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A Data-driven Improved Fuzzy Logic Control Optimization-simulation Tool for Reducing Flooding Volume at Downstream Urban Drainage Systems

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Highlights

1. An open-to-public tool called SWMM_FLC was developed for co-simulating fuzzy logic control and hydraulic-hydrologic procedure;

2. A data-driven method was used to train the relationship between inputs and outputs of fuzzy inference system;

3. Genetic algorithm was implemented to improve the fuzzy inference system performance by minifying the deviations between predictions and expectations;

4. SWMM_FLC can be used as an optimization-simulation tool to reduce total flooding volume at downstream urban drainage systems.

Abstract

The uncertainty of climate change and urbanization imposed additional stress for urban drainage systems (UDSs) by intensifying rainfall frequency and magnifying peak runoff rate. UDSs are among the stormwater infrastructures that can be controlled in real-time for mitigating downstream urban flooding. In this paper, a data-driven improved real-time control optimization-simulation tool called SWMM_FLC, which is based on the FLC (fuzzy logic control theory) and GA (genetic algorithm) was developed for smart decision-making of flooding mitigation. A calibrated and validated SWMM model was used for applying SWMM_FLC to explore the potential in reducing downstream flooding volume at UDSs. The results show that the data-driven enhanced GA optimization significantly reduces fuzzy system deviations from 0.22 (non_optmial scenario) to 0.07 (optimal scenario). The accumulated flooding volume reduction by up to 4.55% under eight artificial rainfall scenarios rules out the possibility of adopting SWMM_FLC as appropriate software to assist decision-makers to effectively minimize urban flooding volume at downstream urban drainage systems.

***Keywords*:** Urban drainage systems, Real-time control, Fuzzy logic control, Genetic algorithm, SWMM_FLC, Accumulated flooding volume

1. Introduction

Urban drainage systems (UDSs) are designed to collect urban runoff and convey residential discharges to receiving water bodies. However, the limited storage and conveyance capacity of UDSs yield difficulties in delaying flood peaks, buffering over-size runoff, and reducing peak water depth under extreme storm events (O'Donnell et al., 2019). Urban flooding entails adverse impacts on social, environmental, ecological, and economic perspectives and, consequently, endangers residential areas (Wing et al., 2018). These consequences include life and property losses by street overflows, traffic jam due to drainage systems' failure, health issues resulting from possible pollutant intrusion into drinking water system, species reduction because of habitat loss, pollutant over-loading in watersheds, and availability decrease of freshwater resources for meeting increased population growth (Arrighi et al., 2018). Thus, it is of great importance to keep UDSs in an adaptive status to be against the mounting flood challenges.

Historically, engineers get used to upgrading the existing stormwater grey infrastructure for reducing flood peaks or implementing new green infrastructure (GI) to mimic nature-based flood mitigation (Li et al., 2019c). However, these alternatives have some inherent disadvantages when subject to alleviate urban flooding severity. These drawbacks contain, for instance, high cost due to constructions of gray stormwater infrastructure, public open space loss due to GI implementation, and limited adaptability due to distributed low impact development (LID) practices (Di

Matteo et al., 2019; Kerkez et al., 2016). Even though these traditional solutions can provide a range of benefits in controlling urban flooding, their defects might be magnified by exceptional urbanized and climatic changes (Changnon and Demissie, 2004; Huong and Pathirana, 2013; Miller et al., 2014; Rozario et al., 2017; Wang et al., 2017, 2016; Zahmatkesh et al., 2014).

Recently, real-time control (RTC) has been widely adopted as an adaptive solution for addressing urban drainage flooding issues by installing controllers at UDSs. RTC can be considered as a dynamic, heuristic, and low-cost technique for three perspectives: optimizing operation strategy, adapting UDSs to changing conditions, and improving eco-system (García et al., 2015). By retrofitting the existing UDSs with smart device such as digital controllers and sensors, instead of renewing pipelines or re-sizing storage facilities, RTC adaptively allows existing UDSs to make full use of capacity to selectively purge retained water before the next storm comes by operating remote-controlled actuators (weirs, gates, valves, and orifices) (Wong and Kerkez, 2018). Although RTC has been applied to UDSs for over 50 years since the 1960s, there are still some gaps calling for participation and efforts (Schütze et al., 2004). One key challenge is identifying the optimal settings before implementing controller in UDSs, which involves in hydraulic and hydrology simulation-optimization process (Darsono and Labadie, 2007; Li et al., 2019b; Marinaki and Papageorgiou, 2002)

It is true that controller setting optimization is crucial for propagating RTC in UDSs field (Cembrano et al., 2004; Mullapudi et al., 2017a). RTC adaptability to watershed alterations such as land-use land-cover (LULC) change and rainfall pattern variation might not be fully exploited due to the unpredicted hydraulic stress, exceptional flood loading, heavy computational expense, and low operating efficiency (Bilodeau et al., 2018). So far, the limitation regarding RTC settings has motivated researchers to develop controller setting optimization algorithms, in order to make most of RTC effectiveness and efficiency in mitigating urban flooding (Bartos et al., 2018; Bartos and Kerkez, 2019; Duchesne et al., 2001; Muschalla et al., 2014).

Fuzzy logic control (FLC) in UDSs are attracted extensive attention for lessening urban flooding stress (Chang et al., 2008; Leitão et al., 2017; Meneses et al., 2018; Wang and Altunkaynak, 2011). FLC, which was first put forward by Zadeh, (1965), has been used in control systems for a long time. FLC is composed of membership functions and rule sets where linguistic and imprecise expressions are applied to describe their relationship (Arslan and Kaya, 2001). This quantitative relationship between membership functions and rule sets is used for controlling the model inputs and outputs (Mamdani and Assilian, 1975).

As fuzzy logic is based on the linguistic and imprecise description for networks, and thus it doesn’t need complex mathematical algorithms for FLC simulation (Deka and Chandramouli, 2008). This feature makes FLC look potentially more advantageous to improve controller performance. Moreover, FLC simplifies the control methodology and can provide easy-to-understand and easy-to-modify approaches in terms of classical or state-space settings (Krejčí, 2018; S Ostojin et al., 2011). Therefore, this paper hypothesized fuzzy logic algorithm is more suitable for improving controller performance concerning urban flooding mitigation under changing hydrologic conditions.

In the FLC, to get the outputs that are close to the anticipated values, CMFPs (Controller Membership Function Parameters) need to be tuned optimally and then be obtained efficiently. However, the initial set-up of CMFPs is based on expert knowledge while final CMFPs are normally obtained by trials and errors in the simulation process (Bingül and Karahan, 2011; Lee, 1990). Such a time-consuming manual modification procedure becomes the main disadvantage of FLC. Minimizing deviations through trying different CMFPs is an evolutionary process that can be done through different algorithms. Previous studies utilized evolutionary algorithms, for instance, genetic algorithms (GA), particle swarm optimization (PSO), artificial neural network (ANN) to reduce deviation and achieve CMFPs optimization. Jin et al. (2005) used a GA for tuning the optimal parameters of FLC in different engineering networks. Deka and Chandramouli (2008) used GA based fuzzy inference for finding the optimal operating rule of a reservoir. Ostojin et al. (2011) utilized GA to adjust CMFPs to minimize energy costs and switching totals in urban water pumping station. Their results find GA system can be transferable to other water systems with different pump sizes, wet well capacity, and inflow pattern. Rauch and Harremoës (1999) also applied GA for gaining the minimization of pollutant concentrations in urban wastewater system. Mehta and Jain (2009) considered ANN as a reliable way to train fuzzy inference systems to find the optimality of reservoir control operation. Talei et al. (2010) presented a neuro-fuzzy computational work based on fuzzy logic and ANN to order to compare the capability for simulating rainfall-runoff with SWMM tool. This artificially intelligent modeling tool was discovered to be better at peak flow routing. Shoorehdeli et al. (2007) developed a learning approach for tuning the CMFPs by using the PSO. Muthukaruppan and Er (2012) used the PSO method to tune the developed CMFPs of a fuzzy expert system and got a 93.27% accuracy.

In spite of the CMFPs optimization studies mentioned above, there is limited work considering combining real UDSs' measurements with an optimization algorithm. Since different optimization approaches generate different errors and deviations under different scenarios, it is sometimes hard to identify which single optimization approach can produce truly optimal outcomes. Zamani Sabzi et al. (2016) selected three popular optimization algorithms (GA, ANN, and PSO) and compared their performance according to the resulting error values under various scenarios. This research recommended using the algorithms with the lowest error value between outputs and measurements for finding the optimal CMFPs. Still, the shortage of integrating field monitoring and model simulation is related to the controller optimal performance (Razavi Termeh et al., 2018; Tien Bui et al., 2016), and the deviations (error values) between the expectations and predictions of fuzzy logic systems needs reduction. Additionally, less attention was paid to incorporate FLC into rainfall-runoff simulation for evaluating FLC performance at UDSs. Although previous studies have tried to implement FLC into stormwater management model (SWMM) (USEPA, 2015) for simulating flood control (Jafari et al., 2018; Wang and Altunkaynak, 2011), their methodology didn't directly connect SWMM and FLC as an efficient open-source optimization-simulation tool. Recent FLC studies contributed to implementing FLC into SWMM, but they seldom consider valuing FLC performance in terms of flooding severity alleviation on downstream UDSs under varying rainfall scenarios (Abdel-Aal et al., 2017; Mounce et al., 2019; Ostojin et al., 2017; Shepherd et al., 2016)

To address these two problems, the first step of this study is to combine historical hydraulic measurements and GA to optimize the CMFPs in fuzzy logic simulation. Secondly, this research proposed to build a MATLAB wrapper and directly implement FLC into SWMM for flood control simulation. Accordingly, the goal of this research can be divided into two parts： 1) developing an efficient optimization-simulation approach for optimizing the CMFPs (Controller Membership Function Parameters) and evaluating COP (Controller Optimal Performance) in the fuzzy logic system; 2) implementing fuzzy logic control (FLC) into rainfall-runoff simulation tool to evaluate SWMM_FLC performance under synthetic rainfall events. The accomplishments of this paper are summarized as bellows;

1) A data-driven improved genetic algorithm optimization approach was developed for automatically tuning CMFPs, and also a newly defined COP was used to assess the optimized controller performance;

2) An RTC tool for implementing FLC into storm water management model (SWMM) simulation was developed; this optimization-simulation tool called 'SWMM_FLC' ;

3) SWMM_FLC tool was tested to reduce accumulated flooding volume at downstream storage unit of a real-world urban drainage system under rainfall variations.

2. Study Area and Model

2.1 Study Case

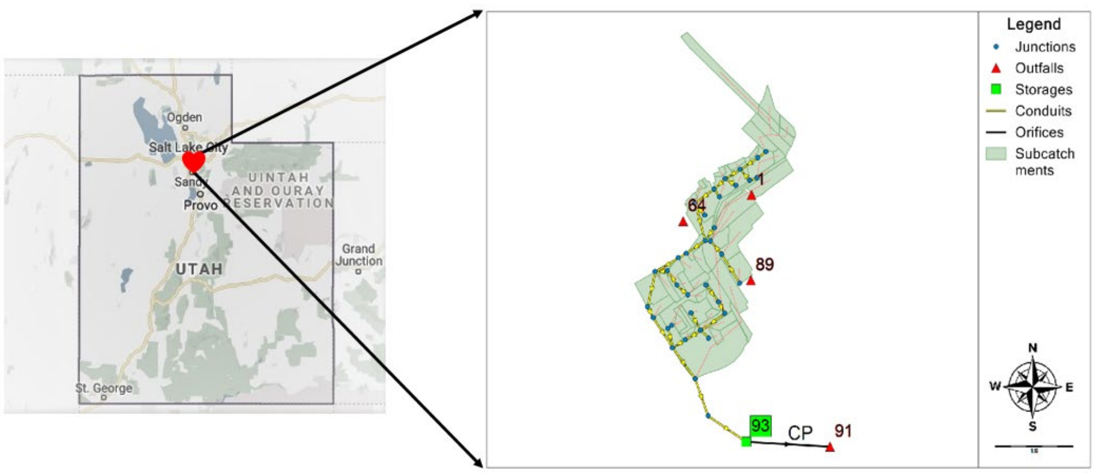


Fig.1. The study drainage catchment is located in the north of Utah state, the U.S., (left plot: the red heart-shape is the location of the study area) and the topological view of the SWMM model of RBC Urban Drainage Network, plotted by using PCSWMM v.7.2. (right plot: scale unit is kilometer; green label '93' representing storage unit ID; black label 'CP' meaning orifice ID; red label '91' for outfall ID)

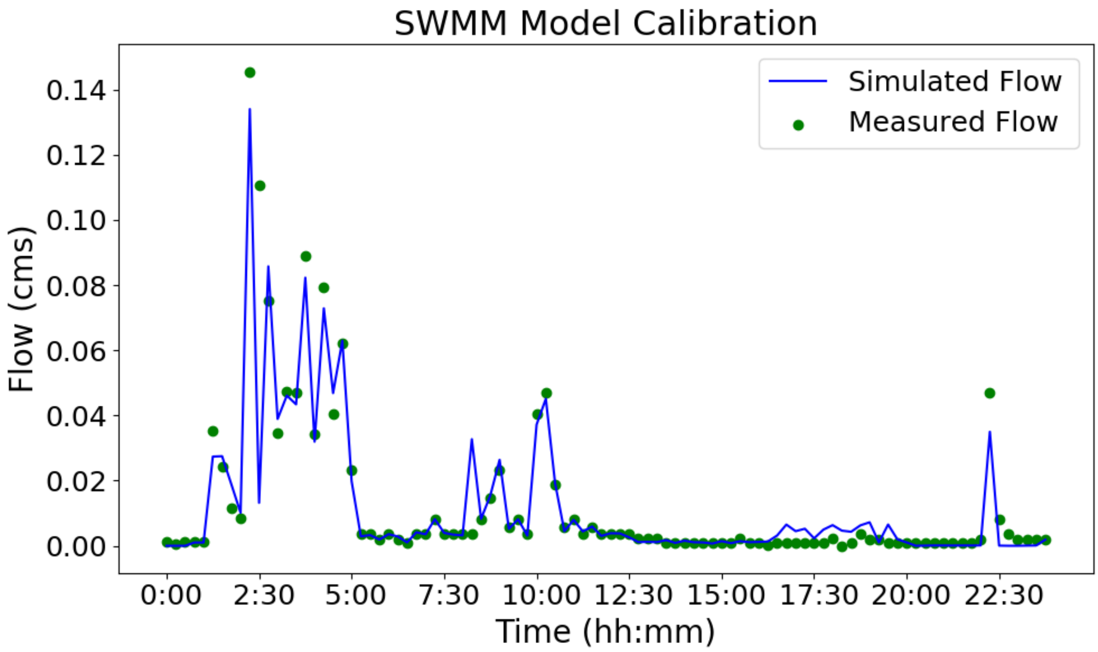
This study selected a real-world urban watershed as the study case (Fig.1). This study case with 0.11kilometer square is located in the northeast of Salt Lake City, Utah, the U.S. The stormwater for this area is collected by a small drainage network, which discharges runoff into the nearby creek. Salt Lake City was classified as the district semi-arid climate. Historical records from 1981 to 2010 show this study area has annual precipitation with 409 mm and the average annual air temperature is 11.5 ºC. A web survey in the U.S. Department of Agriculture (USDA)'s Natural Resources Conservation Service found that the primary soil type of the drainage catchment is Bingham gravelly loam. The water table was measured as 38.26 meters below the land surface by a U.S. Geological Survey (USGS) groundwater station near the study site (Gundersen et al., 2011). The average thickness of the local valley-fill aquifer was estimated as 823m (Cook et al., 1964).

2.2 Rainfall-Runoff Model

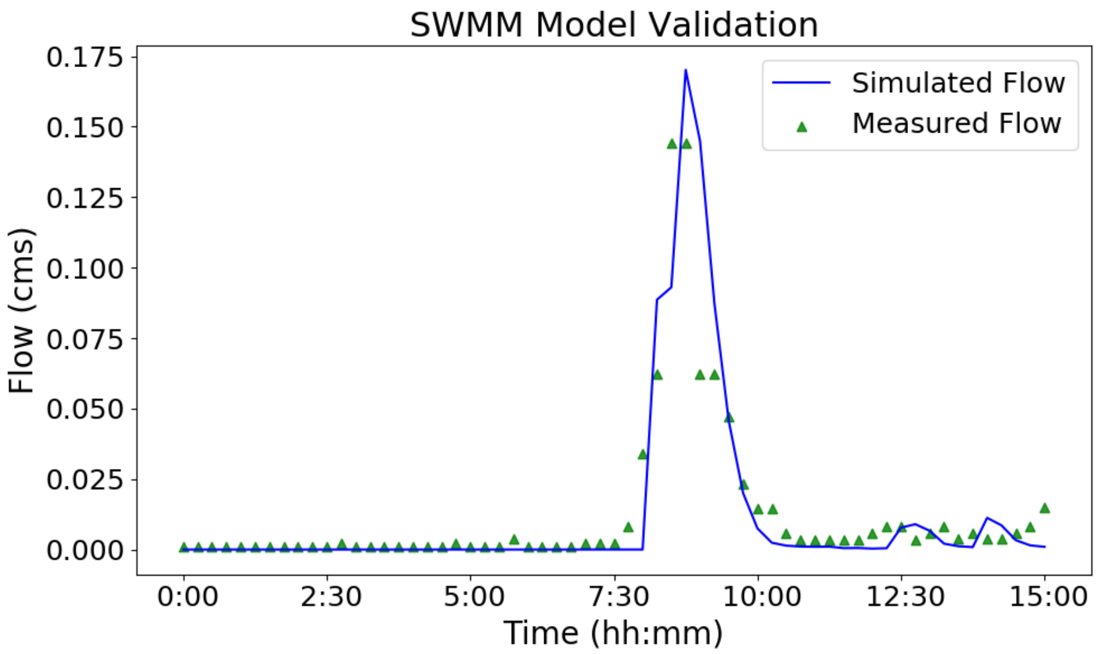
The rainfall-runoff model named RBC model for the drainage network was built by state-of-art hydraulic-hydrologic simulation tool SWMM (USEPA, 2015). According to Fig.1, there are a total of 52 sub-catchments, 36 nodes, four outfalls, one storage unit, one orifice and 36 conduits in the RBC SWMM model. The storage unit called node 93 in Fig.1 is the study interest. Precipitation measurements at 5-minute intervals were collected from the Mountain Met (MTMET) weather station located within the study catchment. Historical records within two rainfall events were downloaded from the Meso west website (Horel et al., 2002), and a flow sensor was installed in the storm drain at the outlet of the catchment to measure the flow rate in 15-minute interval. These measurements were used to calibrate and validate the RBC SWMM model. Of designing the rainfall for the RBC SWMM model, eight synthetic 3-hour duration rainfall events with different return periods including 1-year, 2-year, 5-year, 10-year, 25-year, 50-year, 100-year and 200-year return period artificial rainfall events were artificially generated by the Intensity-Duration-Frequency curves applied in PCSWMM 7.2 (James et al., 2004; NRCS, 1986).

Even though one previous SWMM model has been previously calibrated by Feng et al. (2016), changes in structure and land-use land-cover require model updates by using the latest hydraulic and hydrologic datasets. Therefore, the new SWMM RBC model used in this study was re-calibrated under one latest rain event measured on 17th May 2017 (Rainfall event 1) (Fig.3a) by using PCSWMM 7.2 (James et al., 2004). After that, another rainfall event on 10th December 2016 (Rainfall event 2) was used to validate the RBC model (Fig.3b). During the model calibration and validation process, the width, slope, imperviousness percentages, Manning's roughness coefficients of sub-catchments, and size, length, and slope of drainage conduits were adjusted accordingly.

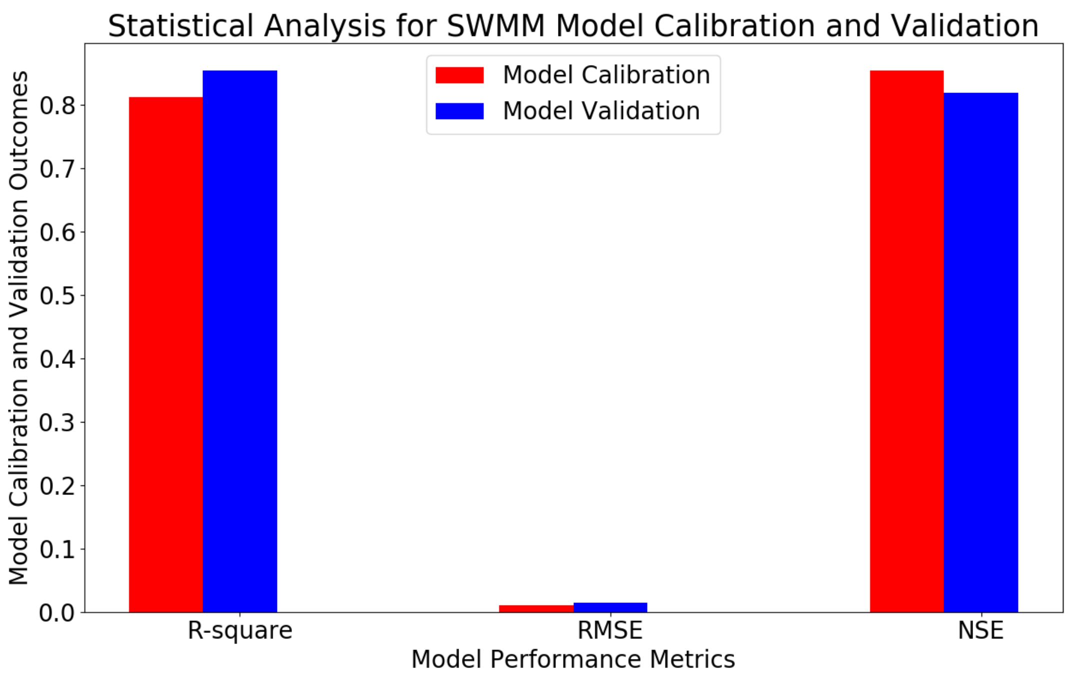
In RBC model calibration, Fig.2c shows that the coefficients of determination (R^2) is 0.8122. The root of mean square (RMSE) is 0.0109 while the Nash–Sutcliffe model efficiency coefficient (NSE) is 0.8549. For RBC model validation, Fig.2c presents that the coefficients of determination (R^2) is 0.8543. The root of the mean square (RMSE) is 0.0143 and the Nash–Sutcliffe model efficiency coefficient (NSE) is 0.8190. The accuracy of model calibration and validation indicate the new RBC SWMM model meets the required level for representing the hydraulic-hydrologic dynamics of the real-world UDSs.



(a)



(b)



(c)

Fig.2. RBC SWMM performance evaluation: a) model calibration based on the 20170517 rainfall event: b) model validation based on the 20161210 rainfall event; c) statistics of model performance metrics

3. Methods

A data-driven enhanced RTC optimization-simulation framework based on fuzzy logic theory and a genetic algorithm was developed to improve the performance of the smart stormwater system for reducing downstream urban flooding volume. This framework falls into three sections including data-driven genetic algorithm optimization part, FLC and hydraulic-hydrologic co-simulation portion, and, finally, the SWMM_FLC performance evaluation section.

3.1 SWMM_FLC Development

A fuzzy logic control (FLC) consists of membership functions (MFs) and fuzzy control rules (FCRs). Two key factors have noticeable impacts on generating an accurate FLC, and they are: (1) Setting up suitable fuzzy control rules (FCRs), and (2) Determining appropriate controller membership function parameters (CMFPs) (Arslan and Kaya, 2001). However, FCRs are defined by experts in most cases. In the output values of MFs, deviations between the expected responses and the simulated responses occur from now and then. Prior studies utilized evolutionary algorithm such as GA, PSO, or ANN, to adjust CMFPs in an efficient way (Mounce et al., 2019; S. Ostojin et al., 2011). Hence, creating an accurate and optimal fuzzy inference system (FIS) significantly relies on applying an appropriate tuning method.

GA-optimized CMFPs was found to reduce flooding volume by 66% in a hypothetical urban drainage network (Mounce et al., 2019), which fairly motivated this study to select a genetic algorithm (GA) to optimize the parameter of membership functions.

And then, the new FIS with optimized CMFPs will be incorporated into SWMM simulation as the components of SWMM_FLC. Shown as the left part of Fig.3, firstly, a collection of 3-year measurements will be used as the inputs for the GA training FLC controller. These records are time-series water level and flow data with a 15-mins interval from 7/9/2015 to 7/8/2018; these data were sampled by the water depth sensor and flow sensor. There are 2 attributes (water level and flow) for GA training inputs and 1 attribute (orifice setting) for output. The sample number for each attribute is 105119, which determines the simulation steps for FIS (fuzzy inference system). To improve computational efficiency, 1000 random values were selected as the subsets of the total samples for tuning CMFPs. And then, all 105119 simulated values will be compared with 105119 expected values for evaluating COP (controller optimal performance) (Vugar, 2019).

At the beginning of the GA tuning CMFPs process, a group of chromosomes initially produced a population of 300 candidate individuals. The genes in those chromosomes can be regarded as the features of the objective function. In this study, the RMSE representing the error values between expected outcomes and simulated outcomes were calculated, and an error value of objective function was then used to evaluate every individual in the population (Vugar, 2019). During GA optimizing process, crossover and mutate between chromosomes will happen to generate the better next generation of individuals. This process continues until the defined break criteria reach. A total number of 500 iterations (generations) was initially set as the optimization stop criteria but this optimization terminated at generation 427 at which objective function tolerance degree is less than the limited 0.05 in this case.

The GA optimizing process ends with obtaining the tuned CMFPs. Afterward, the optimized FIS will be linked to a MATLAB wrapper of SWMM (Riaño-Briceño et al., 2016), which intends to configure the functionalities of SWMM_FLC. As the right section of Fig.3 displays, the logics of FLC are applied to adjust the orifice open/close status step by step during the hydraulic-hydrologic simulation. At the modeling steps, the simulated nodal water level and conduit flow will be the inputs for FIS and an algorithmic strategy for 'defuzzification' is applied to obtain a single-valued output. In this way, the orifice operation will be conducted according to the defuzzied outputs of FIS. The gate will be set to a new position at step-wise style until the rainfall-runoff simulation stops. A general schematic of SWMM_FLC can be found in Fig.3.

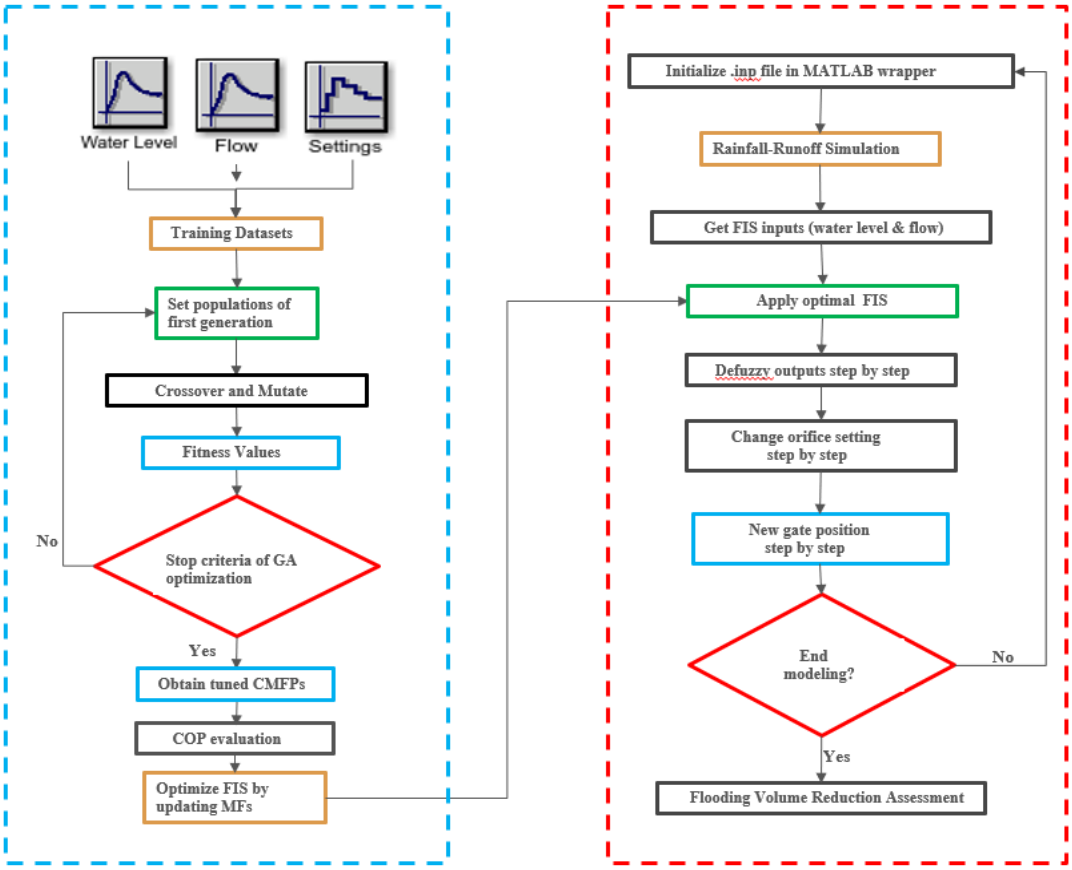


Fig.3. SWMM_FLC general schematic - GA optimization process (Left: GA-Genetic Algorithm; CMFPs-Controller Membership Function Parameters; COP-Control Optimal Performance; FIS-Fuzzy Logic System; MFs-Membership Functions) and FLC simulation flowchart (Right: FIS-Fuzzy Inference System)

3.1.1 Fuzzy Control Rules

A 3D view in Fig.4 (left) graphically shows how FIS inputs and outputs are correlated with each other. FCRs follow on robust fuzzy logic reasoning which employs linguistic rules in the form of IF {condition}–THEN {action} statements (S Ostojin et al., 2011). These FCRs are fired based on values of MFs, so the relationship between MFs and FCRs controls the degree of the IF-THEN rules that will be released. This research designed five levels (Very Low, Low, Middle, High, and Very High) for FIS input variables (Water Level and Flow) and five levels (open1, open2, open3, open4, open5) for the FIS output variable settings. Table1 summarizes a total of 25 basic logic of FCRs. For example, if the water level is ‘Very Low’ and flow is ‘Low’, the output is ‘open 1’. Traditionally, the fuzzy control rules (FCRs or controllers) were designed on the basis of expert knowledge of the system. However, such an empiric set-up for control law might be less efficient and event less reliable when disturbance happens to the dynamical systems (Mounce et al., 2019). To seamlessly connect FCRs to dynamical systems, this study basically employed a data-driven improved GA programming approach to re-shape MFs for promoting the FLC performance. As the system loop of Fig.4 (right) depicts, a dynamical model used hydraulic and water quality solver to generate system outputs (u) which are processed by sensors, and then transferred as the inputs for controllers. These original inputs, on the one hand, are used to train the relationship between measurements and actuators. On the other hand, they can be regarded as the parent generation to produce child generations through genetic crossover and mutation. The optimal solution is finally applied to tune the parameters of MFs Fig.4 (right).

Table 1 Fuzzy Control Rules Set-up

Input variable #2	Flow				
	Very Low	Low	Middle	High	Very High

Input variable #1						
Water Level	Very Low	Open1	Open1	Open1	Open1	Open1
	Low	Open1	Open2	Open2	Open2	Open2
	Middle	Open1	Open2	Open3	Open3	Open3
	High	Open1	Open2	Open3	Open4	Open4
	Very High	Open1	Open2	Open3	Open4	Open5

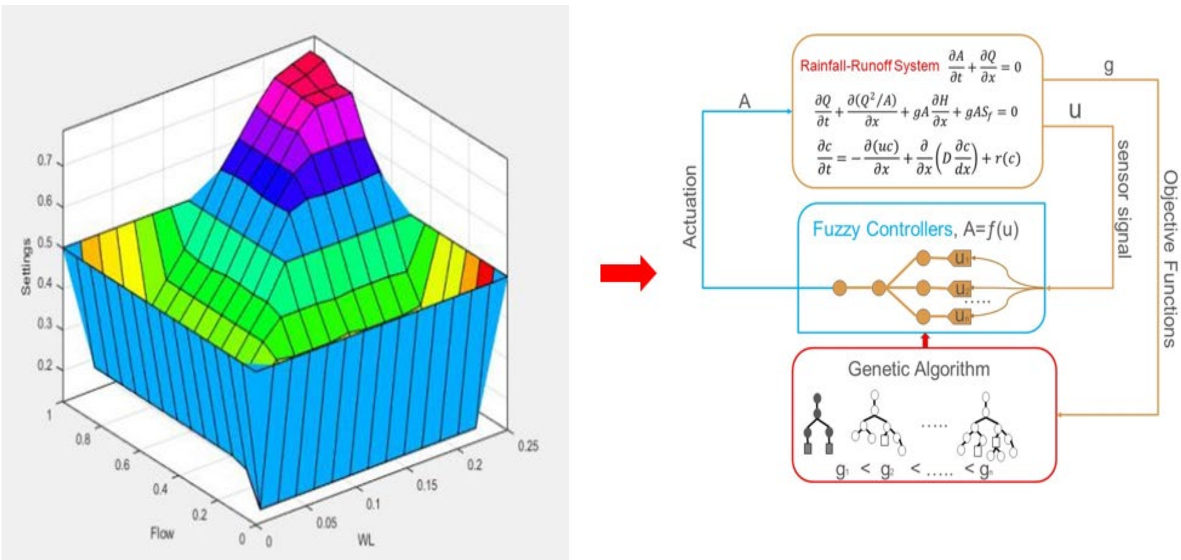
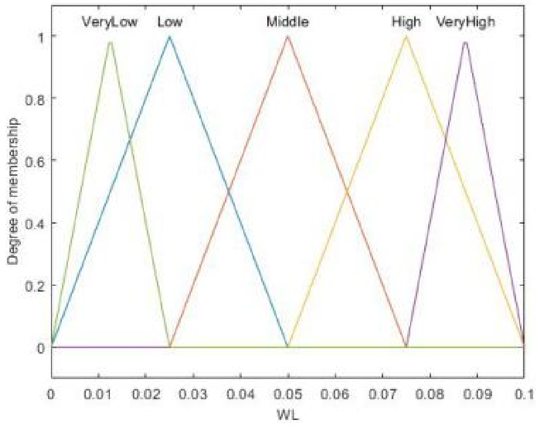


Fig.4. Incorporating fuzzy control rules (left subplot: 3D control rule view) into genetic algorithm optimized fuzzy logic control (right subplot)

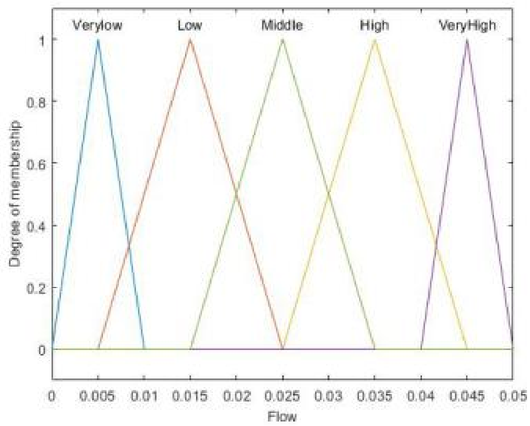
3.1.2 Tuning CMFPs

In FIS, input variables are plotted as overlapping groups in FIS and each of these group functions acts as a membership function (Mamdani and Assilian, 1975). Membership functions (MFs) represent the degree of belonging over a specified range [0, 1]. Each membership function uses a linguistic approach to describe descriptive language, such as high or low. In this study, two input variables, including water level (WL) and flow are set. Both of them have five membership functions (MFs) containing very low (VL), low (L), middle (M), high (H), and very high (VH) with fuzzy descriptive applications in Fig.5 (a, b). Meanwhile, one output variable called 'setting' is selected for characterizing orifice opening with five MFs from open1 to open 5 for fuzzy descriptive usages in Fig.5 (c).

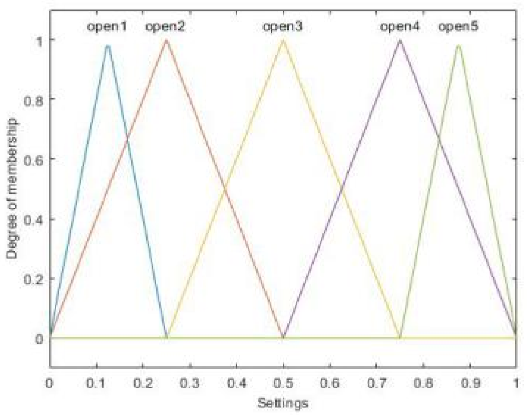
Here, MFs were chosen as the tuning objects. It was found that FIS is sensitive to changes in MFs shapes and positions which can be used produce significantly different results (S Ostojin et al., 2011). As Fig.5 demonstrates, this study pre-set three variables' (Water Level; Flow, and Setting) MFs shapes; all of them are triangles with same peak points but different base points (Water Level with 5 base points; Flow with 9 base points, and Setting with 5 base points), whose position will be the tuning objects. Since the .fis file of FIS has two inputs variables with 5 MFs per input, there are totally 10 (2*5) MFs to be tuned. Further, each triangular MF is normally described by 3 parameters, so 30 (3*10) CMFPs are to be tuned. Therefore, the GA searched for 19 (5+9+5=19) base points to automatically tune the 30 CMFPs and then generate optimal MFs shown in Fig.6.


VeryLow
Low
Middle
High
VeryHigh
Degree of membership
0
0.2
0.4
0.6
0.8
1
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
WL

(a)

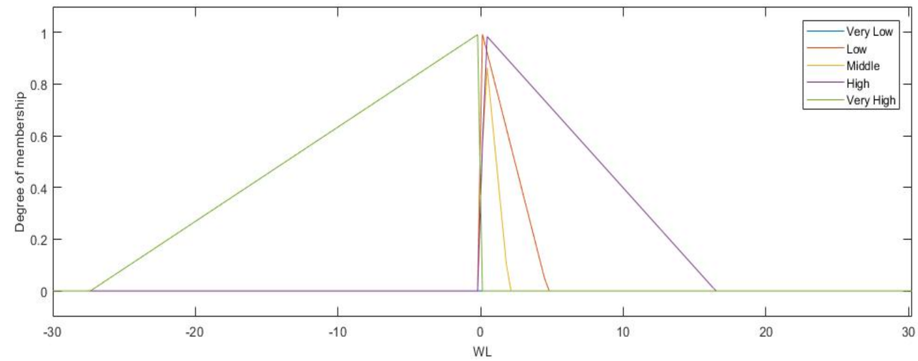

Verylow
Low
Middle
High
VeryHigh
Degree of membership
0
0.2
0.4
0.6
0.8
1
0
0.005
0.01
0.015
0.02
0.025
0.03
0.035
0.04
0.045
0.05
Flow

(b)

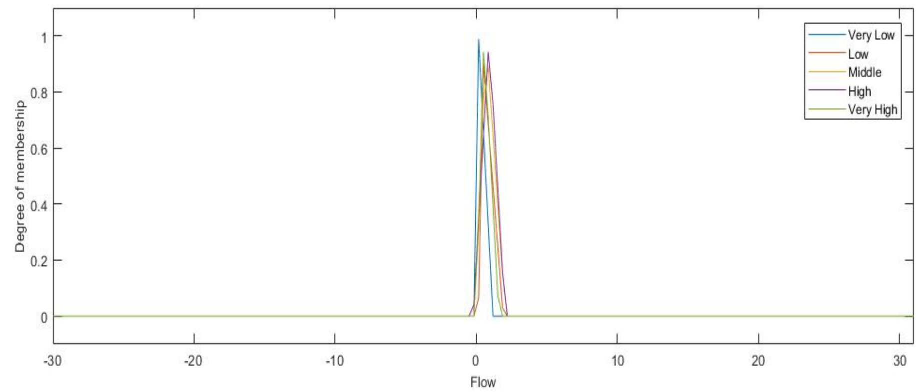

open1
open2
open3
open4
open5
Degree of membership
0
0.2
0.4
0.6
0.8
1
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Settings

(c)

Fig.5. Pre-determined (Non_optimal) membership functions for input variables (WL-Water Level: Fig.5 a; Flow: Fig.5 b) and output variable (Orifice Settings: Fig.5 c)



(a)



(b)

Fig.6. Optimal membership functions for input variables (WL-Water Level: Fig.6 a; Flow: Fig.6 b)

3.2 Controller Performance Assessment

After the FIS is optimized by updating the CMFPs, the FLC controller is assessed by Controller optimal performance (COP) measure. COP has been used in some studies as the metric for assessing optimized controller performance in fuzzy logic systems (Osman et al., 2005; Talei et al., 2010; Zamani Sabzi et al., 2016). It is generally defined as the performance that reduces the average of total deviations (error values). However, most of them consider COP as the single-event based index for assessing controller performance. Rare studies apply COP to evaluate controller behavior under scenarios of long-term measurements (Boughton and Droop, 2003). The event-based modeling approach might result in inaccurate simulated outputs (Grimaldi et al., 2012; Pathiraja et al., 2012; Yazdanfar and Sharma, 2015).

To that end, this study re-defined the COP by including long-term historical records such as precipitation, water level, and flow rate into the controller performance metric, which could be intuitively utilized to compare MFs before and after GA optimizing based on the RMSE value. COP is defined as the performance that reduces the average of total deviations (error values) under different rainfall years. To achieve this, COP is formulated as equation (1) below. For each sampling attribute, there are a total of 105119 historical records, equals to the simulation steps for a fuzzy logic system. In spite of only 1000 random values selected as the subsets for tuning CMFPs, all of the 105119 simulated values are eventually compared with 105119 expected values for evaluating COP. The lower COP value means a more favorable CMFPs optimization while a lower COP value can be less acceptable.

$$COP = \frac{\sum_{1}^{j}\left\{\sum_{i=1}^{N}\left[\left(f_{d_i}-f_{e_i}\right)^2 / N\right]\right\}^{0.5}}{M} \tag{1}$$

Where j is the rainfall sceanrio; i is the number of fuzzy logic modeling step; f_{d_i} is the ith derived fuzzy logic value in the FIS system; f_{s_i} is the ith expected fuzzy logic value from the expert system; N is the total simulation steps; M is the total rainfall scenarios.

3.3 FLC Implementation to SWMM

Based on the open-source toolbox for real-time control of UDSs developed by (Riaño-Briceño et al., 2016), this study created a code wrapper to make the .fis file of FIS compatible with the SWMM in MATLAB environment (Hunt et al., 2001). To implement FLC into SWMM simulation process, firstly, the SWMM .inp file is initialized, and also the SWMM hydraulic solver is called within this wrapper. Then, the .fis file of FIS would be read and loaded to the hydraulic-hydrologic simulation. The main body of this wrapper is a loop to step through RTC simulation. As there are two variables, including water level and flow in this .fis file of FIS, this study selects the water level of downstream node '90' and flow of link '40' in Fig.1, which are physically close to the locations of sensor, as the FIS input sources. Thus, outputs of RTC simulation on downstream orifice 'CP' will be determined by the simulated water depth of node '90' and flow of link '40' in Fig.1. In other words, the water depth of node '90' and the flow of link '40' will be the inputs for getting the fuzzy outputs for orifice 'CP'. These fuzzy outputs are preferably defuzzied to orifice settings in a stepwise approach when hydraulic-hydrologic simulation proceeds. The downstream orifice 'CP' would be adjusted according to the defuzzied outputs until the SWMM simulation stops. The targeted object is the storage unit (node '93') with a maximum depth of 0.9 meter and maximum storage capacity of 40 cubic meters. Finally, the flooding severity of the hypothetical storage unit will be evaluated.

3.4 SWMM_FLC Evaluation: Changes in Flooding Severity

In order to assess the performance of fuzzy logic control, the changes in flooding severity of downstream storage unit were compared between baseline scenarios (with non_optimized FIS) and optimal scenarios (with optimized FIS). This study considered accumulated flooding volume reduction (AFVR) as the index for quantitatively describing flooding severity changes at the downstream storage unit (Node 93) shown in Fig.1. The equation for calculating AFVR under various rainfall scenarios are formulated as follows:

$$AFVR = \int_{t_0}^{t_n} \left({V_{o,i} - V_{b,i}} \middle/ {V_{b,i}} \right) d_t \times 100\% \quad (2)$$

Where $V_{o,i}$ is the downstream storage unit flood volume with optimal FIS under ith rainfall-runoff simulation datetime; $V_{b,i}$ is the system downstream flood volume with non_optimal (baseline) FIS under ith rainfall-runoff simulation datetime; t_0 is the starting time of rainfall-runoff simulation while t_n is the ending time of the modeling process.

4. Results

In the basis of fuzzy logic theory and genetic algorithm, this study developed an optimization-simulation tool to determine the optimal orifice settings of UDSs, aimed to test the performance of fuzzy logic control in reducing total flooding volume under multiple scenarios with artificially designed rainfall events.

4.1 GA Performance in Optimizing FIS

As mentioned in section 2.3, a genetic algorithm (GA) was used to tune the controller membership function parameters (CMFPs). Fig.7 presents the changes in 30 CMFPs during the optimization process. Generally, most of the CMFPs get small modifications. Only four CMFPs show relatively higher variations, which indicates their shape of MFs might be significantly modified. This implication can be found with the predominant MFs re-shaping when subject to compare Fig.5 with Fig.6.

In this study, 300 populations and 500 generations are set to trace the optimal solution that satisfies the GA algorithm stop criteria. Referring to Fig.8, this optimization process was terminated at #427 generation where the changes in error values (fitness scores) of all populations are less than objective tolerance degree. Although the error values represented as RMSE are higher than 0.065 of all populations, the largest error value is lower than threshold 0.15 at the 427 generations (Fig.8). This finding suggests that generation 427 can be adopted as the terminal step and the optimal solution at generation 427 is acceptable for optimizing CMFPs.

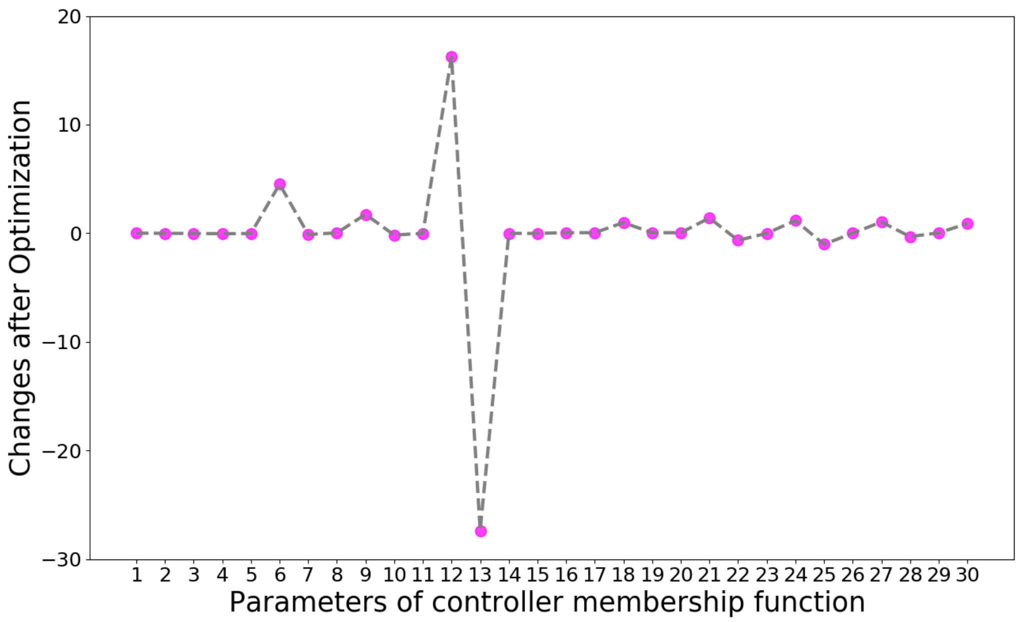


Fig.7. Modifications of CMFPs (Controller Membership Function Parameters) when shifting non_optimal to optimal FIS (Fuzzy Inference System)

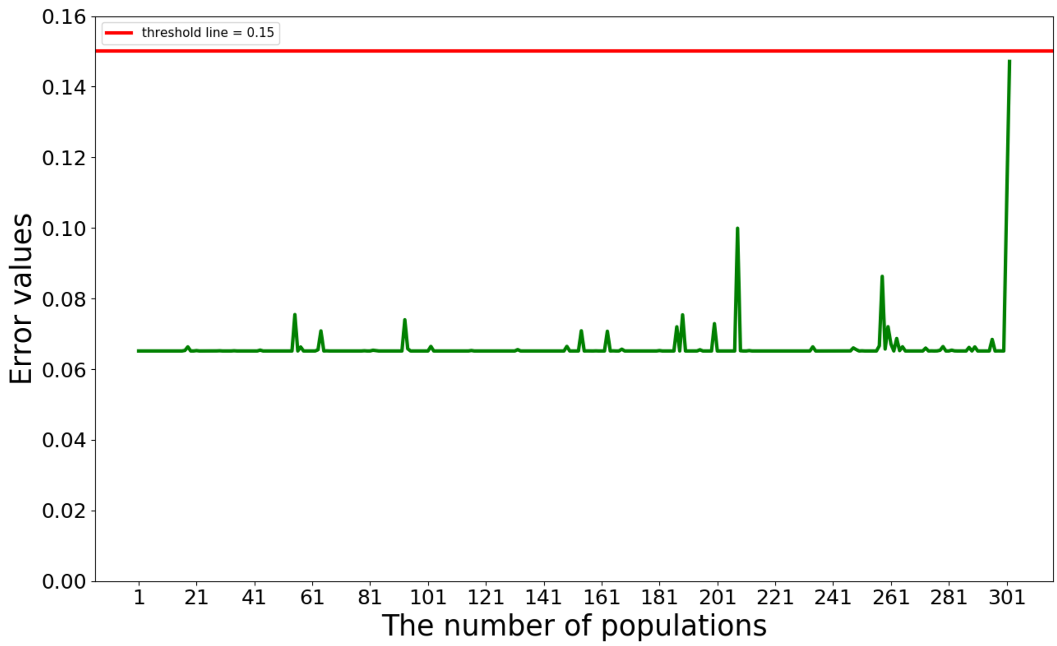
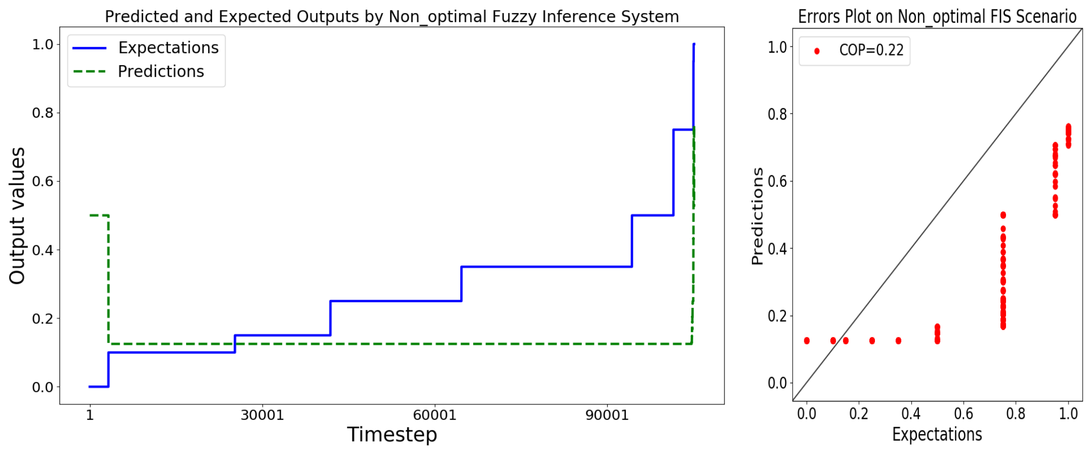


Fig.8. Error values (from 0 to 1; 0 means the best performance while 1 means the least

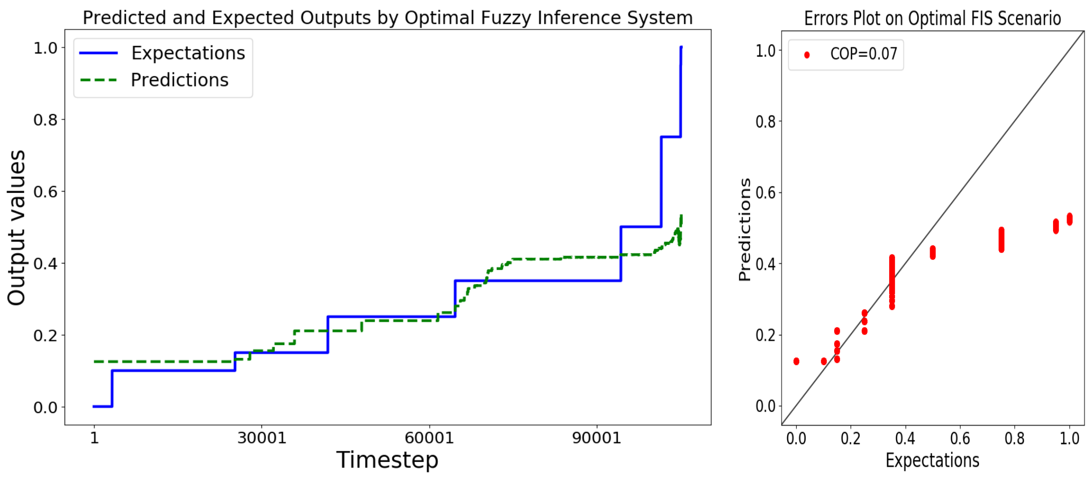
performance) for each population in the terminated generation (#427) in the genetic algorithm optimization procedure.

4.2 COP Evaluation

Fig.9 clearly displays that the COP declines from 0.2200 (non_optmial FIS) to 0.0722 (optimal FIS) after optimization. The COP values in this study are similar to results from (Razavi Termeh et al., 2018), whose highest value is 0.26, and the lowest value is 0.239, generated from GA based adaptive neuro-fuzzy inference system. In Fig.9 (a), before modeling step 42706, the predicted outputs have a good fit with the expected outputs in the non-optimal FIS system. However, the predictions are unable to catch the growing trend of expectations after step 42706. Such significant deviations between expectations and predictions exactly explain why the COP in non-optimal FIS is unfavorably 0.2200. Conversely, Fig.9 (b) shows that predictions slightly differentiate expectations during the whole simulation steps in optimal FIS scenario with a very small COP value of 0.07. The demonstrations above reveal that the fuzzy logic system can be dramatically improved by using data-driven optimization to tune the CMFPs. It is crucial to assimilate the measurements to theoretical modeling research activities when subject to enhance system performance (Li et al., 2019a).



(a)



(b)

Fig.9. Comparison of predicted and expected outputs within: a) non_optimal fuzzy inference system; b) optimal fuzzy inference system.

4.3 SWMM_FLC Performance Assessment

By visualizing the AFRV value under the artificial rainfall scenarios, it is clear that all of them are positive values in Fig.10. These consequences indicate that optimal FLC outperforms FLC in terms of using SWMM_FLC to reduce total system flooding volume. In particular, Fig.10 shows a decreasing trend for the AFRV values from

1yr_3hrs rainfall scenario to 200yr_3hrs scenario. This phenomenon illustrates that the optimized FLC in this study is more suitable for alleviating flooding severity under short return period storm events. Nevertheless, it should be reminded that the CMFPs are tuned based on water level, and flow measurements, which comes from a semi-arid city in middle-western states of U.S. In such a dry weather area, the long-term measurements might not be like the rainfalls with higher return period, and the CMFPs tuned by these historical records could not be suitable for mitigating flooding under short-duration high-return period rainfall scenarios. That is the reason why there is a larger AFVR value under shorter return period rainfall scenarios while lower AFVR value under longer return period rainfall scenarios.

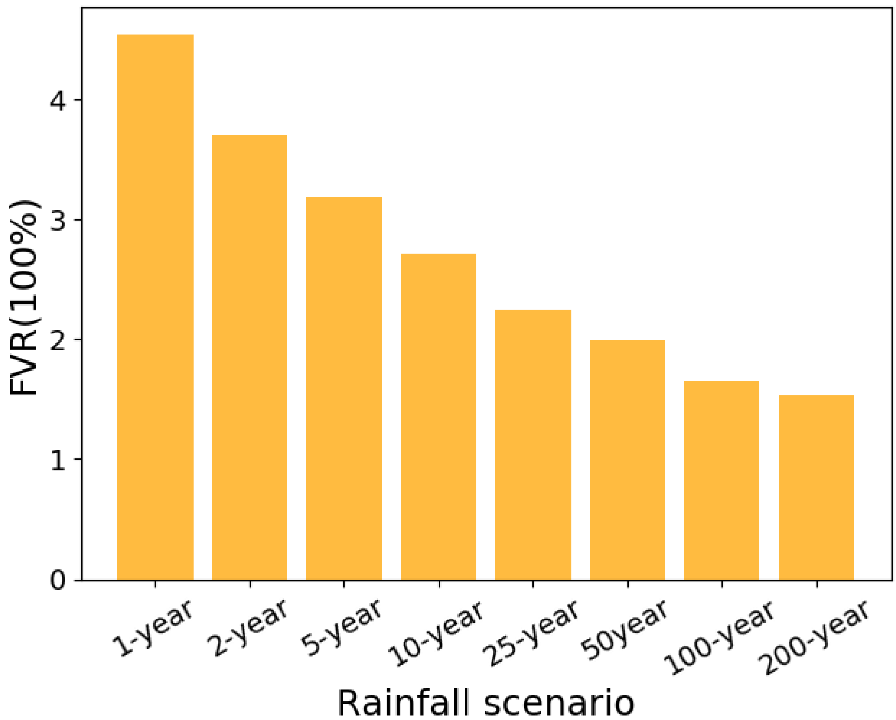


Fig.10. Performance of SWMM_FLC in reducing accumulated flooding volume at the Downstream Storage Unit (Node 93) under Three-hour Duration Artificial Rainfalls.

5. Discussions and Limitations

In this study, firstly, a data-driven GA method was employed to tune the CMFPs and to further modify the MFs in fuzzy inference systems (FISs). Such a parameter optimization process was driven by the long-term measurements for obtaining the relationship between fuzzy system inputs and outputs. The optimization outcomes will be evaluated by using the COP metric. Secondly, the optimized FISs were comprised of the SWMM MATLAB wrapper for co-simulating fuzzy logic control and hydraulic-hydrologic procedure, aimed to assess the performance of SWMM_FLC in accumulated flooding volume reduction under different artificial rainfall scenarios.

Prior modeling studies have documented the performance of real-time control strategies in decreasing flooding magnitude and peak water level approximately by 40% to 70% (Sadler et al., 2019; Wong and Kerkez, 2018). However, these studies, on the one hand, ignore the physical dynamics by a linearizing system or manually set-up the control rules based on experts' experience. One the other hand, the expensive computation requires high-performance computing infrastructure or cloud parallel computing environment (Sadler et al., 2020). Considering these possible shortcomings, this study extended the traditional fuzzy logic control by developing a data-driven enhanced optimization-simulation tool (SWMM_FLC) to represent the hydraulic-hydrologic dynamics and to reduce computational expense. Although this tool needs many data for fuzzy controller training, it is efficient to optimize the fuzzy inference system only based on a personal computer. Also, the decrease in COP from 0.22 to 0.07 reflects that GA optimization can significantly improve FIS performance by reducing the deviations between fuzzy logic predictions and expectations. In comparison with prior approaches to optimize FIS settings (Razavi Termeh et al., 2018; Zamani Sabzi et al., 2016), this study obtained substantially lower COP values in optimal FIS scenario. This work, therefore, indicates that the data-driven optimization-simulation method may have the potential to transfer the empiric and reactive settings to automatic and proactive settings of fuzzy logic control.

Compared with the recent study which diminished the flooding volume by 25% (Mounce et al., 2019), the most noticeable benefit for using SWMM_FLC might be the applicability to case-specific simulation studies. It was found that SWMM_FLC is more appropriate to mitigate urban flooding under short-duration, short-return period rainfall scenarios according the simulated results where AFVR values are 4.55%, 3.70%, 3.18%, 2.71%, 2.25%, 1.99%, 1.66%, and 1.53% corresponding to 1yr_3hrs, 2yr_3hrs, 5yr_3hrs, 10yr_3hrs, 25yr_3hrs, 50yr_3hrs, 100yr_3hrs, and 200yr_3hrs scenarios. The relative lower AFVR values remind the modeler that this study used precipitation, water level, and flow measurements, which come from a semi-arid city in the middle-western states of the U.S., to tune CMFPs. In dry climatic areas, the features, structurcs, and correlations of long-term datasets might not be like the wet climatic areas' rainfall records with higher intensity. CMFPs tuned by dry weather historical records is not suitable for mitigating flooding under short-duration high-return period rainfalls scenarios, but CMFPs tuned by wet weather historical records might can. By understanding this explanation, applying SWMM_FLC to other cities with the rainy weather condition would be helpful to expand the application of SWMM_FLC. Even though we cannot conclude that SWMM_FLC is suitable for all cases at current stage, this research, at least, steps forward to successfully co-simulate FLC and hydraulic-hydrologic processes in a real-world case study under varying storms.

However, this study also encounters some limitations. Despite the data (precipitation, water level, and flow) availability, temporal resolution for these measurements is necessary to be higher enough like a one-minute or five-minute interval for more accurately training the relationship between FIS input and output. Another disadvantage of this study can be found from the AFVR values, which are comparatively lower than the previous study (Talei et al., 2010). The reason for this is perhaps because some pre-determined control rules can not match the actual measurements, which leads to the warnings in running optimization. Finally, the lack of testing cases impedes performance improvement, and it is recommended to apply SWMM_FLC to different types of UDSs for broader testing and a deeper understanding of how CMFPs would be modified by data-driven GA optimization.

Regarding future work, rather than using historical records, considering forecasting information like rainfall forecasts as the FIS optimization inputs to tune CMFPs is valuable for control operation decsision-making (Shishegar et al., 2019). This could facilitate the performance of SWMM_FLC by making the fuzzy control strategy more adaptive to the coming storm events and more resilient to the potential failures (Parolari et al., 2018; Sharior et al., 2019). Although this study has address the downstream flooding problem, future work can switch to water quantity improvement by reducing the pollutant concentration and sedimentation issues in UDSs, especially in some cases with frequent combined sewer overflow and severe illicit intrusions. Finally, only one fuzzy logic controlled gate (orifice) and one storage unit were conceptually implemented and simulated at the downstream location of urban drainage networks. Such centralized-local control can not necessarily achieve global benefits at the system-level watershed (Mullapudi et al., 2017). Future work will focus on distributing multiple FLC controlled gates (orifices) among different storage sites to investigate how the system-level fuzzy logic control strategy can be improved by data-driven and GA optimization.

6. Conclusions

This study proposed a data-driven improved optimization-simulation open-source tool based on the fuzzy logic theory and genetic algorithm, aimed to optimize fuzzy control efficiency and to reduce downstream flooding volume at a real-world UDSs. The results show that traditional UDSs can be controlled by FLC to take advantage of their functionalities to handle downstream urban flooding issues. The major advantage of this tool lies in the noticeable performance improvement in COP and flooding volume reduction conducted by this data-driven enhanced optimization-simulation SWMM_FLC. This open-source simulation-optimization tool is supposed to be implemented with different metaheuristic algorithms to promote applicability and help decision-makers and researchers to find effective solutions for mitigating urban flooding. The main contributions of this work are summarized as four parts below:

1) A real-time control simulation-optimization tool called SWMM_FLC is developed for incorporating FLC into rainfall-runoff dynamics simulations in UDSs. This tool is distributed at https://github.com/Jiadalee/SWMM_FLC for public access. More information about how to run and modify this tool for personal usage can be found in the 'Software Availability' section below.

2) Long-term water depth and flow rate measurements are used to train the fuzzy relationship between inputs and outputs in FIS (fuzzy inference system). Compared with manually building such relations, this data-driven method significantly enhances the efficiency of FIS training process;

3) GA (Genetic algorithm) was used to tune the CMFPs (Controller Membership Function Parameters) before implementing FIS into SWMM MATLAB wrapper. The error metric COP value decreasing from 0.22 in non-optimal FIS to 0.07 in optimal FIS scenario indicates that GA can improve FIS performance by reducing the deviations between predictions and expectations.

4) The SWMM_FLC performance testing finds that SWMM_FLC can reduce total urban flooding volume by up to 4.55% under varying rainfall scenarios, which

illustrates the possibility that urban flooding severity can be alleviated by implementing FLC into UDSs.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Software Availability

Name of software: ‘SWMM_FLC’ package

Developers: Jiada Li (Urban Water Group, University of Utah)

Year first available: 2020

URL: https://github.com/Jiadalee/SWMM_FLC

Contact address: Department of Civil and Environmental Engineering, University of Utah, 201 Presidents Cir, Salt Lake City, UT 84112, U.S

Telephone: N/A

Fax: N/A

E-mail: jiada.li@utah.edu

Access: Please visit the URL above to get the access to SWMM_FLC

Hardware required: PC

Software required: MATLAB 2018 Version, MatSWMM MATLAB module, and GOFIS toolbox;

Optimization-Simulation set:

1) Setting 1: Before you train the fuzzy 'controller' for characterizing the relationship between fuzzy system inputs and outputs, please store your training datasets in GA_Optimization folder;

2) Setting 2: Before you run genetic algorithm optimization for tuning parameters of membership functions, please put fuzzy logic inference system '.fis' file, which you previously created in MATLAB, into GA_Optimization folder;

3) Setting 3: Before you run 'SWMM_FLC' simulation, please put SWMM .inp file in the folder of 'swmm_files' of MATLAB module folder of FLC_Simulation, and

also save the fuzzy inference system '.fis' file in the folder of MATLAB module folder of FLC_Simulation.

4) Current SWMM_FLC version can only be run on MATLAB 2018.

Availability: The 'SWMM_FLC' tool must be run after set-up the required software and optimization-simulation settings above. The urban drainage system simulation model used is EPASWMM, which is available at https://www.epa.gov/water-research/stormwater-management-model-swmm. Data including flow and water level measurements, SWMM models, and optimal fuzzy inference system outputs;

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