Objective Function	E_2	E_1, E_2, E_3	E_1, E_2, E_3
Validation	For rest of the objection function	All objective functions for remaining nodes	All objective functions for remaining nodes for all rainfall events

Case study

Badalona, a city in the Barcelona metropolitan area with 21.2 km^2 area with more than 200 thousand inhabitants was chosen for this study. The vulnerability of the city to urban flash floods as observed in the past decades, combined with the availability of the drainage network data and rainfall event records made it an excellent choice to progress with this study. The city dominantly functions on a combined sewer system both incorporating stormwater runoff and the sewage, with 26% of the network being human-accessible extending over 318km (Martinez-Gomariz et al., 2019). The network is comprised of more than 11,000 junctions and conduits, along with 132 storages, all connected to the same pipeline leading to the Besòs Wastewater Treatment Plant (WWTP). The Estrella detention tank plays a vital role in preventing Combined Sewer Overflows (CSOs) and flooding during intense rainfall events (Joseph-Duran et al., n.d.). The study was done for the four rainfall events and calibrated across three outfalls, called as nodes.

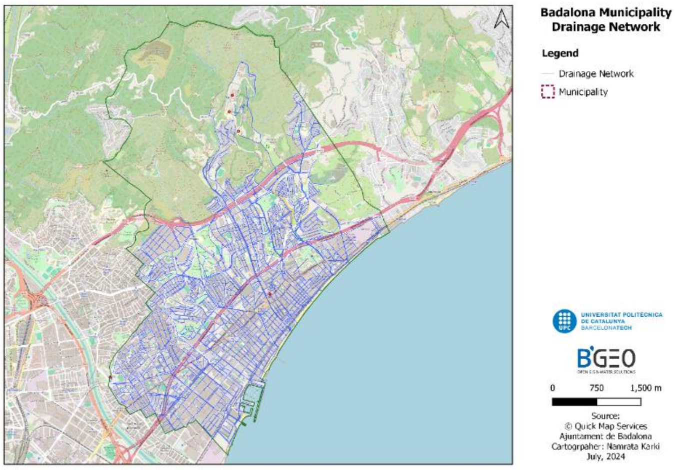

Figure 1. Drainage Network of Badalona

Results and discussion

Results of this study demonstrates that single objective strategy may be sufficient while optimizing for simple models focusing solely on the model's accuracy as depicted by the NSE value 0.56 (>0.5), showcasing a satisfactory level of performance (Moriasi et al., 2015). However, it lacks the ability to provide a holistic approach with balanced inclusivity of all the necessary objectives which includes model's performance along with flood preventions, and water quality. A pareto plot (Figure 2) was also observed to see the nature of the GA under the optimization strategy. The decrease in the error value of E_1 from 0.50 as obtained from single objective strategy to 0.27 with the implication of multi-objective strategy, along with a satisfactory model's performance (NSE = 0.55), indicates that more robust and versatile models can be produced through a proper balance between the goals. Furthermore, through the hybrid optimization strategy achieved by combining multi-objective strategy with multiple rainfall events and objective functions at multiple outfall points resulted in better overall balanced outcomes compared to other strategy as shown in Table 2 below.

Table 2. NSE and RMS values at nodes obtained from all strategies

	Single Objective Function Strategy		Multi-Objective Function Strategy		Hybrid Optimization Strategy	
Nodes	**NSE**	**RMSE**	**NSE**	**RMSE**	**NSE**	**RMSE**
26787	0.56	0.49	0.55	0.49	0.51	0.51
7093	-0.66	0.14	-0.81	0.14	-0.44	0.13
26187	-3.40	0.51	-4.35	0.51	-2.15	0.37

Table 3. Objective function values obtained from single and multi-objective strategies at node 26787

	Single Objective Function Strategy	Multi-Objective Function Strategy
E1	0.50	0.27
E2	0.44	0.45
E3	2.60	2.60

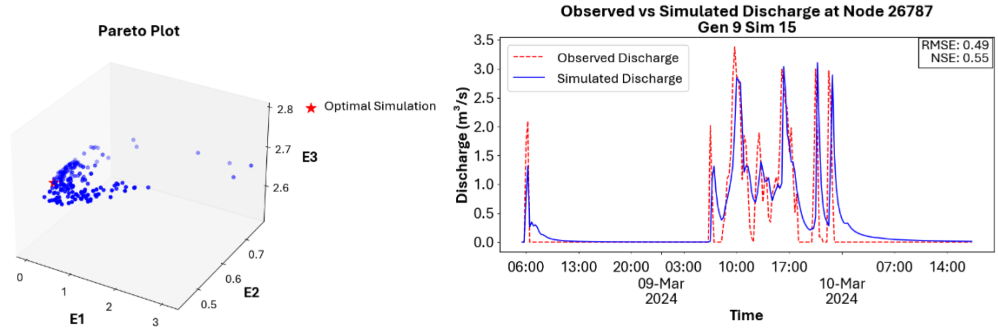

Figure 2. Pareto plot corresponding to multi-objective function strategy optimization (left) and hydrograph outlet 26787 after optimization (right).

Conclusions and future work

In conclusion, the study indicates that the multi-objective GA optimization provides robust solutions to parameter balancing all the objectives which is a vital key in holistic approach of water resource management for flood prevention, water quality and runoff control, and model accuracy. While it is worth mentioning that for a simple drainage network with less complexities and objectives, single-objective function strategy may suffice. The use of the open-source integration of QGIS - Giswater (for SWMM inp file) - Python (GA) enhances the accessibility of optimization of such drainage network by any user, even with data scarcity, although greater the amount of data is preferred for better outputs. To address the limitations occurred due to high-computational time and lack of inclusivity of the decision of the stakeholders, further works can be done such as opting for better simulation processing extension other than SWMM, simplifying the network focusing only on the major CSO points and including objective functions based on the effective decision-making strategy leading better pareto solution selection.

Acknowledgement

My heartfelt appreciation to my supervisor, Vicente Medina, for his constant guidance and support during the entire duration of my master thesis. Special thanks to Badalona municipality for providing the required data for the research and to Xavier Torret and whole BGEO team for providing the opportunity to contribute to this project and their invaluable support.
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Master's degree in:

MSc. Flood Risk Management

Barcelona, September 2024

Erasmus Mundus Program in

Flood Risk Management

MASTER FINAL THESIS

Master Program in

Flood Risk Management

COMPARISON BETWEEN SINGLE AND MULTI-OBJECTIVE STRATEGIES FOR URBAN DRAINAGE MODEL OPTIMIZATION USING GENETIC ALGORITHMS: A case study of Badalona Urban drainage network.

NAMRATA KARKI

MSc Thesis

September 2024

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Master of Science Thesis

by

Namrata Karki

Supervisor

Dr. Vicente Medina [UPC]

Examination Committee

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This research is done for the partial fulfillment of requirements for the Joint Degree Master of Science at the UNESCO-IHE Institute for Water Education, Delft, the Netherlands and the Universitat Politènica de Catalunya BarcelonaTech (UPC).

Barcelona, Spain
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To everyone who made this journey a remarkable and transformative experience of my life, I thank you from the bottom of my heart.

ABSTRACT

Urban flooding has become a worldwide catastrophic disaster including in Spain due to increased urbanization, reduced infiltration capacity, and climate change. Though the annual average rainfall is low in Badalona, a city located in eastern Catalonia and a part of the Barcelona metropolitan area, it experiences pluvial and flash floods due to the intense rainfall that occurred in a short interval of time brought by the Mediterranean climate. The combined sewer system of the drainage network in Badalona City acts as the conveyor of the urban sewer system, stormwater runoff, and industrial wastewater system. To minimize the surcharging of the drainage networks, it is necessary to predict the surface runoff and forecast the floods as accurately as possible. Drainage models such as MOUSE, Infor Works, and SWMM were developed for such applications for the city. However, the manual calibration results in a long and tedious process, primarily based on the educated guess of the modeler which could lead to a possibility of missing the optimum parameter sets during calibration. This makes an automatic process preferable. Additionally, the optimization done using multi-objective function strategies has been shown to provide more reliable results compared to the traditional methods. This project aimed to develop and compare the single and multi-objective function strategies to optimize the urban drainage model parameters using genetic algorithms. Upon the comparative analysis of single and multi-objective optimization strategies, it was demonstrated that the multi-objective optimization provides more robust and versatile model compared to single objective approach providing a balanced trade-off between the multiple objectives. This aids in providing a holistic approach for drainage network management of an area providing resiliency and efficiency through a robust framework for addressing various issues such as flood preventions, water quality management and model performance.

Key words: Urban Drainage, SWMM, Sensitivity Analysis, Genetic Algorithms, Multi-objectives

Table of contents

List of symbol and abbreviations

UDS	:	Urban Drainage System
WSS	:	Water Supply System
GA	:	Genetic Algorithms
UDN	:	Urban Drainage Networks
WWTP	:	Wastewater Treatment Plants
UDM	:	Urban Drainage Models
CSO	:	Combined Sewer Overflows
EPA	:	Environment Protection Agency
SWMM	:	Storm Water Management Model
GIS	:	Geographic Information System
QGIS	:	Quantum GIS
SCADA	:	Supervisory Control and Data Acquisition
NSGA-II	:	Non-dominating Sorting Genetic Algorithm
RMSE	:	Root Mean Square Error
NSE	:	Nash-Sutcliffe Efficiency
UPC	:	Universitat Politècnica de Catalunya
km	:	Kilometer
mm	:	Millimeter

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Chapter 1. Introduction

1.1 Background

Hydrological events such as precipitation, runoff, floods, and drought play a significant role in the hydrological cycle and the livelihood of the human population. With the growing anthropogenic activities, hydrological events have been greatly affected resulting in extreme events of floods, and droughts due to climate change. Water, being the most critical resource for humans, its regular supply and treatments are essential for reliable water services, especially in an urban area. This can be obtained with proper management of the urban drainage system (UDS) and the water supply system (WSS). However, the extreme events of precipitation and the increased urbanization have led to a series of flooding events such as pluvial and flash floods in the urban system.

Flooding has been a catastrophic disaster causing a lot of damage worldwide including Spain (Martínez-Gomariz et al., 2019). The increased uncertainties in the precipitation events in addition to the other climatic variables such as sea level rise and temperature variability demands local studies and proper forecasting methodologies to properly assess the flood probabilities and ensure public safety and lowering of the flood consequences. Although the regions in Spain such as Badalona City, lying in the eastern region of Catalonia, a part of the Barcelona Municipality Council receive the low level of annual rainfall on average, the urban drainage system gets flooded during intense rainfall periods in short intervals of time brought by the Mediterranean Climate. The growing population and the expansion of urban development have led to an increment of the impervious area resulting in a change in the hydrology of the area as compared to the pre-urban situation resulting in higher peak flow rates and a larger number of flash floods.

Thus, a proper risk assessment is needed to assess the recurrent pluvial floods in Badalona resulting in the surcharge of the urban drainage network. The management of urban flooding relies greatly on the overall stormwater management process as the continuing urban development highly demands a proper stormwater drainage system. This demands a proper model calibration of the drainage network.

The calibration of the model is performed through the iterative process of comparison of the simulated data with the observed values of the model output. Hit and trial method is one of the methods done through generations of modeling initiated with an educated guess. However, this educated guess of the initial value of the parameters could lead to overlooking the optimum parameter set highlighting the subjectivity and inefficiency of the method. Thus, it is necessary to follow a modern approach such as using genetic algorithms for optimization which leads to better, reliable, and efficient delivery of the desired outcomes. Studies have shown genetic algorithms to be more robust compared to the traditional methods, and successful in finding the optimal solutions (Siriwardene, 2003). Nonetheless, it is also necessary to select the proper algorithm method to achieve better outcomes. The GA operators used for the optimization process also play an incredibly significant role in this process. However, there are limited guidelines on the selection of GA operators especially for the optimization of urban drainage model parameters (Siriwardene, 2003).

Furthermore, optimization of the sewer systems can be done through single and multi-objective functions. The single-objective functions focus on a unique purpose which is targeted to maximize or minimize a particular function that could be such as minimizing the spills or increasing response time in the drainage networks to simplify the decision-making process. The multi-objective functions, however, focus on providing a holistic approach to the decision-making for the optimized operation of the urban drainage network. It considers multiple conflicting objectives such as cost-effectiveness, system resilience, and environmental impact targeting to balance them all. The multi-objective functions thus provide more robust solutions offering a thorough understanding of the system performance via exploration of trade-offs between the objectives.

1.2 Problem Statement

The frequent pluvial floods occurred in the Badalona resulting in flooding in the sewer network (Martínez-Gomariz et al., 2019) has clearly identified the need of proper risk assessment of the drainage network. The necessity of automated well-calibrated model for accurately simulating the performance of the system and aid in decision-making demands further research studies to improve the management strategies of the Badalona drainage network (Kumar et al., 2019). The multi-objective optimization for the optimal design of the network is necessary to have a holistic approach to ensure comprehensive and integrated solutions for the issues faced in managing the drainage network system (Muleta & Boulos, 2007). The model, when coupled with automated calibration techniques such as a genetic algorithm (GAs), results in a well-calibrated model and provides robust solutions considering multiple conflicting objectives such as resilience, environmental impact, cost, etc. for the optimized operation of the drainage networks with improved model performance (Muleta & Boulos, 2007).

This research study focuses to address these gaps by developing and evaluating the single and multi-objective GA optimization approaches for urban drainage models in the context of Badalona. It provides an in-depth study on the application of genetic algorithms using single and multi-objective function strategies for the better performance of optimized urban drainage models leading to more accurate and reliable drainage system simulations, thereby aiding the decision-making in the operation of the drainage network in the city.

1.3 Objectives

1.3.1 Primary objective

The primary objective of the research is:

i. To develop and compare the single and multi-objective function strategies to optimize the urban drainage model parameters using genetic algorithms.

1.3.2 Secondary objectives

The secondary objectives act as supplementary components that enrich the overall extent and detail of this research. They are:

i. To determine the characteristics of the input data and catchment from existing literature and provided data to analyze which parameters to optimize and what multi-objective functions to compare.
ii. To examine limitations and improvements of the genetic algorithm for the optimization of parameters as a calibration strategy in urban drainage model calibration.
iii. To evaluate the efficiency, applicability, and robustness of the proposed GA optimization method by comparing multi-objective functions.

1.4 Research questions

1.4.1 Primary question

The primary research question is:

i. How effective are single-objective and multi-objective function strategies in optimizing parameters of urban drainage networks using genetic algorithms?

1.4.2 Secondary questions

In order to aid in answering the primary questions, secondary questions were proposed as follows:

i. What parameters should be optimized to obtain the best results for the urban drainage model calibration?
ii. Which objective functions should be used for the comparison of the optimization of the parameters in the urban drainage calibration strategy using genetic algorithms?
iii. What are the drawbacks and possible enhancements of using a genetic algorithm as a calibration method to optimize the parameters of an urban drainage system?
iv. How effective are simplified optimized methods compared to sophisticated genetic algorithm methods for model optimization based on single-objective function for urban drainage networks?

1.5 Innovation

Several drainage models for the Badalona drainage network using Mouse, Infor works etc. have been developed. However, the city lacks a well calibrated drainage model based on the real time-series data. This research aims to explore the field of auto calibration of drainage models using genetic algorithms and making a comprehensive understanding of the limitations and strengths of the single and multi-objective function strategies used in the algorithms. The algorithm coupled with the SWMM model is developed and its efficiency and applicability in the real project is evaluated which could help in identifying the most suitable optimization approach for urban drainage systems.

1.6 Thesis outline

This thesis includes seven chapters in total each containing information as explained below:

Chapter 2: This chapter includes the literature review containing the required information about the models and methods used in this research project.

Chapter 3: The case study area of this research project is described in this chapter.

Chapter 4: This chapter provides a comprehensive explanation of the methods followed in this research, the data collection and screening approaches and the complete step-by-step framework of the research study.

Chapter 5: The results obtained from the research is presented and the analyzation of the findings along with their implications are presented in this chapter providing an in-depth analysis of the study's outcomes.

Chapter 6: A summary of the conclusions drawn from the research and recommendations for future research is provided in this chapter.

Chapter 7: This chapter includes the bibliography to all the literature materials used in this research study.

Chapter 2. Literature Review

2.1 Urban Drainage Model

The urban drainage systems are primarily comprised of urban drainage networks (UDN), wastewater treatment plants (WWTP), and other water-receiving bodies such as reservoirs or tanks in the network (Sun et al., 2018). These are responsible for collecting and convey the urban sewer and wastewater along with the stormwater runoff from the streets through the network for treatment to the WWTPs before being discharged into the environment or other water bodies such as rivers, seas, and oceans. In order to meticulously plan and have the optimal design of these UDNs, Urban Drainage Models (UDM) are widely used which aids in the management of the drainage systems (Li et al., 2014). These models are developed to incorporate the stormwater runoff along with the combined sewer overflows (CSO) during intense rainfall events which leads to flooding in the drainage network and contamination in the water bodies where the sewage water is drained out. These UDMs aid in improving the efficiency of management of the UDS and minimizing the impact of pollutants in the receiver. This demands a model with both hydrology and hydraulic modeling showcasing the accurate representation of the flows in the network with calibration capability offering higher efficiency, accuracy, and reliability. These are particularly important during intense precipitation events with CSO to guarantee the correct representation of the dynamics of an urban drainage system (Siriwardene, 2003).

Various UDMs such as the Environment Protection Agency (EPA) Storm Water Management Model (SWMM), Info-works, Mouse, XP-UDD, DRAINS, etc. are available for the modelling of urban catchment drainage networks (Siriwardene, 2003). In this research study, SWMM is chosen for the modeling purpose, elaborated in detail in **section 2.1.1**.

2.1.1 SWMM

One of the most widely used software for the simulation of urban drainage systems is the Storm Water Management Model (SWMM). It is developed by the United States Environmental Protection Agency (EPA). This software can simulate the stormwater runoff quantity and quality in storm and CSO through its comprehensive simulation model of rainfall-runoff dynamics (Siriwardene, 2003). It can simulate both singular and continuous storm events. All hydrological aspects of an urban drainage system including the stormwater runoff and its conveyance through the conduits of the drainage networks and water receiving bodies can be simulated using SWMM.

It has intrinsic modeling and optimizing capabilities in GIS embedded in its decision support system (Muleta & Boulos, 2007). The GIS interface allows smooth communication between the several modeling applications facilitating the development and calibration of the models, screening and analysis of the alternatives for optimum design, and reporting and visualization of the results through the geospatial platform. One of the plugins in QGIS, that can be used for this purpose is Giswater. It makes it easier for the modeler to run, simulate, and compare the numerous simulations performed on different modeling scenarios in order to identify the deficiency in the system and determine the economical physical and operational enhancements. This helps in achieving the best performance, accuracy, and reliability of the calibrated model. Together, these integrated functionalities establish a harmonized setting for the systematic planning, designing, and operational management of a secure and reliable urban drainage system.

2.1.2 Giswater

Giswater, an open-source software solution, serves as a tool for managing and utilizing the hydraulic infrastructure elements in the urban drainage and water supply systems. In addition to offering accessibility through database operators and graphical representation using diverse Geographic Information Systems (GIS) platforms, it serves as a driver that connects spatial databases with hydraulic analysis tools. It also allows a connection with SCADA, with real-time applications in the network through its central element i.e., Database-GIS. Giswater allows the interface to incorporate the SWMM program to its own use through which the user can visualize the results of the SWMM hydraulic model through data tables and elements symbolized on the map. Data related to the hydraulic model simulation result such as surface water values, infiltration parameters, and instability indexes among others can be obtained through Giswater (*Introduction | Giswater Manual*, 2024).

2.2 Sensitivity Analysis

The parameters integrated into the model calibration have diverse impact behavior on its output. The assessment of such impact on the model output due to the changes in the input parameters helps in providing valuable insights into the reliability and robustness of the outcomes. Such analysis is considered a sensitivity analysis (Del Giudice & Padulano, 2016). Sensitivity analysis plays a significant role in building urban drainage models and evaluating their performance. It helps in finding the relative influence of the parameters on the model outputs through various techniques, differentiated as Global or Local methods (Li et al., 2014). The global approach calculates the uncertainties considering the variation of all parameters simultaneously, while the local approach does it by evaluating the change by altering one parameter at a time. The methods used for conducting sensitivity analysis are elaborated in detail in subsequent sections.

2.2.1 Morris Screening Method

The Morris Screening Method includes choosing a parameter amongst the set of parameters that are being investigated while maintaining the default values of other parameters (Deb et al., 2002; Zhong et al., 2022). The chosen one is then adjusted within its defined range arbitrarily. The impact on the objective functions due to the change in the parameters is then analyzed by running the model several times producing numerous outcomes. Lastly, the effect of the changes made in the input parameters are calculated using the influence value, e_i.

$$e_i = (y^* - y)/\Delta_i$$

Where,

e_i : Influence value

y^* : Output value after the parameter change

y : Output value before the parameter change

Δ_i : Value of the magnitude of the parameter *i* change

The modified Morris screening method involves systematically changing the independent parameters with defined increments/decrements. The average of numerous Morris coefficients is considered to be the final sensitivity index of the parameter for the specific model.

$$S = \frac{\sum_{i=0}^{n-1} \frac{(Y_{i+1} - Y_i)/Y_0}{P_{i+1} - P_i}}{n-1}$$

Where,

S	:	Parameter sensitivity index
Y_i	:	Output value of the ith run of the model
Y_{i+1}	:	Output value of the *i* +1th run of the model
Y_0	:	Initial value of the calculated result after the parameter calibration
P_i	:	Percentage change in the *i*th model operation compared to the parameter value after calibration
P_{i+1}	:	Percentage change in the *i* +1th model operation compared to the parameter value after calibration
n	:	Number of model runs

The parameters with different values of the sensitivity index are then analyzed as:

$\lvert S \rvert < 0.05$	:	Insensitive parameter
$0.05 < \lvert S \rvert < 0.2$	:	Moderately sensitive parameter
$0.2 < \lvert S \rvert < 1.0$	:	Sensitive parameter
$\lvert S \rvert > 1.0$	:	Overly sensitive parameter

However, the sensitivity of the parameters obtained from this method could be influenced by the initial parameter value and the perturbation range. Thus, the potential misclassification issues should be addressed carefully (Zhong et al., 2022). Different rainfall events with varying intensities were selected and evaluated in this study.

2.3 Genetic Algorithm

Genetic Algorithm, GA, is a powerful tool widely used for global search to discover nearly optimal solutions for complex non-linear optimization problems (Del Giudice & Padulano, 2016). It was originally developed by Holland in 1975 (Siriwardene, 2003). It is a stochastic model which offers greater flexibility as compared to other methods. Inspired by natural selection and genetics, this method produces effective results with minimal information, aiming at the quality of the solutions produced by each parameter set.

GA relies primarily on feedback from its environmental operators such as mating, crossover, and mutation despite no prior knowledge of the exact solutions to determine the optimal solution (Kumar et al., 2019). A randomly generated population of suitable parameters is assessed according to their fitness in the population (Del Giudice & Padulano, 2016). Then, the GA utilizes the outcomes from the first process to produce the second-generation individuals, which are again evaluated individually. Mutation is expected to occur with the parent parameters so that the algorithm provides the best optimal solutions to the stage where the probability of acceptance of the parameter is attained (Del Giudice & Padulano, 2016 ; Siriwardene, 2003). GAs can handle both single and multi-objective functions. As they are population based, it takes the benefit of the whole search region to produce nearly-globally optimal solutions (Maier et al., 2019). With

GA, the problems can be customized in such a way that it escapes the local optima in the fitness landscape and tries to converge with the global optimal outputs, which most of the conventional algorithms lack to perform. Producing higher degree of performance with greater diversity of the population and its search party, GA aid in optimizing even the functions of heuristic natures with very rugged landscapes comprising of many troughs which makes it harder to navigate to the best optimal solution which could be the global or the local optima.

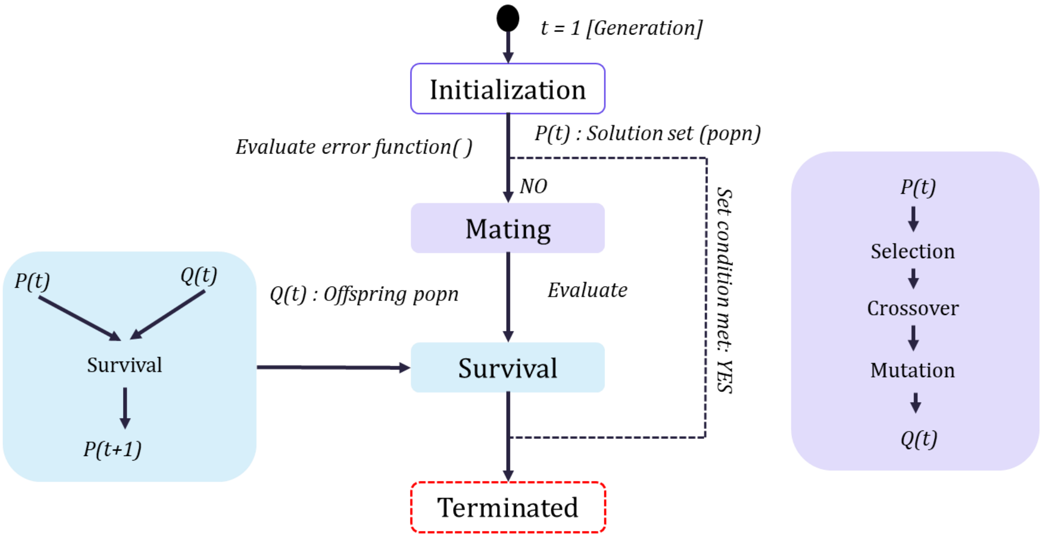


Figure 1: Overall GA process

Non-dominating Sorting Genetic Algorithm, NSGA-II has been chosen amongst the several genetic algorithms tailored for multi-objective functions. It is used due to its robustness and effectiveness as a search method. Recent studies (Deb et al., 2002) have shown its ability of high performance in case of hydrological and hydraulic modeling. It adheres to the general outline of the GA incorporated with adjustments in mating and survival selection.

The Pymoo package in Python offers both single and multi-objective algorithms, NSGA-II being one of them which covers the multi-facets of multi-objective optimization (*Pymoo - NSGA-II*, n.d.). The PiPy facilitates quick installation of the Pymoo package with the "pip install -U pymoo" command. **Figure 1** depicts the flow of genetic algorithm in the Pymoo which is further explained in detail below:

a. Initialization

Initial sampling is done to introduce the population. This could be done using a simple NumPy array of fixed population size (pop_size) of a fixed number of variables (n_var), or sampling through either the Random Sampling Method or Latin Hypercube Sampling, or a predefined Population with the X and F values.

b. Evaluation

The problem is then defined which can contain single or multi-objective functions to be solved to identify the minimum error among all possible solutions. These problems are evaluated to decide which individual population survives for the next phase.

c. Survival

The survival of the population is based on the fitness score. The best-fitted individuals are selected for the generation of the next set of population.

d. Selection

The selection of individuals is important for the next process of mating or crossover of the parent population. It is done through various selection methods such as random or tournament selection which impact the convergence rate of the algorithm.

e. Crossover

After the selection of the parents, the offsprings are produced based on the complexity of the problem and the problem information provided such as the variable bonds. The problem could be customized however it requires additional information regarding the current generation or the population's diversity measure.

f. Mutation

The offsprings produced in the crossover step undergo the mutation process with a predefined probability which helps in introducing diversity in the population. The population's inclination towards convergence is counteracted through this operator which prevents the algorithm from being trapped in the local optima.

The NSGA-II algorithm in Pymoo framework is based on (Deb et al., 2002). The objective functions could be made custom as per the requirements of the modeler and the best optimal solutions is provided by the algorithm. The multi-objective functions, it's constraint and the problem solving of the NSGA-II can be expressed as follows:

Minimize	:	$F_n(x)$	$(n = 1, 2, ..., N)$	
Constraints	:	$g_i(x) \leq 0$	$(i = 1, 2, ..., I)$	[Inequality constraint]
		$h_j(x) = 0$	$(j = 1, 2, ...,J)$	[Equality constraint]
Upper and lower bounds	:	$x_k l < x_k < x_k u$	$(k = 1, 2, ...,K)$	

Where,

X	: Parameter to be optimized	$x_k l$	: Lower bound of X
x_k	: Kth variable of X	$x_k u$	: Upper bound of X

In the scenario where the function F(x) is to be maximized, the objective function has to be redefined as the negative value is -F(x).

The flow of NSGA-II algorithm as shown in **Figure 1** ensures its effectiveness of finding a diverse set of the optimal solutions also known as Pareto front. This allows the comprehensive handling of the objectives of different units and natures. It is pivotal to understand the pareto dominance concept while working with algorithms that handle multi-objective optimization.

Given two solution vectors : (a) and (b), If solution (a) is superior to solution (b) in at least one objective and is not worse than (b) in any other objective, then the solution (a) is said to dominate the solution (b).

In general, for a set of objectives $F_1, F_2, ... , F_N$:

a is said to dominate b:

if $\forall i \in \{1, 2, 3, ..., N\} : F_i(a) \leq F_i(b)$ and $\exists i \in \{1, 2, 3, ..., N\} : F_i(a) < F_i(b)$

A pareto front is formed by the set of all non-dominated solutions as shown in **Figure 2**.

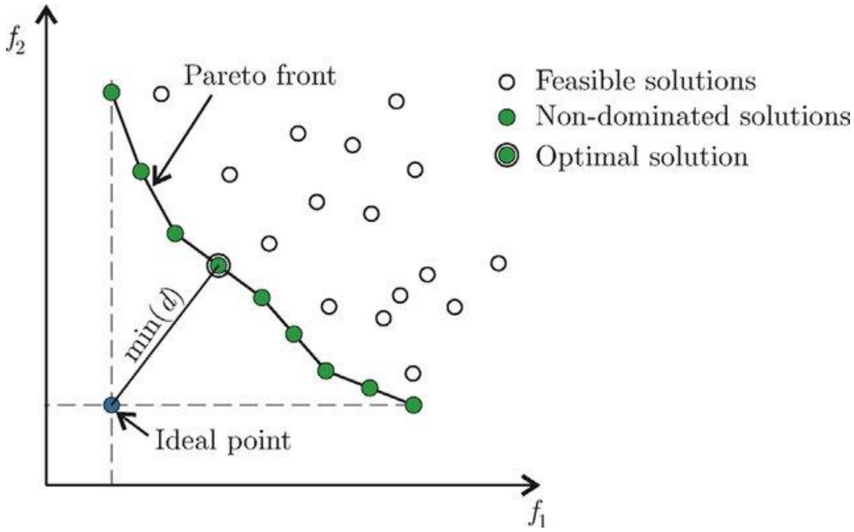


Figure 2: Schema of Pareto front, ideal point, and the final optimal solution for minimizing two objective functions (Bre & Fachinotti, 2017)

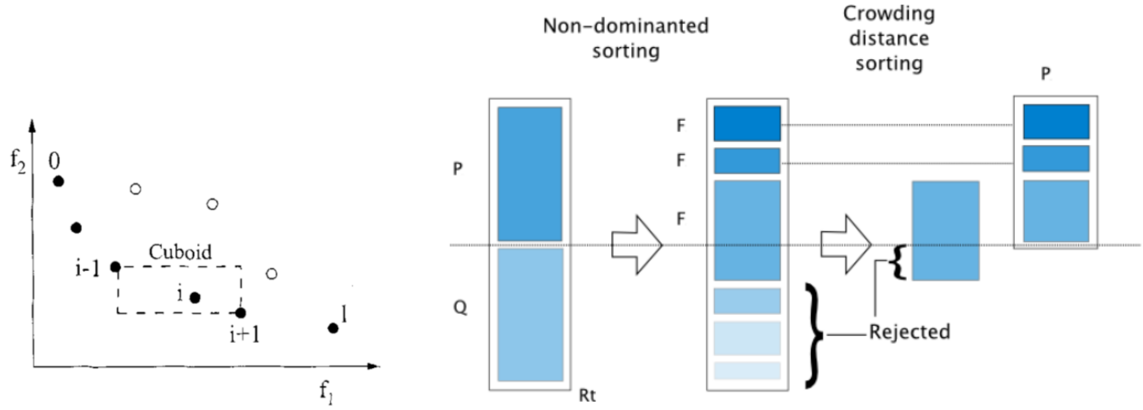


Figure 3: NSGA-II Selection process (*Pymoo - NSGA-II*, n.d.)

The initial population generated by the algorithm is evaluated for the Pareto dominance and a fitness value is allocated accordingly. The first front with rank 1 represents the non-dominated solutions set which dominates all other solutions in the objective space, while the second and other subsequent fronts represent the dominated solutions. The crowding distance is then calculated for each solution within the pareto front which is the average distance between a single solution and its closest neighbor in the solution domain. Extreme points are maintained across each new generation of population which leads to their allocation of infinite crowding distance. The enhancement of the selection process is done by implementing a binary tournament mating selection evaluating the individuals by rank and then by the crowding distance. By favoring solutions in less crowded regions of the Pareto front, the diversity of the population is maintained.

The optimal solution is selected through the combination of the pareto front and crowding distance by the NSGA-II algorithm. The crowding distance of the non-dominated solutions present in the pareto front is calculated. The non-dominated solution with the highest value of crowding distance is preferred since they indicate the area of the Pareto front that is less populated and is considered as the ideal point.

Occasionally, a specific solution called as "knee-point" solution can be selected which represents the best trade-off solution or the optimal compromise. This can be calculated through normalization of the objective values and computing the Euclidean distance to the ideal point (0,0 , ,0). The solution with the minimal distance is selected as the "knee-point" solution. In the research study, after the identification of the pareto front , the knee-point solution is chosen as the optimal solution indicating the best tradeoff between the objective functions.

For given set of objectives F_1, F_2,.... , F_N and considering each objective F_i has a range [F_i(min), F_i(max)], the normalized value for objective function F_i(x) can be calculated as :

$$\mathrm{F_i}^{\mathrm{norm}}(x) = \frac{\mathrm{F}_i(\mathrm{x}) - \mathrm{F}_i(\mathrm{min})}{\mathrm{F}_i(\mathrm{max}) - \mathrm{F}_i(\mathrm{min})}$$

Where,

F_i(min) = Minimum value of objective F_i for solution x

F_i(max) = Maximum value of objective F_i for solution x

The Euclidean distance is then computed from each solution to the ideal point (0, 0,…,0) in the normalized objective using the following formula:

$$D(x) = \sqrt{\sum_{i=1}^{N} (\mathrm{F_i norm}(x))^2}$$

Where,

N = Total no. of objective functions

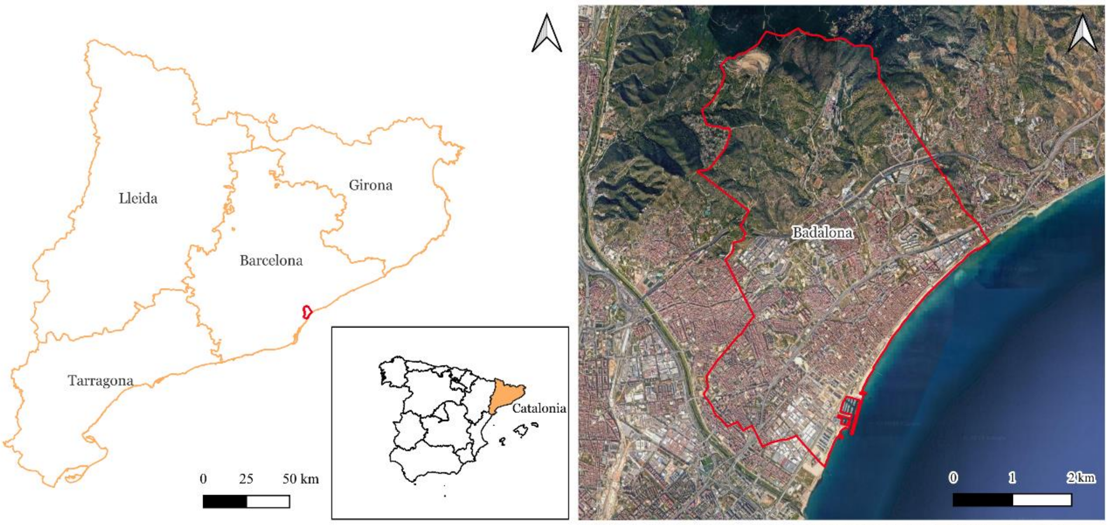
$\mathrm{F_i norm}(x)$ = Normalized value for objective function F_i(x)

The knee point , which represents the ideal trade-off between the objectives, is the solution with the least Euclidean distance i.e. $D(x)$.

Chapter 3. Case Study Area

Badalona, a city within the Barcelona metropolitan area, is situated in the eastern part of Catalonia, Spain. It has an area of 21.2 km^2 with 225, 957 inhabitants (*Badalona Population*, 2023) making the city the third largest city in Catalonia. It occasionally experiences high-intensity rainfall leading to flash flood events. The basin topography is distinguished by steep slopes (4% on average) in the upper urban area near Serra del la Marina while flat terrain in the lower regions near the Mediterranean Sea. During the last decades, the city has been heavily urbanized making the city vulnerable to urban flash floods driven by high-intensity and short-duration Mediterranean rainfalls (Locatelli et al., 2019; Martínez-Gomariz et al., 2019).

The sewer network of Badalona operates dominantly as a combined sewer network that channels the domestic sewage, stormwater runoff and industrial wastewater. This network is connected to the same pipeline to the Besòs Wastewater Treatment Plant (WWTP). Twenty-six percent of the overall network conduits are human-accessible altogether extending over 318 kilometers (Martínez-Gomariz et al., 2019). The Estrella detention tank acts as the main actuator element, which plays a crucial role in preventing combined sewer overflows and flooding during intense rainfall events (Joseph-Duran et al., n.d.). A rule-based system that evaluates the hydraulic measurements within the drainage system is utilized for the local control strategy for the two operational modes of the network. The anti-flooding measures are implemented as the primary operational mode followed by the anti-combined sewer overflow as the secondary one. The overflow of the sewer system combined with the stormwater runoff poses environmental, economic, and social risks to the region.



Source: Cartographic and Geological Institute of Catalonia ICGC, Google satellite image
Cartogrpaher: Namrata Karki

Figure 4: Badalona Municipality Area Location

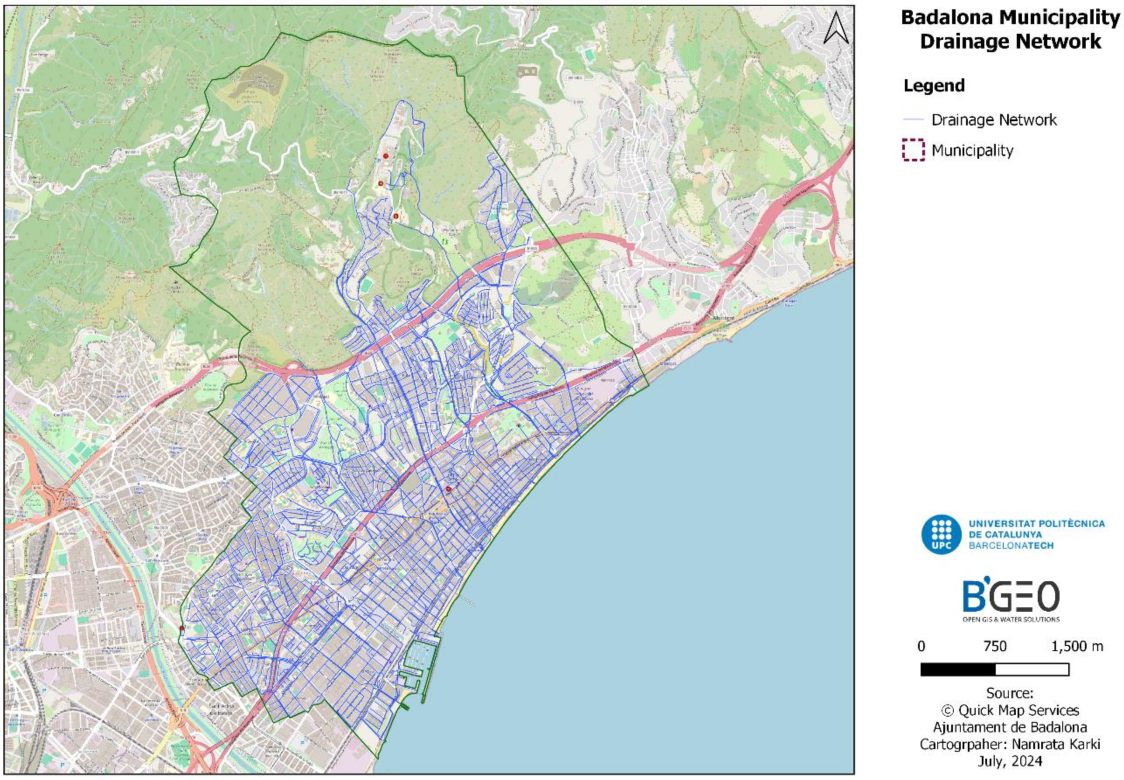


Figure 5: Drainage Network of Badalona

The catchment area of the drainage network is 21.13 km^2. It is a combined drainage network comprising of the following features listed in **Table 1**:

Table 1: Drainage network information

S.N.	Features	Count
1	Junctions	11,384
2	Conduits	11,717
3	Outfalls	53
4	Storage	132
5	Gully	1024
6	Rain gauges	3

Chapter 4. Research Methodology

This section outlines the systematic approach to obtain the research objectives and address the core inquiries, expected results and the timeline for the research development ensuring the authenticity and reliability of the results.

To obtain the primary objective, the main research activity [i.e., data collection and algorithm development] is divided into two parts. i.e. Part A: Model Calibration and Part B: Model Optimization as shown in **Figure 13**, explained in detail in **section 4.3**. In addition to that, required literature review and data collection were performed to facilitate the continuous advancement of the research project ensuring the comprehensive analysis and understanding of the results.

In summary, the research methodology is divided into four stages as follows:

1. Literature review
2. Data collection and screening
3. Data analysis and algorithm development
4. Interpretation of the results

Further explanations on each of the stages are elucidated in **sections 4.1**, **4.2**, **4.3**, and **4.4**.

4.1 Literature review

The literature review provides a comprehensive understanding of the research project idea based on the existing scholarly sources through different forms of platforms. Several sources such as books, journals, scientific papers and articles, news articles, and other relevant findings were analyzed and evaluated for a thorough understanding of the subject background. This provided a base to identify the pertinent theories, methodologies, and gaps existing in current research demanding further investigation. This aids in establishing the theoretical foundation of the research, validating methodologies, and demonstrating the importance of the proposed research by putting it in the wider academic discourse. Platforms such as Google, ResearchGate, SpringerLink, Google Scholar, etc. were primarily used for research investigation due to their recognized credibility and relevance in academic studies and research.

In this phase, the relevant theories in the urban drainage network optimization and utilization of the genetic algorithms for model optimization were discovered through a comprehensive review of relevant papers and research studies from the aforementioned platforms as described in **Chapter 2**. The identification of the research gap highlighted the need for rigorous methodology, which is developed based on the research objective and desired results for the project.

4.2 Data collection and screening

4.2.1 Data collection

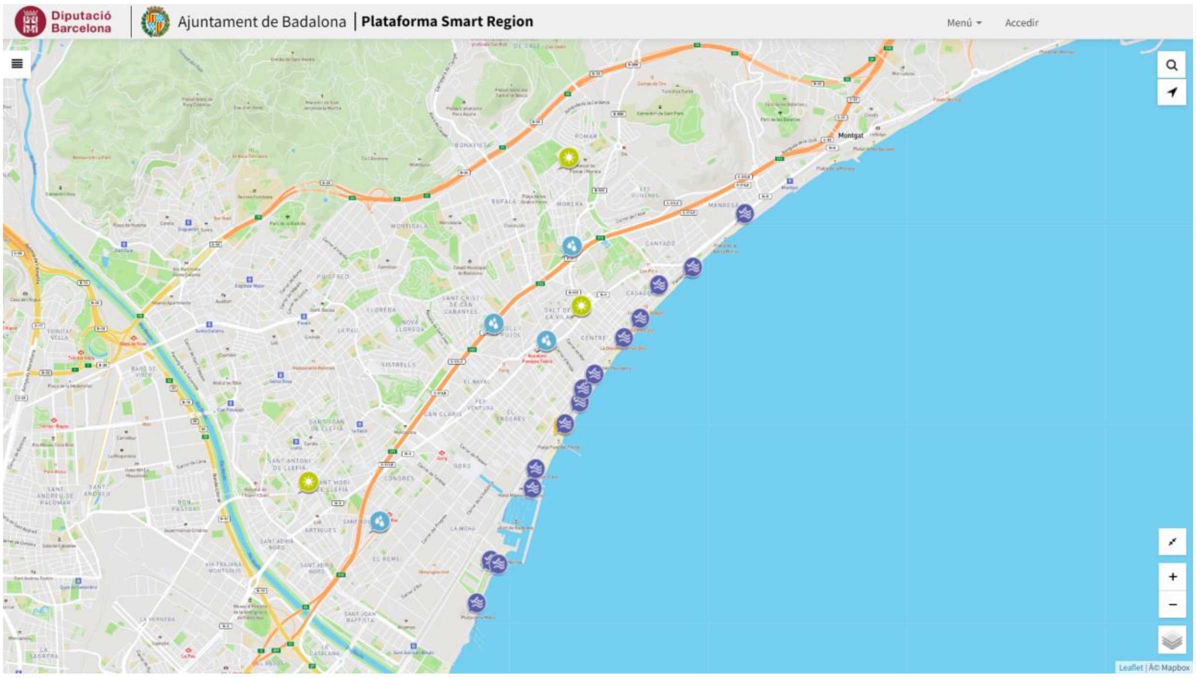
The data for the Badalona drainage network was obtained from the Badalona city council, facilitated by BGEO, Open GIS & Water Solutions, acting as the mediator between UPC and Badalona city council. An agreement between the UPC, represented by Vicente Medina, project supervisor, and the city council was signed to ensure the professional use of the data provided for the research purpose. Then INP file and initial set of parameter values used for the SWMM calibration were provided by BGEO through their server. In this research study, it is assumed that the provided network accurately represents the drainage inventories and related details.

The list of data provided by the city council through the smart region platform "Sentilo" as shown in which was crucial for the research purpose is presented in the table below:

Table 2: Data obtained from Badalona City Council

Data obtained	Units/Type	Interval (min)	Period
Rainfall Timeseries Daily Accumulated mm	mm	10	2022-07-6 to 2024-05-09
Rainfall Intensity	mm/h	10	2022-07-6 to 2024-05-09
Water level in the pipes/conduits	mm	15	2022-07-6 to 2024-05-09
Water level in the outfalls	mm	15	2022-07-6 to 2024-05-09
Discharge in the outfalls	m^3/h	15	2022-07-6 to 2024-05-09
Volume in the outfalls	m^3	15	2022-08-04 to 2024-03-01

In summary, data listed in **Table 2** was obtained for 3 rainfall stations, 15 water level sensors, and 4 surface water level sensors.



Rainfall Stations

Surface water level sensors

Water level sensors in conduits

Figure 6: Sentilo Platform for data acquisition (*Smart Region Platform*, n.d.)

Additional data such as vector maps, administrative boundaries, and aerial and satellite images is obtained from the open data source provided by the "Institut Cartogràfic i Geològic de Catalunya" official website.

4.2.2 Data screening

The rainfall data collected from the three rainfall stations: El Viver, Salvador Espriu, and Torre Mena were screened out for calibration purposes. When there was no rainfall for more than 24 consecutive hours, the two events were classified as distinct events. In total, there was found to be a slight variance in the total number of rainfall events recorded at each station as shown in **Figure 7** below. Events with accumulated rainfall exceeding 1 mm were considered for calibration to ensure robustness. However, in total 47 events uniformly capped for each station were selected after thoroughly checking to ensure consistency and comparability.

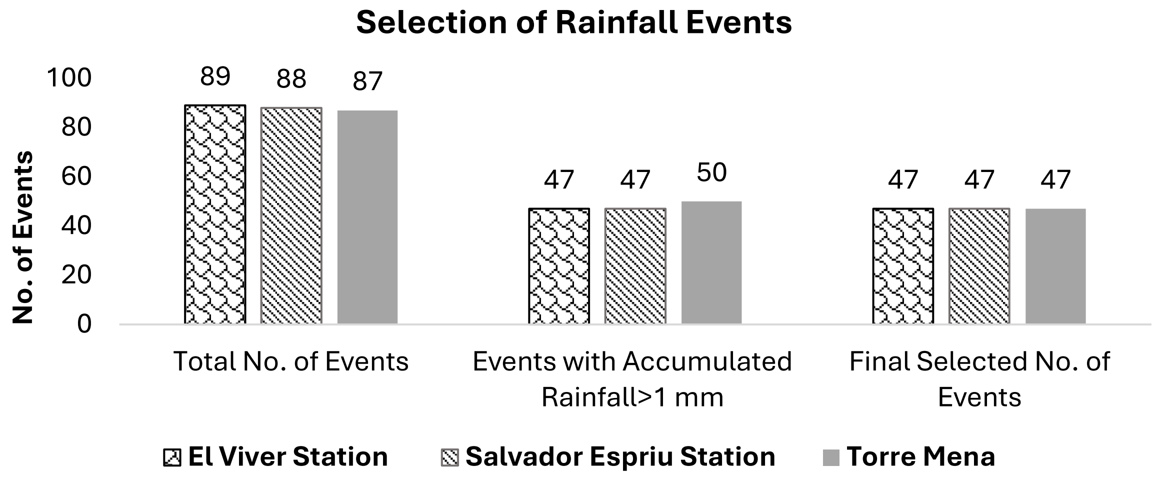


Figure 7: Rainfall event selection

Finally, four events were selected from the pool of initially selected events for the calibration and validation stages, ensuring complete data availability from all three rainfall stations and the corresponding discharge, water depth, and volume data from the water level sensors for the specific period of time. Events 26 and 41 were taken for the calibration and optimization respectively, and events 6, and 46 were used for the validation. This thorough data collection, screening, and selection procedure is crucial to the accuracy and dependability of later hydrological model calibration and validation. The plots showcasing the rainfall timeseries of the selected rainfall events at El Viver Rainfall Station are shown in Figure **8**.

Table 3: Rainfall Event Information

Event	Date	Total Accumulated Rainfall(mm)	Maximum Intensity (mm/h)	Time step (min)	Duration (hours)
6	31 August 2022	38.2	101.0	10	11.3
26	26 August 2023	50.1	67.2	10	25.5
41	08 March 2024	31.0	24.0	10	59.7
46	28 April 2024	65.0	30.0	10	48.8

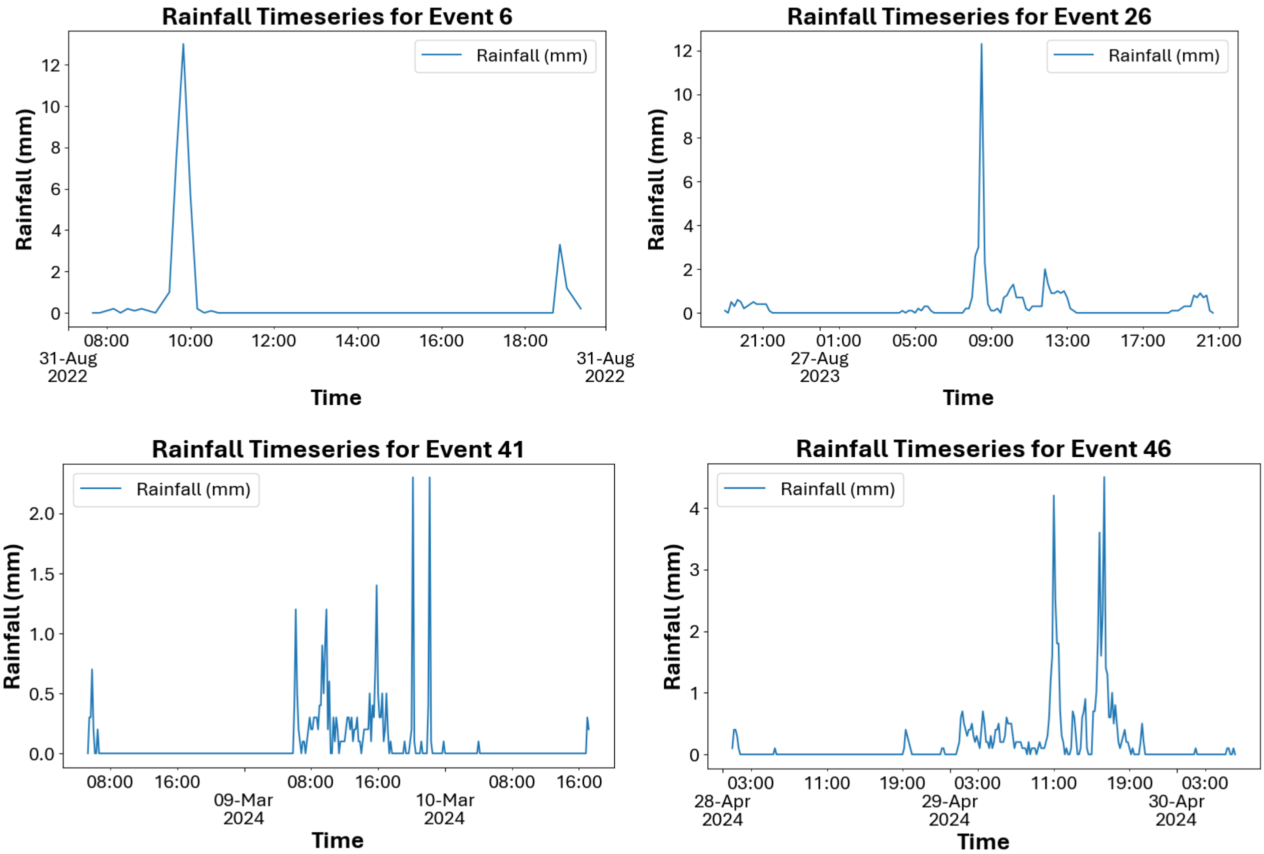


Figure 8: Rainfall Timeseries for selected events at El Viver Rainfall station

In SWMM calibration, an essential tool for evaluating the data quality is the rating curve. The rating curve establishes the relationship between the water level at the sensor and discharge, which is essential for the precise hydrological and hydraulic process modeling. It helps in locating potential data issues such as discrepancies, abnormalities or measurement mistakes. Better modelling approaches are made possible by its assistance in detecting the non-linear relationship between water levels and discharge. The accuracy of the SWMM calibration relies greatly on quality of the input data thus rating curves are crucial for evaluation of the quality of data in the SWMM calibration.

Figure 9: Water level sensor F303, F0401-F0402, and F0601-F0602 in the network (*Smart Region Platform*, n.d.)

Therefore, the data obtained from the 15 water level sensors were assessed and corresponding rating curves were constructed as shown in **Figure 11**. The majority of the plots demonstrate a positive correlation meaning as one variable i.e. water level rises, the other i.e. discharge does too, which is the general nature of the rating curve. However, it is worth noting that not all plots display a tighter clustering of the points as shown by plots from F0303 representing a stronger and more consistent relationship between water level and the discharge. Plot from F0401-F0402 (**Figure 10**) exhibits more dispersion suggesting potential noise or variability in the data, which could make the calibration more complicated demanding sophisticated modeling methods (Jakubczyk & Szulczewski, 2023). The presence of multiple lines suggests two possibilities: a) the water level sensors are moved up and down from their original position and corresponding water depth captured by them is used to calculate the discharges at the respective time period and b) water level sensors are stationary and different rating curve equations are used in order to obtain the discharge values for the different time periods. The **Figure 9** clearly suggests the water level sensors being mounted to the wall which concludes the use of different rating curve equations to obtain the discharge values at the node across various time periods. The analysis of the rating curves is further explained in detail in section **5.1**.

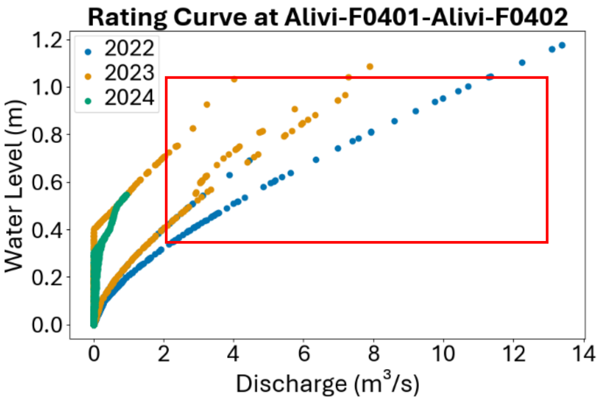
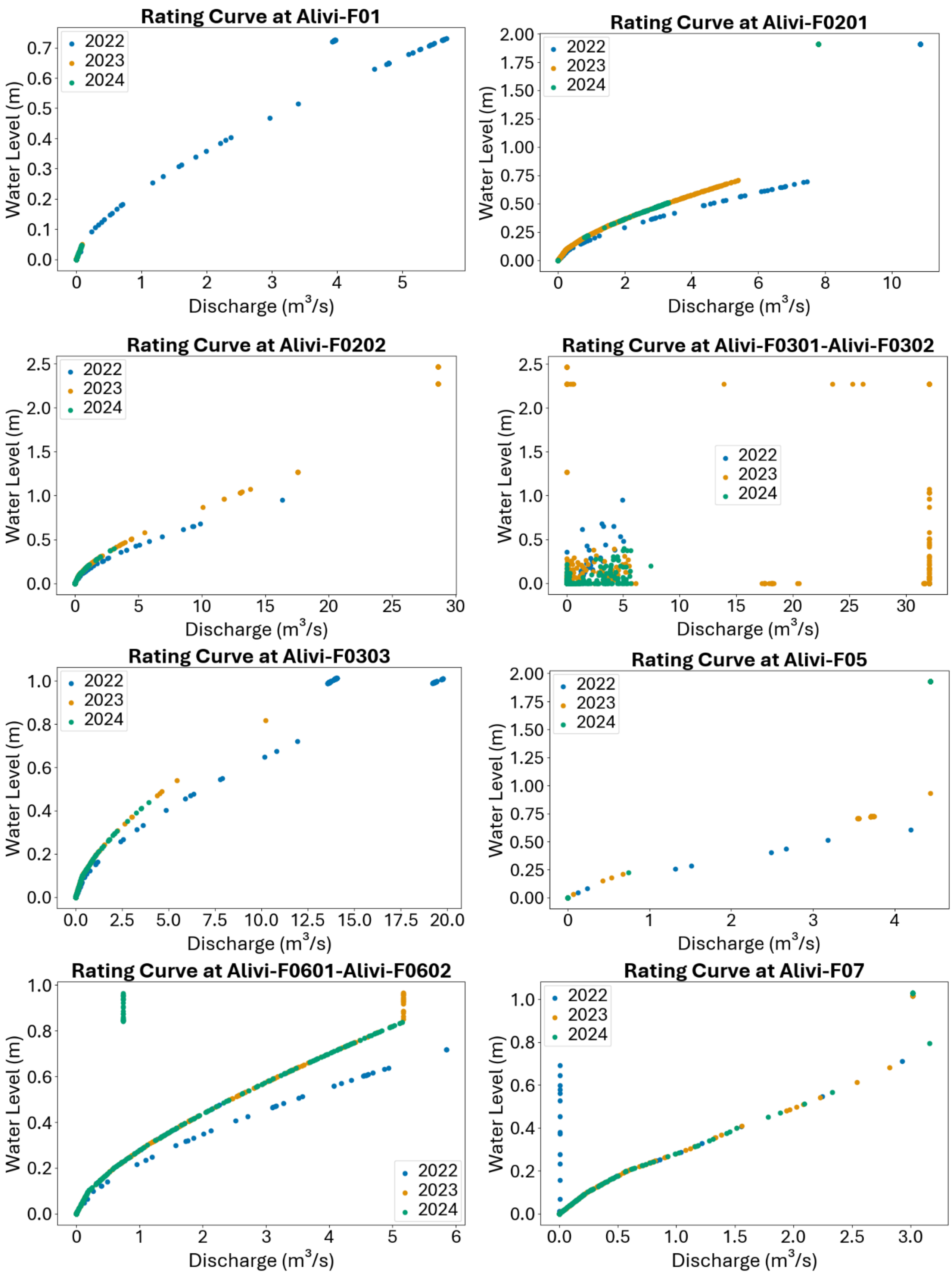


Figure 10: Rating curve at F0401-F0402 water level sensor

Plots from F05 and F08 include outliers that substantially depart from the original pattern, which might make the calibration challenging. Likewise, plot from F0601 and F10 depicts a non-linear correlations between the variables, suggesting that in order to get a reasonable fit, non-linear models or data manipulations could be required. During calibration, the quality of the fit is important. Accurate calibration findings are more likely to be produced from plots where the points closely follow a predicted curve such as plot from F0303 in contrast to the plots from F0301-F0302 and F0402 with higher degree of scatter and irregular patterns where further research into the data gathering procedures or complex modelling methods may be required (Jakubczyk & Szulczewski, 2023). In addition to that, the data availability corresponding to the period of rainfall events that have been selected for the calibration were checked to ensure the consistency and comparability of the simulated and the observed values of the model calibration.


Rating Curve at Alivi-F01
Rating Curve at Alivi-F0201
Rating Curve at Alivi-F0202
Rating Curve at Alivi-F0301-Alivi-F0302
Rating Curve at Alivi-F0303
Rating Curve at Alivi-F05
Rating Curve at Alivi-F0601-Alivi-F0602
Rating Curve at Alivi-F07
2022
2023
2024
Water Level (m)
Discharge (m³/s)

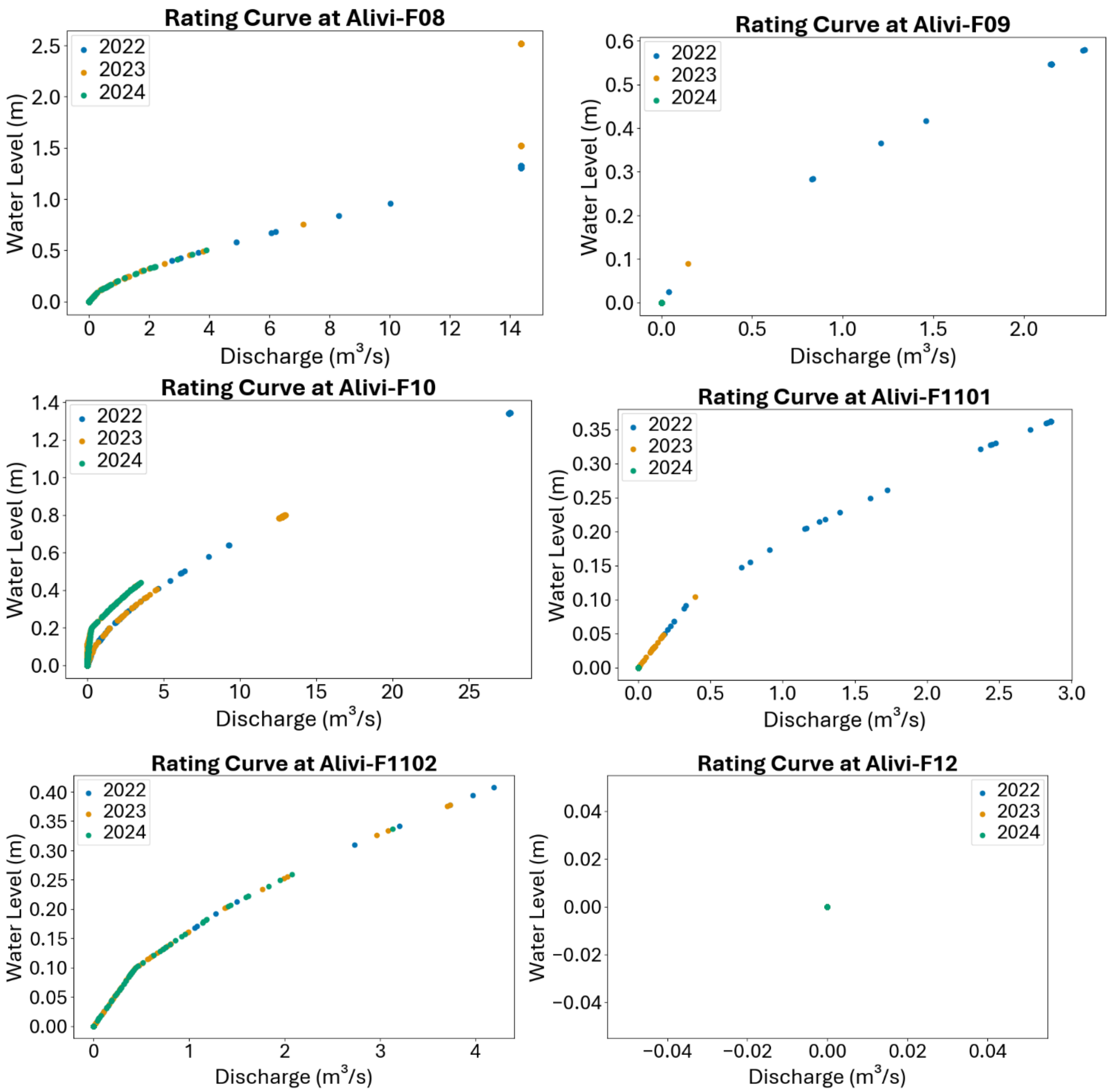


Figure 11: Rating curves from corresponding water level sensors

In conclusion, out of the 15 water level sensors as listed in **Table 4**, data from 3 water level sensors Alivi-F0303, Alivi-F0401-Alivi-F0402, and Alivi-F0601-Alivi-F0602 were selected for further proceedings in the calibration of the SWMM model for the drainage network. The corresponding node number in the SWMM model for the selected water level sensor is also listed in **Table 5**.

Table 4: Water level sensors information

S.N.	Water level sensor stations	Wall Heights (mm)
1	Alivi-F01	850
2	Alivi-F0202	3
3	Alivi-F0201	500

S.N.	Water level sensor stations	Wall Heights (mm)
4	Alivi-F0301-Alivi-F0302	50
5	Alivi-F0303	280
6	Alivi-F0401-Alivi-F0402	350
7	Alivi-F0601-Alivi-F0602	420
8	Alivi-F09	500
9	Alivi-F07	370
10	Alivi-F08	260
11	Alivi-F09	500
12	Alivi-F10	3
13	Alivi-F1101	620
14	Alivi-F1102	650
15	Alivi-F12	1050

Table 5: Selected Water level sensors information

S.N.	SELECTED WATER LEVEL SENSORS	Node Number	Wall Heights (mm)
1	Alivi-F0303	7093	280
2	Alivi-F0401-Alivi-F0402	26817	350
3	Alivi-F0601-Alivi-F0602	26787	420

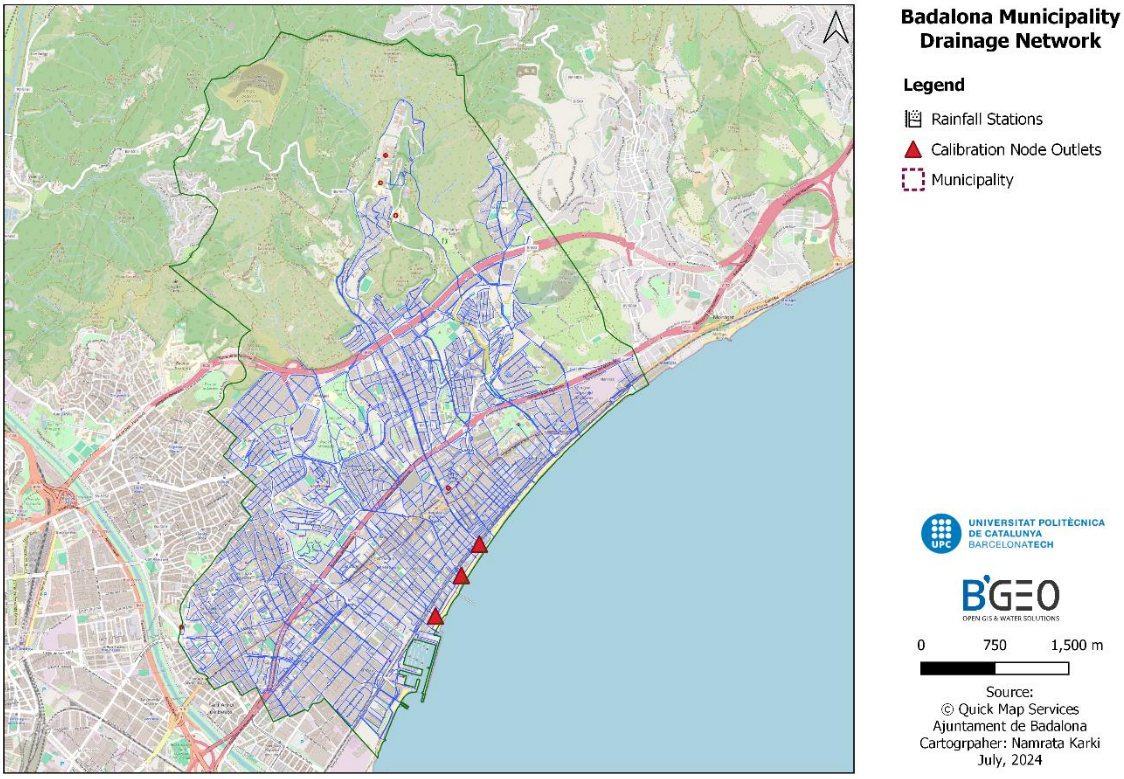


Figure 12: Drainage network of Badalona with selected water level sensors and rainfall stations

4.3 Data analysis and algorithm development

This phase of data analysis and algorithm development is subdivided into two parts as shown in **Figure 13**, each of which is elaborated in detail in the subsequent sections.

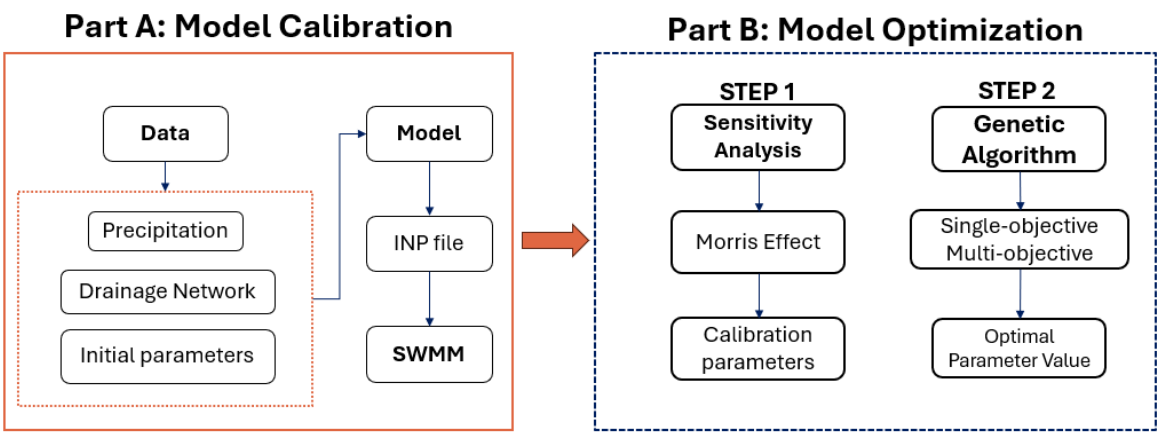


Figure 13: Methodology for algorithm development

PART A: Model Calibration

In this part, the initial model was set up manually for calibration. The Storm Water Management Model (SWMM) was selected for this model calibration due to its advantages and versatility. Recent studies have shown how the SWMM addresses uncertainties effectively with automated calibration strategies improving the flood control facility, peak flow estimations, and water quality volume (Kumar et al., 2019; Li et al., 2014; Muleta & Boulos, 2007). The SWMM model was calibrated after the input parameters and data preparation in optimum settings using the Giswater plugin within QGIS. The Giswater plugin is used due to its unique feature of linking the drainage network to the SWMM model automatically, providing the user with the required INP file for calibration. The drainage network of the city was carefully examined to guarantee its accurate depiction of the junctions, inlet and outlet nodes, conduits, and any additional features in alignment with the current official guidelines. Finally, an INP file fit for the simulation was exported, which was used to run the simulation using the Python PySWMM module. This simplified method leveraging the capabilities of Python for automated and repeatable hydrological modeling guaranteed the simulations' smooth integration and effective operation.

The SWMM input data provided was analyzed meticulously to identify any anomalies and discrepancies by thorough filtering with scrutiny as explained in section **4.2.2**. The rainfall time-series files were created in accordance with the SWMM user manual for each rainfall station and its corresponding rainfall event. In this scenario, separate files were formed instead of consolidating all the time series into one INP file which would have expanded the file size and may affect the simulation run time. The manageability and speed of the simulation process were optimized by this modular approach, which guaranteed that the correct time-series file was automatically picked for the corresponding event number during the SWMM simulation triggered by the Python code in the VS Code platform.

Similarly, the calibration files for the data corresponding to discharge, water level, and volume at the water level sensors were created using the SWMM user manual for each sensor and its corresponding rainfall event time period. This was essential to make sure that the correct observed values were being tallied against the simulated values allowing for a precise error analysis and calibration of the model. This acts as a benchmark for the SWMM model outputs which helps in identifying the discrepancies between the observed and the simulated values, further assisting in the required adjustments to the model parameters. It allows effective and efficient troubleshooting and refinement of the SWMM model.

The initial conditions were then defined as per the selected events for the rainfall timeseries. The parameters to optimize (auto-calibration), as listed in the **Table 6**, were chosen based on their influence in the SWMM model and practical limitations in its measurement.

Table 6: Parameters for optimization

Parameter	Symbol	Description	Range
N-imperv	Ni	Manning's n for impervious area	(0.011-0.05)
N-perv	Np	Manning's n for pervious area	(0.011-0.8)
N-conduit	Nc	Manning's n for conduits	(0.011-0.025)
Curve Number	CN	SCS Curve Number	(50-98)
Destore-imperv	Dsimp	Depression storage for impervious area	(1.2-2.7)
% Imperv	Pimperv	Percentage of impervious area	(35-90)

The parameters N-imperv and N-perv are critical in the SWMM simulations as they highly influence the model simulations outputs such as flow velocity, peak discharge, and overall hydrograph characteristics. Unlike the geometric properties such as diameter, length, and slope of the drainage network inventories like pipelines, conduits, outfalls, etc., they cannot be measured directly. To capture the variability of the drainage area in terms of the roughness caused due to various materials, land use patterns, and vegetation cover, it is necessary to properly optimize these parameters. Similarly, it is equally important to accurately estimate the N-conduit that influences the flow resistance to precisely model the flow attenuation, peak flow time, and volume as it is often estimated using empirical relationships or based on an educated literature guesses due to its measurement challenges. The land use patterns, soil type, and pre-moisture conditions highly influence the CN, which accounts for the total runoff generation in the SWMM simulations. Although it can be estimated through the detailed geospatial analysis of the study area, it can still vary spatially and temporarily within the drainage catchment area. Thus, to have a realistic stormwater runoff, it is essential to estimate the parameter accurately which makes it a parameter needed to be optimized. The parameter Dsimp greatly influences the initial abstraction of the drainage network which ultimately affects the timing and the runoff magnitude. However, their estimation based on the land use characteristics and the empirical data demands its optimization. Lastly, while the Pimperv can be estimated approximately through the land use data of the drainage area, the optimization ensures the accountability of the model to the effective imperviousness of the catchment area in case of potential inaccuracies in land use classification. Thus, these parameters are chosen for the optimization to ensure that the model offers trustworthy forecasts in line with the realistic circumstances of the drainage area for the proper management of the drainage area network.

The calibration process typically aims at achieving a close match between the observed and simulated data with adjustment of the parameters, however, the primary goal in this phase was to set up a functional model to guarantee continuous operation. The optimization, i.e. automated calibration, of the parameters for the enhanced accuracy was done in the subsequent phase, Part B, i.e., Model Optimization. Thus, the emphasis on this methodological step Part A was achieving a fundamental calibration to ensure the model functionality while prioritizing the comprehensive optimization of the parameters for the subsequent phase, Part B to boost model accuracy and performance.

In summary, the outcome of this calibration process was the creation of the INP file which included the details of all the parameters and output obtained from the rigorous calibration processes. The simulation of the model once calibrated was done recurrently through the subsequent steps until the optimum alignment between the simulated and observed data was achieved.

PART B: Model Optimization

Once the baseline calibration model was manually set up, automatic model optimization was taken into priority. This phase is segmented into two distinct steps: Step 1 includes sensitivity analysis using Morris's effect, Step 2 centers on optimizing the model using a genetic algorithm called NSGA-II through Pymoo framework in Python.

Step 1: Sensitivity analysis using Morris screening method

The different parameters as enlisted in the table above were subjected to the sensitivity analysis using the Morris screening method, detailed in the preceding **section 2.2.1**. Research and studies have shown that the models calibrated after parameters have been integrated by the Morris method exhibit lower peak error in a simulation (Zhong et al., 2022). Additionally, it requires fewer model executions as compared to that of other sensitive analysis methods such as E-FAST (Paleari et al., 2021). This is why this method was integrated into this research study.

In this phase, the selected parameters were sampled using a perturbation in the same range on both sides of the initial value (±5% , ±10% , ±15% , and ±20%), each step creating a new INP file using the PySWMM SimulationPreConfig feature (McDonnell et al., 2020). For each parameter, the "add_update_by_token" method (McDonnell et al., 2020) was called to update the desired parameter value by the desired percentage. This allowed the update of each parameter in a loop creating the INP files for the simulations. Then, the outputs of the SWMM simulation were extracted through PySWMM (McDonnell et al., 2020) and SWMM-API (*Swmm_api 0.4.42 Documentation*, n.d.). Finally, the sensitivity analysis was performed for the primary outputs of interest: discharge ***Q***, total runoff volume ***V***, water depth ***D***, and maximum discharge ***Qmax***. These parameters are crucial due to their relevance in different aspects of stormwater management. The peak discharge ***Qmax*** is pivotal for flood prevention, discharge ***Q***, and water depth ***D*** are critical for the prediction of the model accuracy through its Nash- Sutcliffe Efficiency (NSE), while the total runoff volume ***V*** is necessary to ensure pollutant control and maintain the water quality. This multi-objective approach ensures a comprehensive evaluation of the objectives: peak discharge for flood risk, Nash- Sutcliffe Efficiency (NSE) for model's accuracy, and runoff volume for indirect water quality assessment.

The results of this sensitivity analysis are analyzed in detail in **section 5.2**. Additionally, the Nash-Sutcliffe Efficiency (NSE) for the simulated discharge values have been calculated and its relationship with respect to the change in the parameter values is studied for better understanding of the influence of the parameters on the simulation outputs. To compute the NSE, the ratio between the errors of the model to the variance of the observed time-series discharge values is subtracted by one. In order for the model to be perfect, the value of NSE is closer to 1 and the value of the error variance is zero.

$$NSE = 1 - \frac{\sum_i^N (Q_O - Q_S)^2}{(Q_O - \overline{Q_O})^2} \quad \text{[A]}$$

Where,

Q_o = Observed discharge values

Q_s = Simulated discharge values

$\overline{Q_o}$ = Average observed discharge

N = No. of data

Step 2: Model optimization using genetic algorithm

The main objective of research is to compare the single and multi-objective function strategies for model optimization. It is necessary to choose a proper genetic algorithm to have a multi-objective optimizer for the hydraulic model. Based on the literature that have been studied and the nature of objective functions that are selected, the genetic algorithm NSGA-II, detailed in **section 2.3**, is used for further proceedings of the research (Barreto et al., 2010).

A hybrid algorithm that integrates the objective functions with a genetic algorithm is developed in python using the Pymoo package aiming to minimize errors (E) and reach to the acceptance level of the parameters value for more reliable and accurate calibration model. Statistical error metrics such as Root Mean Square Error (RSME), and Nash Sutcliffe Efficiency (NSE) are applied in the model evaluation. An overview of how the algorithm flows in this research study is shown in the **Figure 14** and **Figure 15** below and the detailed step-by-step procedure of the hybrid algorithm is depicted in the flowchart **Figure 16**.

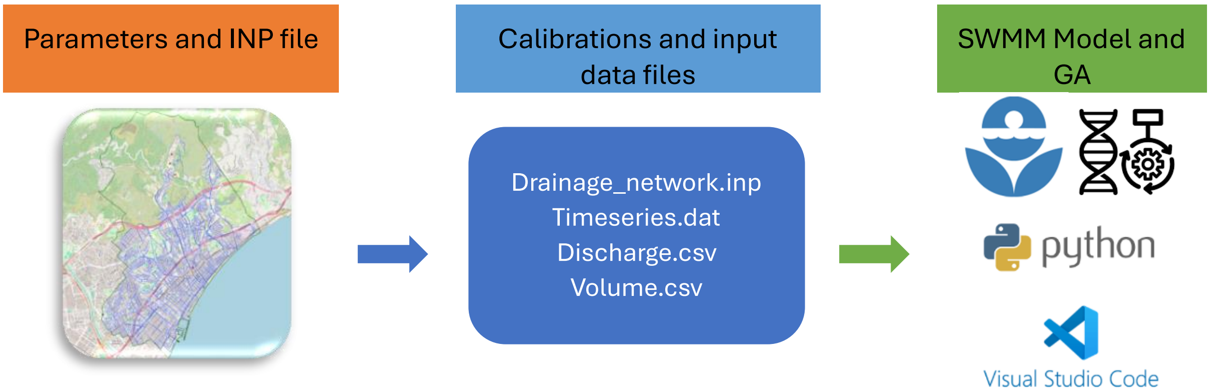


Figure 14: Overall Flow of the algorithm

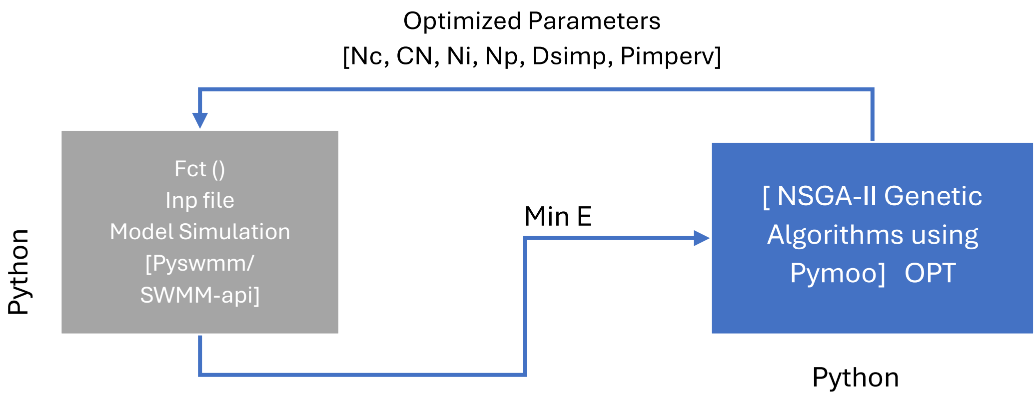


Figure 15: Conceptual framework for parameter optimization using NSGA-II

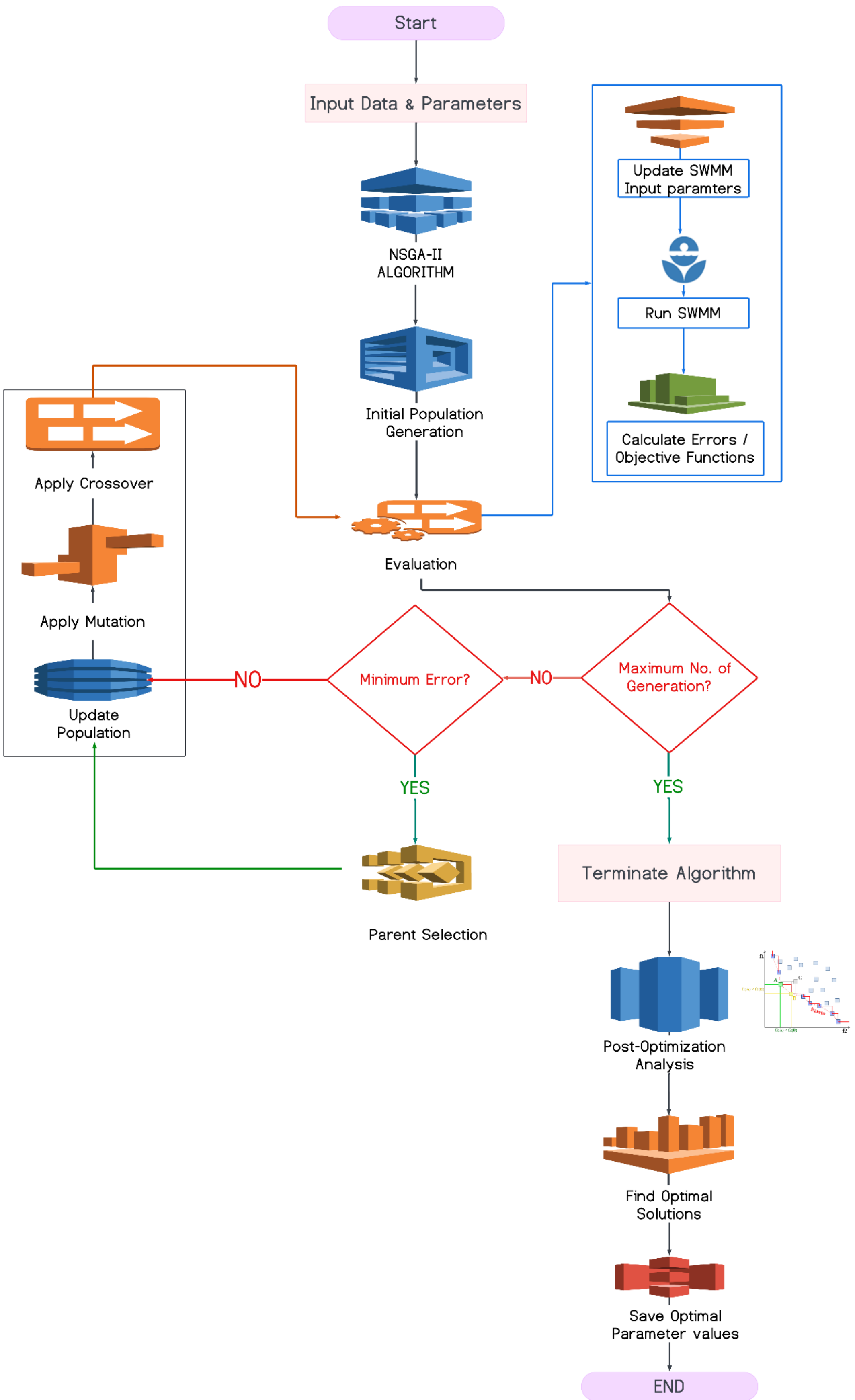


Figure 16: Step-by-step flow of the hybrid algorithm [SWMM coupled with NSGA-II]

In this research, the three objective functions are taken into account for the optimization: a) minimizing the error in peak discharge for flood prevention, b) NSE error in discharge at each timestep for assessing model performance and c) minimizing the error in total runoff volume for pollutants management.

$$\mathrm{E}_1(min) = |Q_{ps} - Q_{po}| \quad [1]$$

$$\mathrm{E}_2(min) = 1 - [1 - \frac{\sum_{i=0}^{n}(Q_{o(i)} - Q_{s(i)})^2}{(Q_{o(i)} - \overline{Q_{o(i)}})^2}] \quad [2]$$

$$\mathrm{E}_3(min) = |V_s - V_o| \quad [3]$$

Where,

Q_{ps} : Peak Simulated flow

Q_{po} : Peak Observed flow

$Q_{o(i)}$: Observed flow value at moment i

$Q_{s(i)}$: Simulated flow value at moment i

V_s : Simulated total runoff volume

V_o : Observed total runoff volume

The NSGA-II algorithm aims to minimize the function, however, the NSE value for a perfect model is closer to 1. Here, in case of the function E_2 , the NSE is subtracted from 1 because according to the model performance criteria for NSE as listed in **Table 7**, a satisfactory model must have the NSE value greater than 0.5 (Moriasi et al., 2015). Additionally, due to limitations of the NSGA-II algorithms such as longer time calculations, convergence issues, constraints are introduced to streamline the process and effectively optimize the model's performance (Blank et al., 2020). These constraints aid in monitoring the optimization process given our time and computational capacity limitations for this research study. The constraints used are as follows:

$\mathrm{G}_1 = \mathrm{E}_2$ - 0.5, if E_2 > 0.5 else 0 [4]

This constraint ensures E_2 <= 0.5 at NSE value of at least 0.5.

G_2 = 0.5 - E_2 , if E_2 < 0.5 else 0 [5]

This constraint ensures E_2 >= 0, guiding the NSE value to be of satisfactory level while maintaining the NSE values <=1.

A singular objective, E_2, is selected in the case of single objective function strategy, while the multi-objective function strategy includes all the functions and constraints as listed above. In this particular case of the drainage network, single objective and multi objective strategies used for the optimization of the model are performed and compared to understand which of them yields better results. They following sections provide a more detailed explanation on the strategy implied in this research study:

a. Single objective function strategy

This strategy involves selection of one objective function at a time E_2 for the optimization. Out of three nodes and five rainfall events selected as explained in section **4.2.2**, only one node and one rainfall event were selected for the optimization of the drainage network. This strategy of optimization was proceeded as follows:

1. **Selection :** One node [26787], one rainfall event [Event number 41] and one objective function [E_2] were selected.
2. **Optimization :** GA for 20 population size and 10 no of generations was run for the optimization of the model.
3. **Validation :** The remaining objective functions E_1 and E_3 were calculated to compute the errors for the same node outputs.

The ideal solution was determined as the set of parameter values that resulted in the lowest objective function (E_2) error value across all the simulation performed by the GA. The subsequent error E_1 and E_3 are calculated and compared against the multi objective function strategy outputs to determine which strategy yields better results.

b. Multi objective function strategy

This strategy involves selecting all the objective functions E_1, E_2, and E_3 for the optimization of the model. The optimization strategy was proceeded as follows:

1. **Selection :** One node [26787], one rainfall event [Event number 41] and all objective functions were selected.
2. **Optimization :** NSGA-II algorithm was employed for the optimization of the model for population size 20 and total number of generations 10. The optimal parameters values were then obtained from the simulation run.
3. **Validation :** The errors were compared against the respective errors obtained from single objective function strategy for the same rainfall event. Additionally, the errors were validated for the other nodes for the same rainfall event.

The NSGA-II algorithm for the multi objective optimization determines the optimal solution using the approach as described in section **2.3** for this strategy. Initially, a pareto front encompassing the non-dominated solutions is created. From this Pareto front, a knee point solution is selected that offers the most balanced tradeoff amongst the objective functions provided. This knee point solution indicates the optimal parameter values, ensuring an equitable compromise between the objectives and delivering the most desirable outcomes.

c. Hybrid optimization strategy

This strategy involves utilizing the advantage of both single and multi-objective function strategy by selecting all the objective functions E_1, E_2, and E_3 for the optimization of the model at all nodes. The optimization strategy was proceeded as follows:

1. **Selection :** All nodes [7093, 26787, and 26817], one rainfall event [Event number 41] and all objective functions were selected.
2. **Optimization :** NSGA-II algorithm was selected for the optimization of the model for population size 20 and total number of generations 10. The optimal parameters values were then obtained from the simulation run.
3. **Validation :** The errors were validated for the other nodes for the different rainfall events.

The optimal parameter settings are determined using the same approach as followed in the multi-objective optimization strategy ensuring the equilibrium between the objective functions and solution yielding the most effective overall performance.

The results from all of these strategies are compared against one another and analyzed in detail in section **5.3**. The two statistical metric errors used to evaluate the performance of the model are Root Mean Square Error (RMSE) and Nash- Sutcliffe Efficiency (NSE) calculated by the given formulas below.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{N}\left(Q_{s(i)} - Q_{o(i)}\right)^2}{N}} \quad [a]$$

$$NSE = 1 - \frac{\sum_{i}^{N}\left(Q_{s(i)} - Q_{o(i)}\right)^2}{\left(Q_{o(i)} - \overline{Q_o}\right)^2} \quad [b]$$

Where,

$Q_{o(i)}$: Observed flow value at moment i

$Q_{s(i)}$: Simulated flow value at moment i

$\overline{Q_o}$ = Average observed discharge

N = No. of data

The RMSE is the square root of the standard error of the estimation between the simulated and observed values in regression analysis. It is typically done for the model outputs with the same units. The NSE is the normalized statistical computation which evaluates the variance relative to the observed data, also known as noise calculation. The evaluation criterion for the respective values of NSE interpreting the quality of the model is listed in the table below:

Table 7 : NSE values Interpretation (Moriasi et al., 2015)

NSE Values	Interpretation
NSE > 0.8	Very Good
0.7 ≤ NSE ≤ 0.8	Good
0.5 ≤ NSE ≤ 0.7	Satisfactory
NSE < 0.5	Not Satisfactory

4.4 Interpretation of the results

The results obtained from the aforementioned steps were analyzed based on the knowledge and insights obtained from the studies done from the literature review and supervisor consultation. Additional literature reviews and studies were conducted in a parallel manner during the research period at any moment when needed. The findings and analysis of the results obtained from the research are described further in detail in **Chapter 5**.

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Chapter 5. Results and discussion

5.1 Rating curve analysis

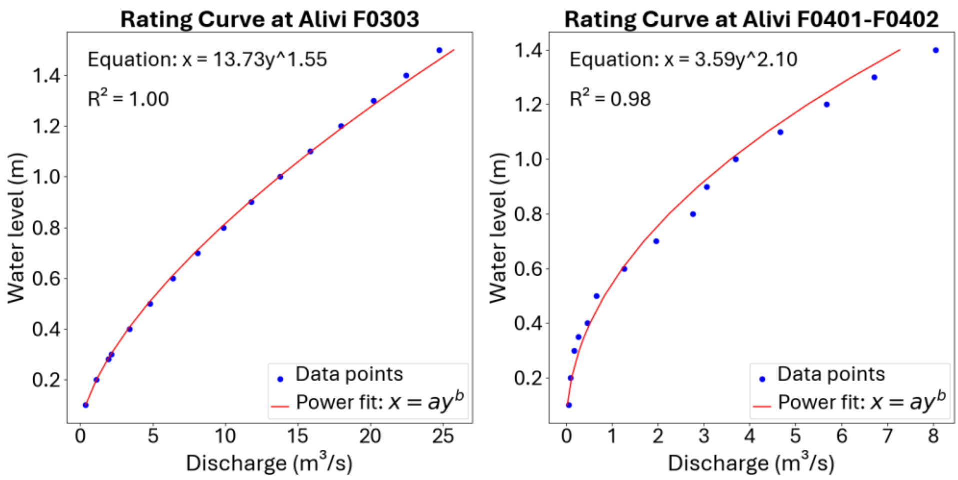
In order to understand the quality of data dealt in this research study, the rating curves of the selected water level sensor (limnimeters) as mentioned in section **4.2.2** were further studied to ensure the better performance and evaluation of the simulated models. The rating curves, shown in **Figure 11** depict multiple relationship between the discharge and stage for these sensors. The sensors are mounted to the wall as shown in **Figure 9**, suggesting that different rating curve equations were used to calculate the discharge values over various time periods. Thus, simulations for rainfall events 41 and 26 were conducted and the observed discharges values derived from the rating curves and the simulated discharges were compared one against the other across three distinct cases. This process was done solely to check the quality of data and determine whether it was needed to form a new rating curve equation to produce the discharge values used as calibration data. The three cases are as follows:

Case A: Using original discharge values

The obtained discharge values from the Sentilo platform were used as it is.

Case B: Developing a new rating curve

A new rating curve was developed using recent data of water level and discharges for the selected limnimeters provided by the municipality to produce a new set of discharge values for corresponding events. These were then used as the observed discharge.



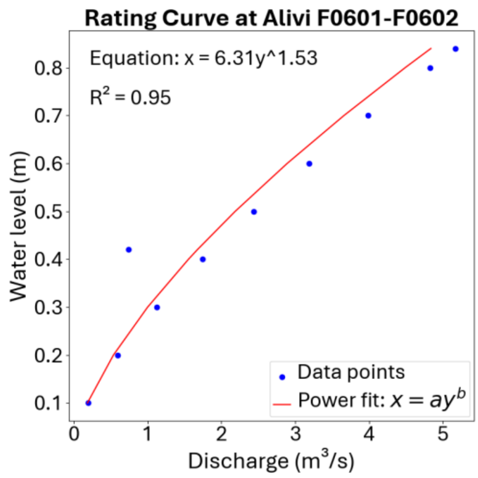


Figure 17: Rating curve at Selected Nodes (Case B)

Case C: Creating a rating curve using recent year data (2024)

A rating curve from the observed discharge values and water level corresponding to the recent year i.e. 2024 obtained from the Sentilo platform was formulated. From that equation, a new set of discharge values was calculated.

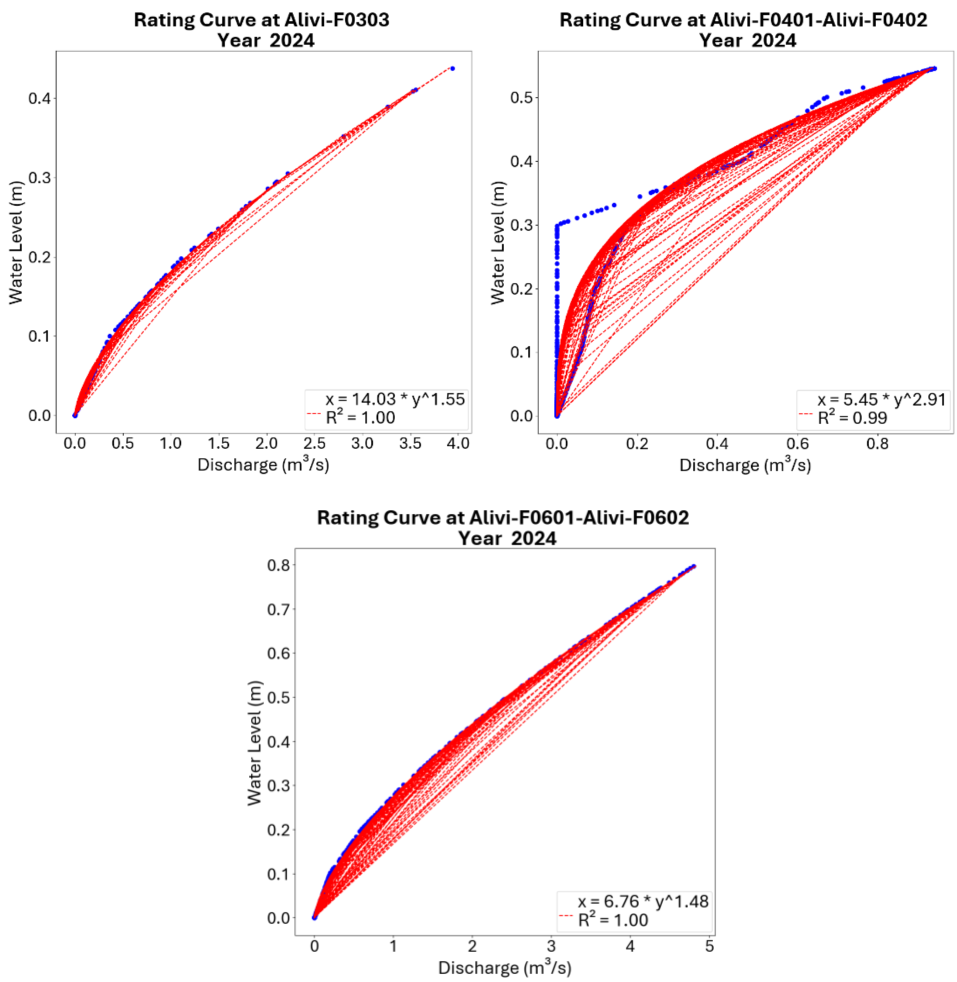


Figure 18: Rating curve at Selected Nodes (Case C)

The statistical measures RMSE and NSE were considered for the comparison of quality discharge values across the three cases. Plots showing the observed and simulated discharges for one of the sensors for rainfall event 41 are shown in **Figure 19**, **Figure 20**, and **Figure 21** for Cases A, B and C respectively. From the figures, it can be concluded that the discharge values obtained from the Case C shows better performance with higher NSE values amongst all simulations. Thus, the discharge calculated from Case C was selected as observed data for further simulations evaluations.

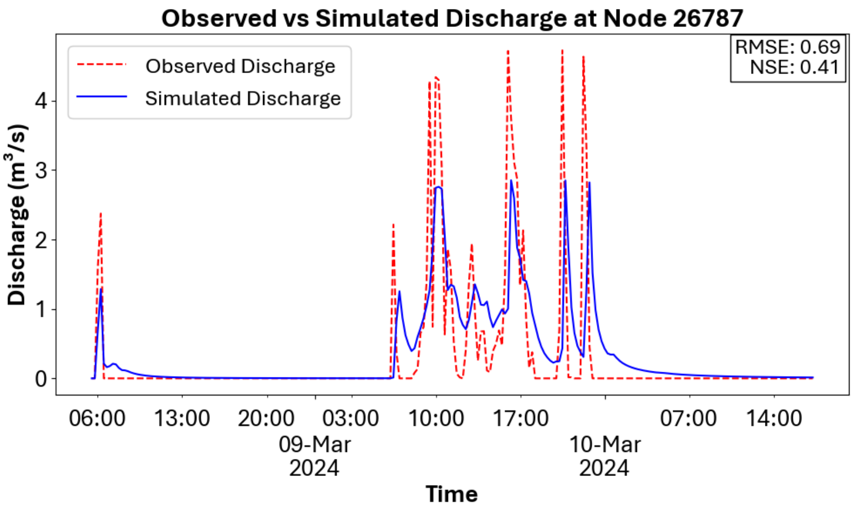


Figure 19: Case A simulation

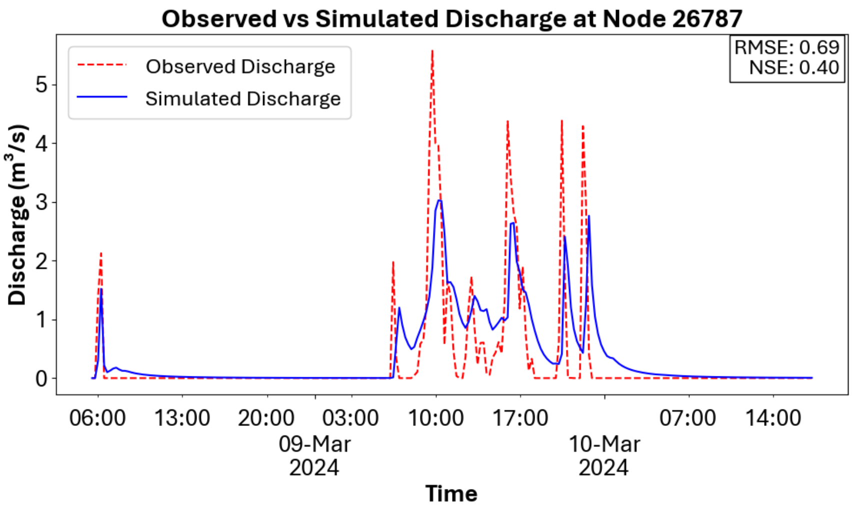


Figure 20: Case B simulation

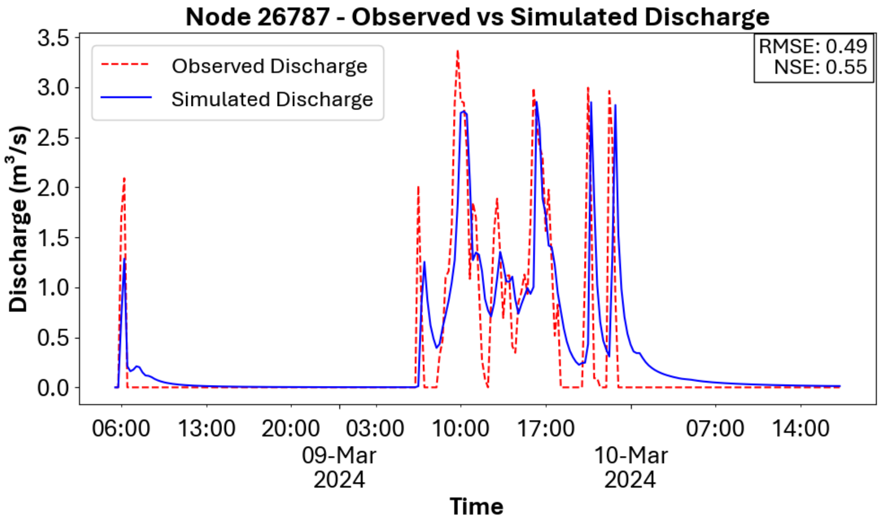


Figure 21: Case C simulation

5.2 Parameter sensitivity analysis

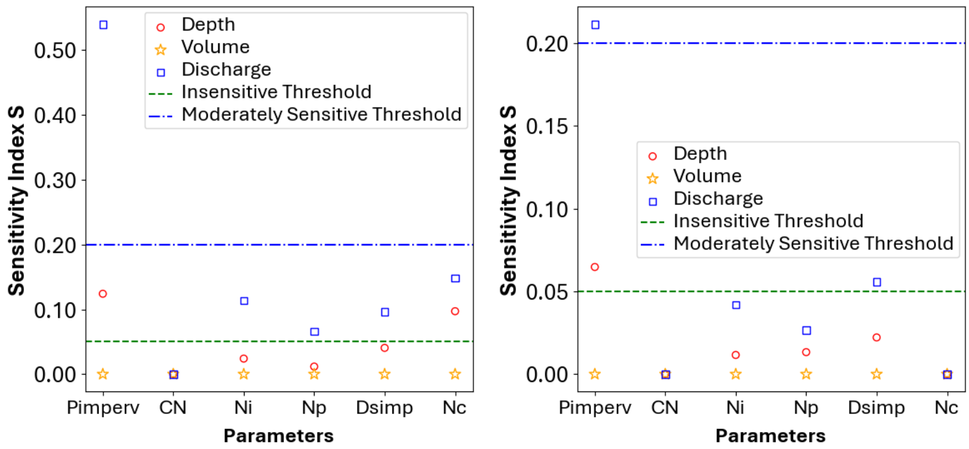


Figure 22: Parameter sensitivity analysis for rainfall event 26 (left) and rainfall event 41(right)

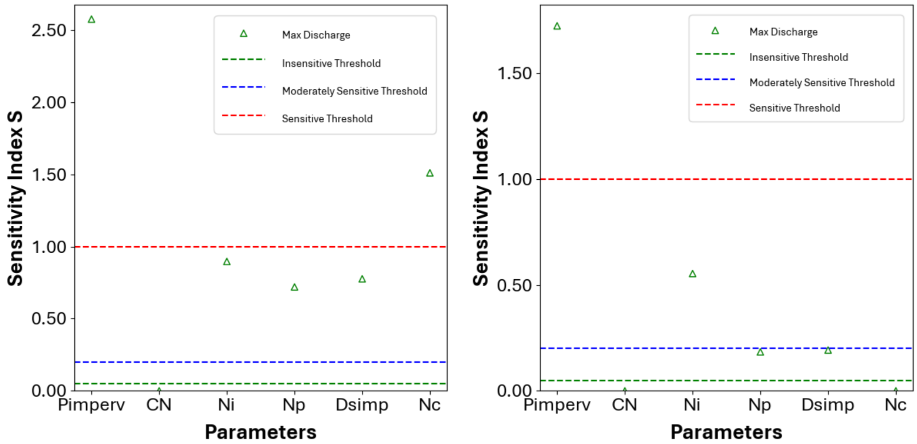


Figure 23: Maximum discharge parameter sensitivity analysis for rainfall event 26 (left) and rainfall event 41(right)

The above **Figure 22** and **Figure 23** illustrate the results of sensitivity analysis done using the Morris screening method for two distinct rainfall intensities events 26 and 41. This approach facilitates the study of the influence on the model outputs such as depth, volume, discharge, and maximum discharge while changing the parameters Pimperv, CN, Ni, Np, Dsimp, and Nc individually one at a time, also known as the local approach. The sensitivity of the parameters for the respective model output results are found to vary with the change in the intensities of the rainfall event.

Overall, **Figure 22** clearly depict that the parameters influence the model outputs more in the case of rainfall event 26 as compared to the rainfall event 41. However, it is noticeable that the parameter CN shows the lowest sensitivity index for all the model outputs for both events 26 and 41. All parameters exclusively lie below the insensitive threshold ($|S|$ < 0.05) for volume outputs indicating very little to no influence of the parameters in the volume model outputs for both rainfall events 26 and 41. As shown in **Figure 22**, in case of rainfall event 26, all parameters except CN show a moderate sensitivity index for the discharge outputs, while parameter Pimperv being the most influential one amongst all; with a greater sensitivity index (0.2 < $|S|$ < 1.0) lying above the moderately sensitive threshold. However, for rainfall event 41, parameter Pimperv shows greater sensitivity and Dsimp influence the discharge moderately while the rest of them lie below the insensitive threshold. As for the depth resulting from the model simulations for rainfall event 26, the parameters Dsimp, Ni, and Np have lower sensitivity indexes and the parameters Pimperv, and NC have moderate sensitivity indexes. For the rainfall event 41, the depth is moderately influenced by the Dsimp parameter alone, whilst rest have little to no influence as depicted in **Figure 22**.

In the case of parameter sensitivity for the maximum discharge, looking at **Figure 23**, it is clear that the change in parameters influence the model simulations more for the rainfall event 26 as compared to rainfall event 41. The parameters Pimperv and Nc contribute greatly to the simulation results with sensitivity index $|S|$ > 1.0 lying in the oversensitive threshold for the rainfall event 26, while the rest lie in the sensitive threshold except for the CN which shows very little influence with sensitivity index below the insensitive threshold. As for event 41, the parameter Pimperv contributes greatly to the maximum discharge results with a high sensitivity index ($|S|$ > 1.0). Parameters Ni depict the sensitivity index in the sensitive threshold, parameters Np and Dsimp with moderate sensitivity index in addition to parameters CN and Nc showing little to no influence in the model simulation results of maximum discharge.

From the above figures, it can be seen that although the discrepancy in the sensitivity index for different rainfall events is minor for majority of the parameters, there are still some variations aiding the identification of the sensitive and insensitive parameters (e.g. CN) in this scenario. Thus, it is advised to perform the Morris screening method for sensitivity analysis for different perturbation ranges or follow a global approach for parameter value variations for better recognition of the sensitive parameters. For this reason, the parameters were varied, specially the Curve Number (CN), since in the previous analysis it showed no influence to all the model outputs for both of the events.

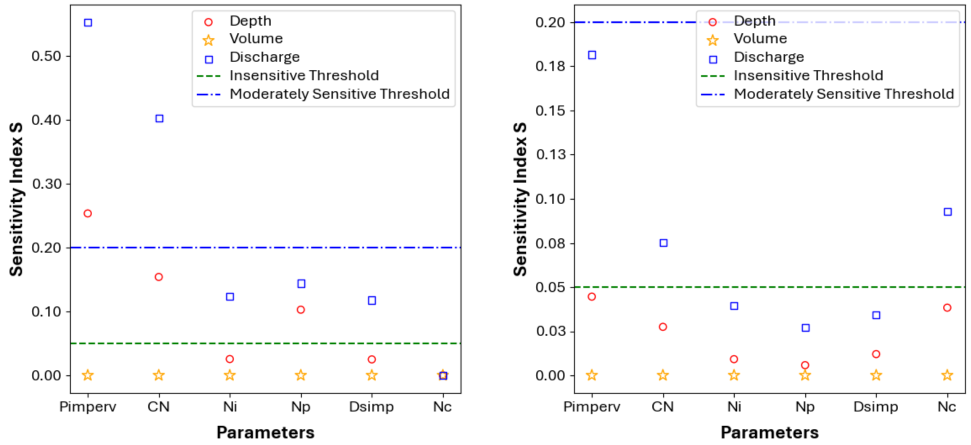


Figure 24: Parameter sensitivity analysis for rainfall event 26 (left) and rainfall event 41(right)

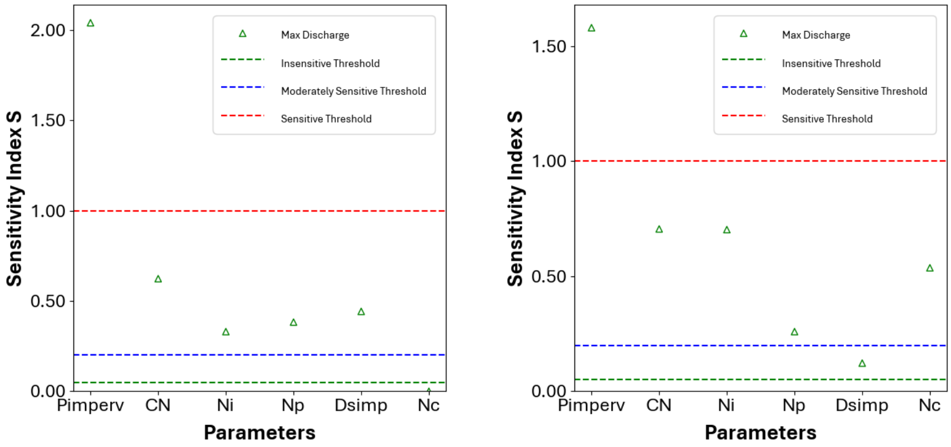


Figure 25: Maximum discharge parameter sensitivity analysis for rainfall event 26 (left) and rainfall event 41(right)

The variation of sensitivity index in **Figure 22** and **Figure 24** shows how the parameters influence one another to a slight change in their values. With an increment in the CN, the sensitivity of the CN to the model outputs became more visible for both rainfall events while in general the other parameters showed irregular pattern of behavior. For example, parameters Ni, Np and Dsimp showed greater influence than before for the rainfall event 26, while the same parameter showed lower sensitivity than earlier for the rainfall event 41. Furthermore, for the case of Nc, there was found to be little to no influence to the model outputs in the new analysis (**Figure 24**) which had moderate influence on the discharge and depth outputs of the model as shown in **Figure 22**. In case of the event 41, both CN and Nc depict moderate influence on the discharge and depth outputs in **Figure 24** as compared to the lower sensitivity index in **Figure 22**. Likewise, the parameters tend to follow a similar pattern for the maximum discharge outputs of the model simulations in **Figure 25**.

In order to understand the characteristics of the parameters influencing the model outputs more clearly, a statistical measure NSE was computed comparing the observed and simulated outputs for each simulation of parameters change. The **Figure 26** depict the NSE values for the discharge outputs corresponding to the simulations done in **Figure 22.** It can be clearly seen that the NSE is not influenced by the CN for both rainfall events 26 and 41 along with the Nc for event 41 as shown in **Figure 22** . However, the nature of the plots for Nc, Ni, Np, and Dsimp in **Figure 26** for both rainfall events 26 and 41 depict a non-linear relationship with highly rugged nature of the NSE values with respect to the change in the parameters value. The presence of such troughs makes it challenging to traverse the environment and identify if a trough is the global optimum or only a local optimum. These sort of fitness landscapes are often complicated for real world problems (Maier et al., 2019). Drainage network simulations could be a perfect example of this.

This shows that the algorithm we need to deal has to be tuned in such a way that each parameter is determined that strikes an optimal equilibrium between the exploration (increasing diversity i.e. population size) and the exploitation (intensive search), adjusting to the specific attributes of the fitness inherent in the problem. Genetic algorithms have such unique features which allows the problem to escape the local optima within the fitness landscape whilst maintaining a rapid convergence towards the global or near-global optima (Maier et al., 2019). Thus, it was concluded that use of the GAs would lead to better optimal results for the drainage network calibration.

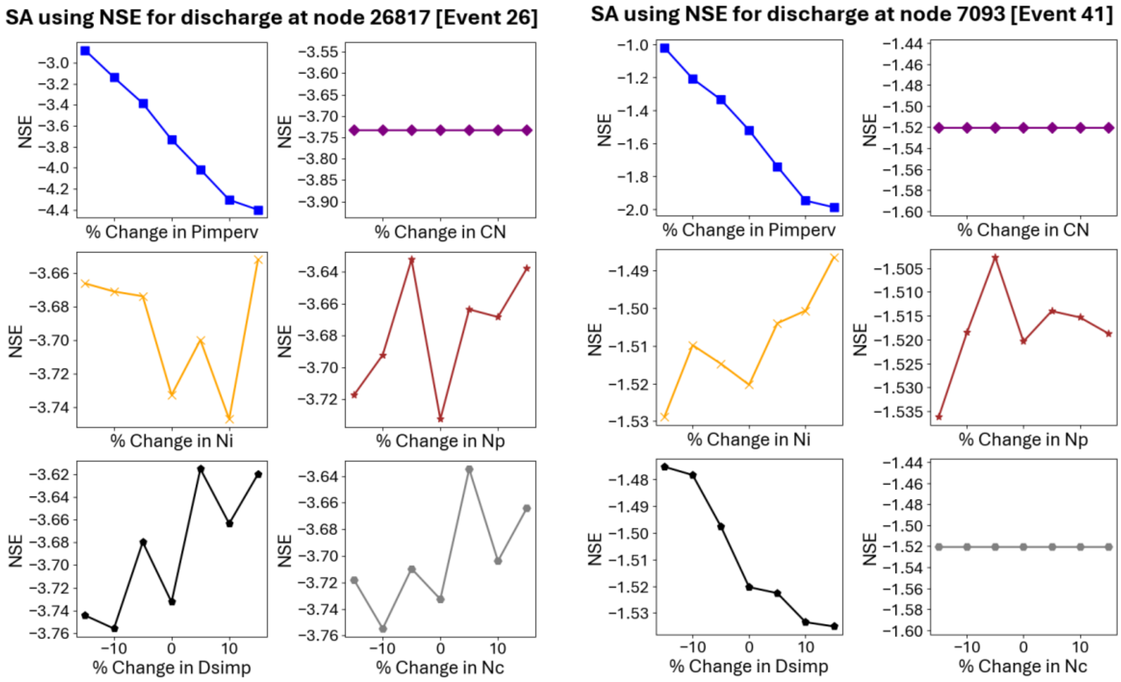


Figure 26: Discharge parameter sensitivity analysis using NSE for rainfall event 26 (left) and rainfall event 41(right)

5.3 Parameter optimization

The results obtained from the optimization algorithm following each strategy as mentioned in section **4.3** are discussed in this segment. The individual result from each strategy is discussed, followed by a comparative analysis, highlighting the distinct advantages of each approach in optimizing the same drainage model. This comparative analysis will allow us to have a deeper understanding of the benefits and contributions of each approach in improving the model's performance.

5.3.1 Single objective function strategy

With the implication of GA, the model was optimized for a rainfall event. The parameter values leading to the minimal error value of the objective function (E_2) were selected as the optimal solution. The logic was simple and straightforward, maximizing the NSE values to improve the model's performance over the given time period. However, it is important to note that the least error doesn't necessarily gives out the maximum NSE value. Hence, the constraints proposed play a fundamental role ensuring that the NSE values lie in the range that guarantees satisfactory model's performance. Out of the 200 simulations performed, the simulation run corresponding to the generation (Gen) 10 and simulation (Sim) 6 was considered to be the optimal simulation run with a minimal error value of E_2 (0.44) resulting in maximum value of NSE (0.56) indicating satisfactory model's performance as per **Table 7**.

The subsequent values of the objective function E_1 (minimizing peak error) and E_3 (minimizing volume error) are 0.5 m^3/s and 2.6 m^3 respectively. Although, the low value of E_1 depict the minimal error in prediction of the peak discharge value during the specified event, it is found to be slightly underestimated as depicted in **Figure 27**. This demonstrates that while the single objective function works effectively for one specific objective function at one specific node for one rainfall event by maximizing the model's performance for this particular metric, it does not account the rest of the objective functions and performance metrics for flood prevention and quality management comprehensively.

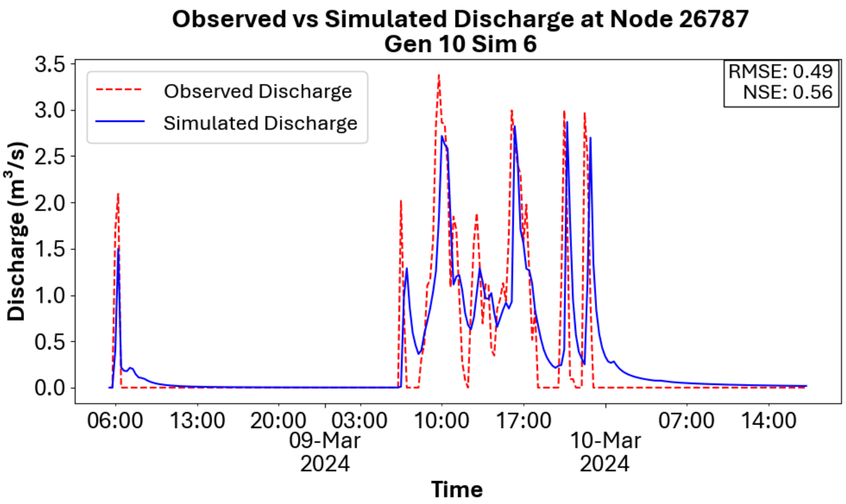


Figure 27: Observed vs Simulated Discharge at node 26787 corresponding to optimal solution parameters simulation using single objective function strategy

Table 8: Optimal parameter values obtained from single objective function strategy optimization

N-imperv	N-perv	N-conduit	Curve Number	Destore-imperv	% Imperv
0.0115	0.398	0.0131	80.382	1.888	51.222

In addition to this, the discharge simulation outputs for the rest of the nodes (**Figure 28**) were obtained from the simulation with optimal parameter setting values as listed in **Table 8.** The respective statistical errors of the discharge outputs were calculated. They indicated that while the model performed satisfactorily for the evaluation node for one objective function, the lower values of NSE indicated decline in model's performance when validated across other nodes. Additionally, the objective values E_1, E_2, and E_3 were calculated for the validation nodes as listed in **Table 9**. The comparative analysis of these values with those obtained from multi-objective approach is detailed in the subsequent section.

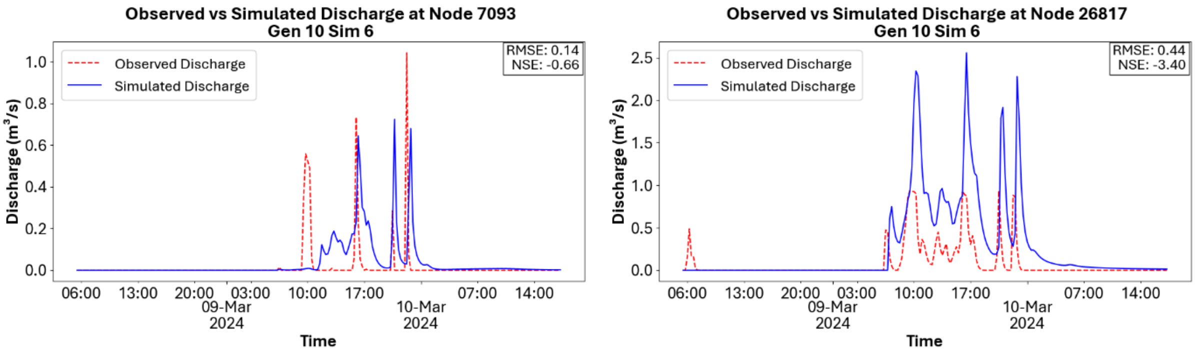


Figure 28: Observed vs Simulated Discharge at node 7093 and 26817 corresponding to optimal solution parameters simulation using single objective function strategy

Table 9: Objective function values at all nodes obtained from single objective optimization

	Optimization node	Validation nodes	
	Node 26787	Node 7093	Node 26817
E_1	0.50	0.32	1.62
E_2	0.44	1.66	4.40
E_3	2.60	2.60	2.60

5.3.2 Multi objective function strategy

The multi-objective strategy aims to provide a balance between all the objective functions proposed i.e. reducing the peak error, volume error and maximizing the NSE value for better model performance. The use of NSGA-II algorithm provided a comprehensive optimization of the drainage network, achieving a proper trade-off amongst the objective functions as depicted by the Pareto plot in **Figure 29**.

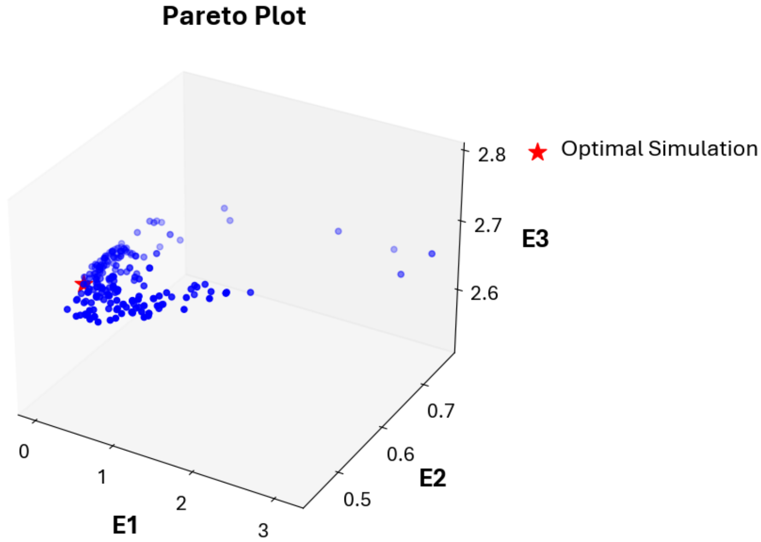


Figure 29: 3D Pareto Plot corresponding to Multi objective function strategy optimization from NSGA-II [E_1, E_2, and E_3]

The Pareto plot allows to visualize the possible set of solutions that could satisfy all the objective functions. However, it was found that the objective function E_3 yielded the same error value across all simulations. This suggests a potential initial discrepancy in the observed volume data or that the function E_3 is already close to its minimum feasible value, causing each new population generated by the algorithm to result in minorly varied error values. Additionally, it also indicates that the Pareto front won't be affected by its exclusion. Thus, a pareto plot highlighting the relation between the objective functions E_1,and E_2 was generated for better visualization of the tradeoffs amongst them. To further enhance the clarity, the Pareto curve was constructed excluding all the values of E_1 greater than 1. This aided in narrowing the analysis to the most critical space of the Pareto front making the curve's characteristics more discernible.

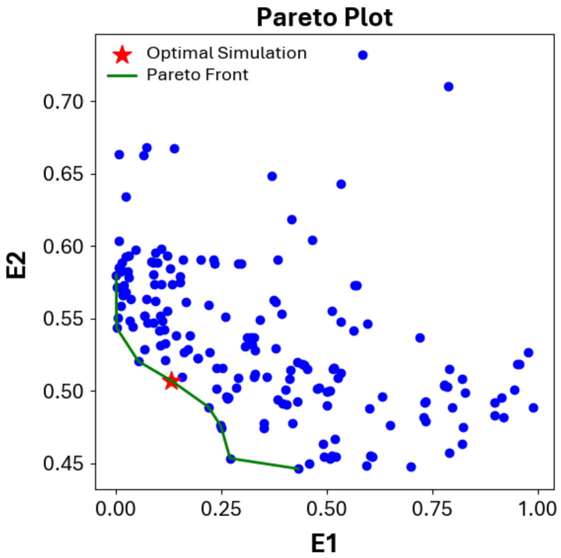


Figure 30: 2D Pareto Plot corresponding to Multi objective function strategy optimization from NSGA-II [E_1 and E_2]

The optimal solutions are selected based on the crowding distance amongst the solution sets as explained in section **2.3**. balancing all three objectives. This crowding distance aids in determining the Pareto front (**Figure 30**) comprising of all the non-dominated solutions. From this pareto front, a knee-point solution was selected representing the optimal parameters sets that ensures a balanced trade-off between the objective functions.

Out of the 200 simulations performed, the simulation run corresponding to the generation (Gen) 9 and simulation (Sim) 15 was considered to be the optimal simulation run. The minimal error values obtained from this non-dominated sorting method at the calibration node are 0.27, 0.45, and 2.6 for E_1, E_2, and E_3 respectively. However, as mentioned earlier, this minimal error does not necessarily indicate the least error amongst all of the solutions. To maintain the balance between the objective functions and the model's performance criteria, the NSE of the corresponding simulation was taken into account through the constraints outlined in the algorithm. Thus, the error value E_2 represents the minimal error value that guarantees the model's performance to be of satisfactory level as depicted in **Table 7** (Moriasi et al., 2015).

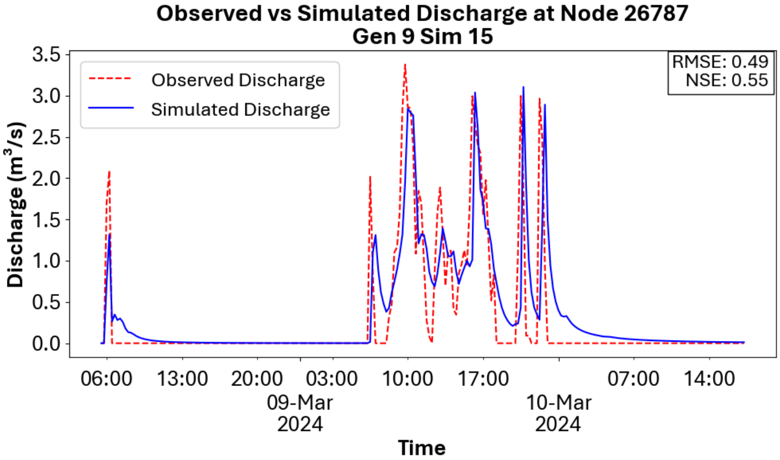


Figure 31: Observed vs Simulated Discharge at node 26787 corresponding to optimal solution parameters simulation using multi objective function strategy

Despite the slight decrease in the E_2 by 0.01 in comparison to the single objective function strategy, the decrease in the E_1 by 0.23 indicates that multi objective function strategy yields overall better model's performance as the primary goal of this strategy is to achieve balanced trade-off amongst all optimizing objectives.

Table 10: Optimal parameter values obtained from multi objective function strategy optimization

N-imperv	N-perv	N-conduit	Curve Number	Destore-imperv	% Imperv
0.0117	0.173	0.0129	81.837	1.623	53.052

Table 11: Objective function values at all nodes obtained from multi objective function strategy optimization

	Optimization node	Validation nodes	
	Node 26787	Node 7093	Node 26817
E_1	0.27	0.26	1.60
E_2	0.45	1.81	5.35
E_3	2.60	2.60	2.60

Furthermore, to validate the optimal solution obtained from the NSGA-II algorithm, the objective functions values were calculated at the nodes 7093 and 26817 obtained from the simulation using the optimal parameter values listed in **Table 10**. These objective function values as listed in **Table 11** indicate that the use of multi-objective function strategy yielded better results for all the objectives function at the optimization node compared to single objective strategy. Thus, this comparison concluded that multi-objective function optimization strategy provided more robust solutions, effectively balancing all the objectives at the optimization node unlike the single-objective function optimization. It ensured that improvements in one specific area such as model's performance, do not disproportionately worsen the other areas like flood prevention and quality management, yielding a more versatile and robust model unlike the single objective optimization where the primary goal was to just maximize the NSE while the other objectives of peak discharge and volume management were not considered.

However, this improvement was not necessarily reflected in the model while being validated at other nodes of the drainage network. The lower NSE values for discharge outputs at nodes 7093 and 26817 further conclude less robust model as depicted in **Figure 32.**

A comparative analysis of the performance metrics at nodes other than the optimization node for single and multi-objective optimization as depicted in **Figure 28** and **Figure 32** respectively and **Table 14**, demonstrates that single objective optimization outperforms the multi-objective optimization in terms of NSE metrics. This superiority is because, the single objective is tailored to optimize one specific metric, the NSE, resulting a model that outshines in this particular metric, despite some minor discrepancies.

In contrast, the multi-objective optimizations strategy aims to balance several metrics rather than just one, which results in potential comprises in individual metrics to achieve an overall equilibrium amongst the multiple objectives. Nonetheless, the multi-objective optimization yields more strength in minimizing the peak discharge errors, critical for flood prevention, as evidenced by its performance in this area (**Table 11** compared to **Table 9**).

This comparison analysis underscores that the effectiveness of the optimization strategy is clearly based on the specific goals of the model and the complexity of the system being studied. For simpler models focused primarily on the NSE metric or one main goal, the single objective optimization approach may suffice. However, for more sophisticated models requiring a balanced inclusivity of all objectives, the multi-objective optimization strategy provides a valuable framework to achieve more robust and versatile solutions.

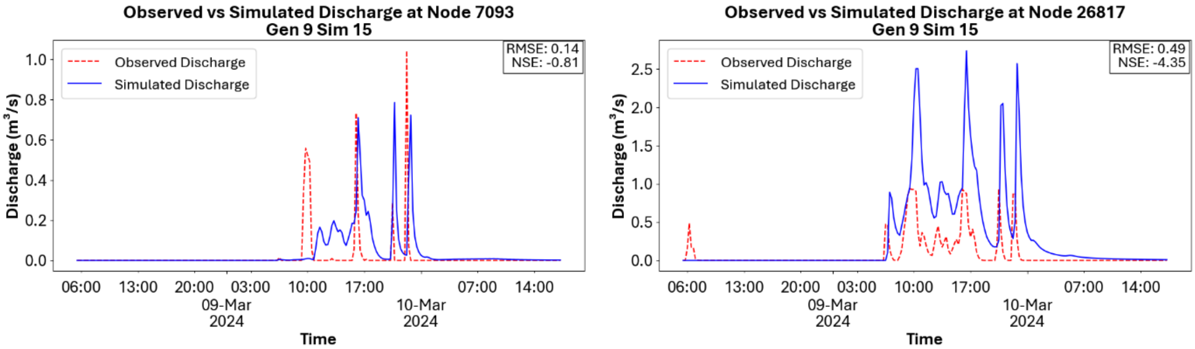


Figure 32: Observed vs Simulated Discharge at node 7093 and 26817 corresponding to optimal solution parameters simulation using multi objective function strategy

5.3.3 Hybrid optimization strategy

The hybrid optimization strategy introduced significant complexity in the overall optimization process leveraging the advantages of the multi-objective function strategy. This approach included all objective functions across all three nodes for two rainfall events 26 and 41, resulting in a total of nine objective functions with six constraints introduced to streamline the optimization process. The algorithm performed SWMM simulations in an iterative manner for both rainfall events, calculating each objective functions, and updating the Pareto front for each generation of population i.e. the random set of parameter value to obtain the best optimal solution possible.

On achieving the error values of the objective functions, it was noted that the objective function for volume error E_3 was seen to produce similar values with slight discrepancies as it did in the multi-objective [explained in section **5.3.2**]. As discussed earlier, this indicates a potential initial discrepancy in the observed data or that the values are already so close to the feasible value that negligible differences were found for any parameter changes. Thus, taking this into account that Pareto front won't be affected due to the exclusion of the Error E_3 , the Pareto front was plotted encompassing the average of E_1 across all nodes for rainfall events 26 and 41 along with average of E_2 in similar manner as depicted in **Figure 33**. Like earlier, the error E_1 greater than 1 were excluded for better clarity and visualization of the Pareto curve. Then, from the simulation performed using the optimal solution parameter settings as listed in **Table 12**, the corresponding discharge outputs and its performance metrics across all nodes (**Figure 34**) was obtained. It can be a seen that the model performs satisfactory for node 26787 during rainfall event 41 with NSE value >0.5. However, the NSE values across other nodes were found to be lower, suggesting room for improvement in the model optimization process.

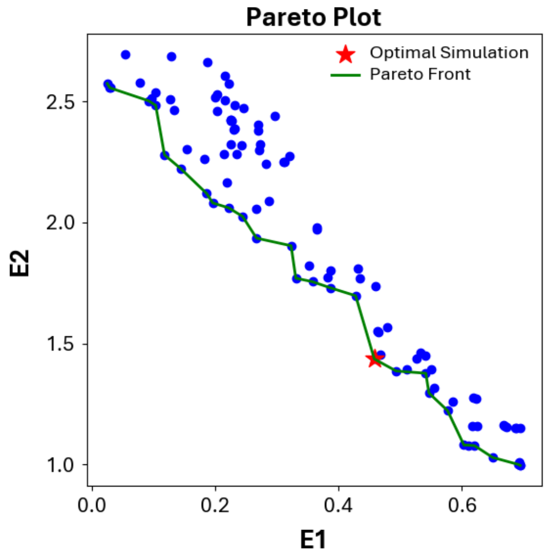
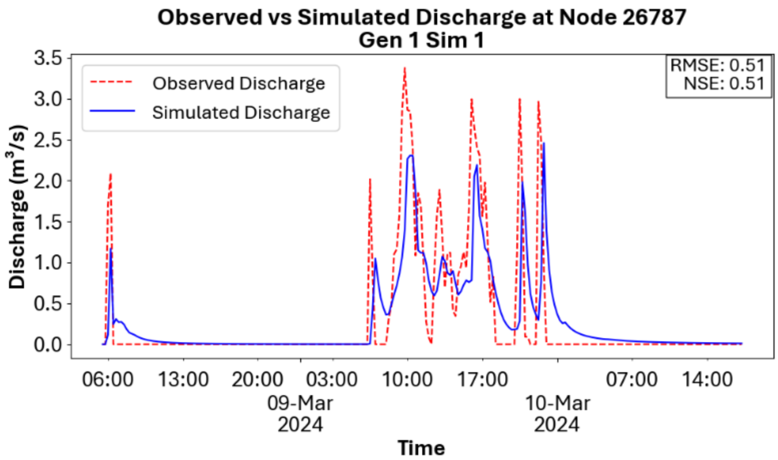


Figure 33: 2D Pareto Plot corresponding to hybrid optimization strategy from NSGA-II [E_1 and E_2]

Table 12: Optimal parameter values obtained from hybrid optimization strategy

N-imperv	N-perv	N-conduit	Curve Number	Destore-imperv	% Imperv
0.021	0.166	0.016	66.41	1.411	46.675



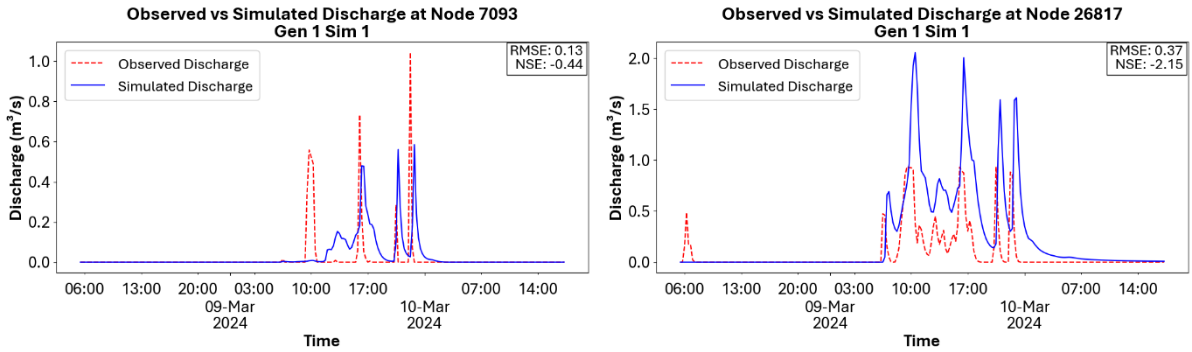


Figure 34: Observed vs Simulated Discharge at node 26787, 7093 and 26817 corresponding to optimal solution parameters simulation for rainfall event 41 using hybrid optimization strategy

Nevertheless, upon comparative analysis of all the performance metrics obtained for all optimization processes (**Table 14**), it was observed that the overall performance metrics from this hybrid optimization approach outshine all other approaches. Although, the peak discharge error E_1 (**Table 13**) was slightly compromised, the NSE values from hybrid strategy was found to outperform the other approaches consistently across all other nodes. The main aim of the multi-objective strategy is to achieve a balanced trade-offs between the objectives. As a consequence, minor compromises in individual metric are anticipated, while improving the overall metric performance. This allows a holistic approach to management of the drainage network by providing more robust and versatile drainage models.

Table 13: Objective function values at nodes obtained from all strategies at node 26787

	Single Objective Function Strategy	Multi-Objective Function Strategy	Hybrid Optimization Strategy
$\mathbf{E_1}$	0.50	0.27	0.90
$\mathbf{E_2}$	0.44	0.45	0.49
$\mathbf{E_3}$	2.60	2.60	2.60

Table 14: NSE and RMSE values at nodes obtained from all strategies

	Single Objective Function Strategy		Multi-Objective Function Strategy		Hybrid Optimization Strategy	
Nodes	**NSE**	**RMSE**	**NSE**	**RMSE**	**NSE**	**RMSE**
26787	**0.56**	**0.49**	**0.55**	**0.49**	**0.51**	**0.51**
7093	-0.66	0.14	-0.81	0.14	**-0.44**	**0.13**
26187	-3.40	0.51	-4.35	0.51	**-2.15**	**0.37**

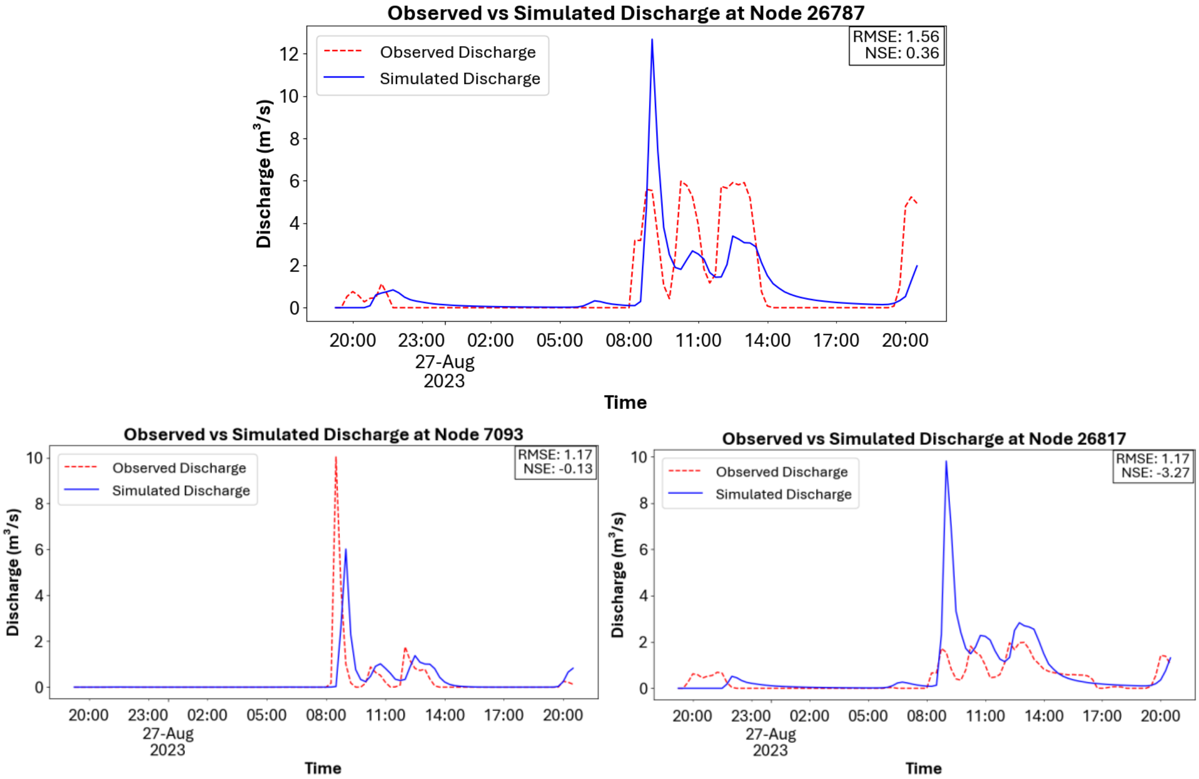


Figure 35: Observed vs Simulated Discharge at node 26787, 7093 and 26817 corresponding to optimal solution parameters simulation for rainfall event 26 using hybrid optimization strategy

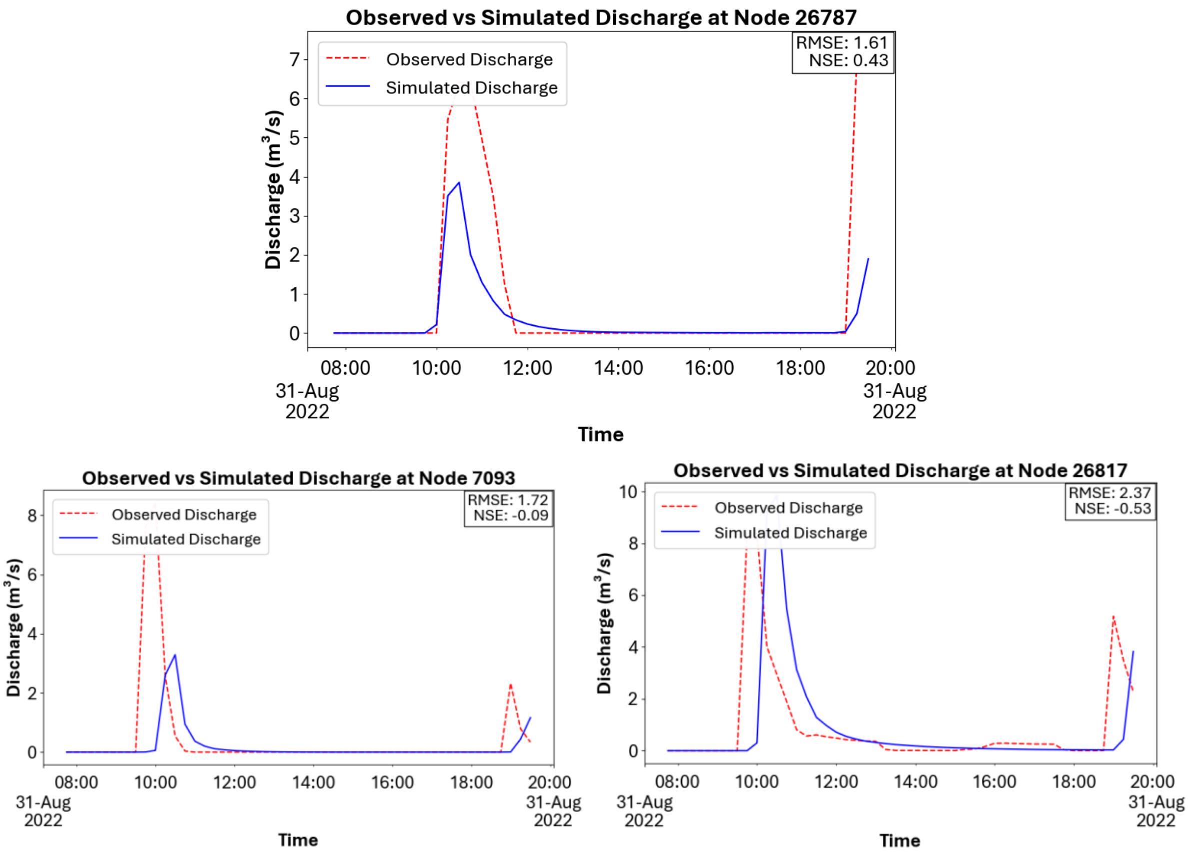


Figure 36: Observed vs Simulated Discharge at node 26787, 7093 and 26817 corresponding to optimal solution parameters simulation for rainfall event 6 using hybrid optimization strategy

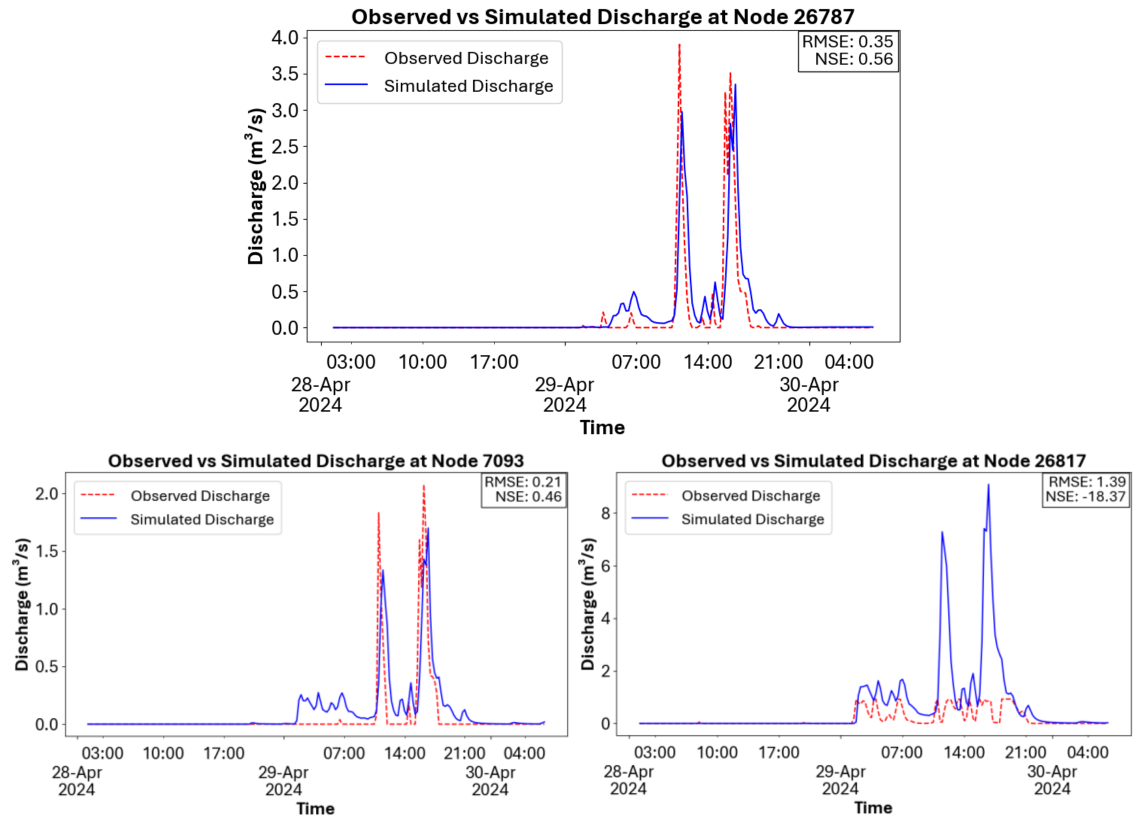


Figure 37: Observed vs Simulated Discharge at node 26787, 7093 and 26817 corresponding to optimal solution parameters simulation for rainfall event 46 using hybrid optimization strategy

Lastly, the model, when validated against rainfall events 6 and 46 (**Figure 36** and **Figure 37**) showed a similar pattern as in the optimized model with highest performance at node 26787 and lower performance at other nodes. The multi-objective optimization technique provides the optimal solution through a Pareto front, where all the objectives are balanced. The variation in the performance at different nodes could potentially indicate the tendency of the optimization technique to improve the performance at some nodes while compromising the performance at the others. Furthermore, the value of the NSE is the highest at node 26787 for all rainfall events, suggesting better data quality at this particular node compared to the others or better model's parameter alignment at this node. Thus, the need for improvement in high quality data acquisition is highlighted from these simulations to ensure the optimization process to be equally represented at all nodes. Moreover, although NSGA-II is said to be more robust than the manual calibration to some level of uncertainty and variation, significant variability in the rainfall events could introduce uncertainties in the optimization algorithm. This can highly influence the model's performance.

5.4 Limitations

NSGA-II has been known for its wide utilization for multi-objective optimization problem due to its capabilities of handling conflicting and complex objective functions efficiently and providing a diverse set of the pareto-optimal solutions. However, in this particular research study numerous limitations are observed when applied to the parameter optimization of the SWMM model such as computational time demands, limitations of population size, convergence and diversity issues, and parameter sensitivity and uncertainties, data homogeneity assumption, and data quality and validation.

A. Computational time demands

The lengthy calculation time needed for the NSGA-II optimization algorithm is one of the most significant limitations for SWMM models. NSGA-II when coupled with sophisticated model such as SWMM; which incorporates detailed hydrological and hydraulic processes, led to prolonged total simulation periods as the algorithm demands multiple SWMM runs in order to assess the population's fitness with each iteration. Furthermore, when the model becomes more complex, like in the urban watershed management scenarios with several catchments and control mechanism, this problem is exacerbated. This makes it difficult to strike a balance between the size of the population and the number of generations under realistic time restrictions, which could result in inadequate exposure to the solution domain. The use of high-performance computers such as supercomputers or distributed computing systems could be opted for speeding up the optimization process using NSGA-II in order to address this issue. However, the use of conventional laptops in this research limited the effectiveness and efficiency of the algorithm due to the difficulty in completion of comprehensive optimizations within reasonable timeframes.

In addition to that the population size and the number of generations were realistically maintained limiting by the lengthy run times needed for each simulation in each iteration, which led to fewer generations and smaller population space. This resulted in hinderance of exploration of the population into the bigger solution space potentially leading to less-than-ideal solutions and poorer algorithm performance.

B. Convergence and diversity issues

In order to find the optimal solutions, the NSGA-II algorithm greatly relies on stochastic techniques and heuristic principles (Deb et al., 2002; Romero et al., 2010). This could result in slower convergence, especially in the intricate or noisy problem often encountered in parameter optimization of the complex SWMM model. This slow convergence increases the algorithm's likelihood of becoming stuck in local optimum rather than reaching a global optimum which ultimately lengthens the overall computational time (Zitzler et al., 2000). Furthermore, solving the SWMM models for multi-modal objective functions such as minimizing the peak flow and total volume as done in this research are particularly challenging. It is difficult for the NSGA-II algorithm to consistently find the best parameters due to rugged nature of the fitness landscape for these scenarios in absence of extensive computational effort (Michalewicz, Z, 1996).

The constraints were introduced to reduce these issues to some extent. However, this results in additional tradeoff between exploration and manipulation for generating new sets of populations potentially impacting the quality and pertinency of the final solution set.

C. Parameter sensitivity and uncertainty

The sensitivity analysis provided an idea on how the parameters influence the model outputs. However, the uncertainties associated with the input data poses major challenges. Even slight errors in the rainfall data or observed input data hinder the actual representation of the influence on the model outputs, affecting the model's performance (Fatone et al., 2021). To address the complexity of the model and the relationship between the parameters and the desired outputs, a traditional sensitivity analysis may not be enough. Thus, these uncertainties present the need for more sophisticated methods while handling the variability of the data and parameters interdependencies, to ensure that the optimization process yields better reliable solutions.

D. Assumption of data homogeneity

The model is based on the assumption of homogeneity of the drainage area by assigning the identical random parameter values within their domain range to all sub-catchments. However, in reality, the sub-catchments comprise of diverse characteristics like various land use patterns, soil types and rainfall distributions (Wu et al., 2012). The effectiveness of the optimization process could have been potentially compromised due to this oversimplification introduced in the model producing inaccurate model predictions. By addressing spatial variability in the parameters while assigning the values during the NSGA-II optimization, the accuracy and performance of the model could be improved.

E. Data quality and model validation

The quality of the input data plays a significant role in the performance of the optimization's algorithm. In this research study, the available data may not have been of optimal quality, leading to the variation in the model's performance across different rainfall events and nodes. This limitation highlights the need for high-resolution data. Additionally, the model should be validated with additional events or high-quality datasets to ensure that the optimization algorithm produces robust and versatile optimization results.

Chapter 6. Conclusions and recommendations

6.1 Conclusions

The demonstration of the NSGA-II algorithm's application coupled with the SWMM model has been successfully demonstrated in this research study for urban watershed management specifically focusing on Badalona drainage network. The NSGA-II algorithm, when coupled with SWMM provided an automated calibration framework resulting in a robust and comprehensive optimized drainage model. In this research study, it is demonstrated that the multi-objective optimization strategy provides more comprehensive solution by providing a balanced tradeoff between the various conflicting objectives such as flood prevention, and water quality management as compared to the single-objective approaches with NSE value of 0.51 (**Table 14**) indicating satisfactory performance level of the model (Moriasi et al., 2015).

The single objective approach may be sufficient in the case of optimizing for one objective for simple models such as focused in maximizing the NSE, i.e. the model's performance as depicted by the NSE value of 0.56 (**Figure 27**) showcasing satisfactory performance (Moriasi et al., 2015). However, it lacks the ability to provide a balanced inclusivity of all objectives for overall drainage network, which is required for a holistic understanding of drainage system. By employing multi-objective strategy, one can produce more robust and versatile models that aids in making better-informed decisions, through balancing various goals such as flood risk, system resilience and environmental impact of an urban drainage system. The decrease in the error values of functions E_1,and E_2 from 0.50 and 0.45 obtained from single objective optimization to 0.25 and 0.44 obtained from multi-objective optimization clearly indicate the inclusivity and tradeoff amongst the objectives through multi-objective optimization. Unlike the single-objective approach, it does not worsen the other areas like flood prevention and quality management while improving in one specific area such as the model's performance. The inclusivity of all the objective functions as in the hybrid optimization strategy leads to overall better performance of the model across all nodes of the drainage network with increase in their respective NSE values as listed in the **Table 14**.

Despite the benefits of having the automatic calibration and robust solutions through such GAs, it has also been identified that certain limitations such as computational time demands, convergence and diversification issues, limited exploration and exploitation space, etc. highlights the room for improvement while using such GAs. The simulations with time-intensive nature required for detailed hydrological and hydraulic modeling presents huge limits regarding the practicality of this approach for real-world and complex drainage areas. Thus, to overcome this particular challenge, an investment in highly advanced computing systems such as "Supercomputers" or parallel computing technologies could be opted for reducing the simulation time and improving the overall efficiency of the algorithm used (Deb et al., 2002).

Furthermore, through the sensitivity and the rating curve analysis, the importance of accurate and high-resolution data collection has been highly signified as even a slight change in the parameters possess a lot of uncertainty while obtaining the robust solutions for such complex drainage area network. Thus, in order to produce a higher efficiency model, higher quality data collection is needed.

Overall, this research provides an important contribution to the management of urban drainage systems by offering a robust framework for drainage network optimization using genetic algorithms, crucial in addressing the challenges posed by urban floods.

6.2 Recommendations

The results discussed in this research study have led to several recommendations for further exploration, as detailed in this section.

6.2.1 Computational Capabilities Enhancement

For the application of this approach to bigger and complex drainage area watersheds, it is necessary to enhance the computational capabilities. By the use of high-performance super computers, efficient algorithms could be developed for model optimization tailed for more specific aspects of it (Deb et al., 2002).

6.2.2 Improving the random sampling technique of the parameters

Unlike the homogeneity assumption made in this research study, the parameters can be experimented under realistic scenarios. For example, grouping Manning's constant coefficient based on the age or year of construction of the pipes or classifying impervious area according to the percentage of urban development in the drainage area and so on. This approach would provide a closer approximation to the real-world scenarios and could potentially yield better results.

6.2.3 Exploration of Genetic Algorithms

Although the NSGA-II results in more robust and versatile models as compared to manual calibrations, issues such as convergence and diversity challenges need to be properly addressed to have more accurate findings. Thus, research on techniques that integrate the strength of different algorithms could be recommended for future. This could result in more comprehensive and versatile model solutions.

6.2.4 Stakeholders Engagement in Solution Selection

The stakeholders engagement on decision-making while working with multi-objective optimization is critical. Although, multiple solution options can be obtained from the Pareto optimal set, different aspects such as policy considerations, socio-economic impacts and not to mention the stakeholder's preference should be taken into account while making the holistic approach for the drainage network management. This may also differ from one drainage area to another. Thus, having this additional perspective of the decision-makers to the results obtained from the algorithm is essential to developing more efficient algorithms tailored to that specific drainage network system.

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