

# Building a Smart City: A Conceptual Approach to Real-Time Urban Flood Control System

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**Abstract**— Controlling urban flooding is a difficult issue for municipal planners. In order to handle the calamity, current research has focused on flood prediction, detection, monitoring, and warning systems. This research study proposes the water sensitive storm water network model. Based on water sensitive storm water network model, the real-time urban flood control method is proposed. The approach is based on real time flood data for water catchments that were gathered by using sensors and autonomous smart controller. The methodology of a smart flood resilient system prevents the surface flood water and is scalable to smart cities, which employ real-time parameters to automatically control urban floods. The proposed method optimizes the action of actuators in the sub catchment area in terms of early control of flood water.

**Keywords**— Urban Flood, Fuzzy logic, Water Network, Internet of Things (IoT), Smart City

## I. INTRODUCTION

Flooding in urban areas is a common occurrence that causes serious issues for local governments and urban planners. Urban flooding has a number of negative repercussions on both the economy and public health, including the loss of life, delays in public transit, damage to both public and private property, and the suspension of utilities like the water and electricity supply. The greenery is destroyed by the intense water flow, severely harming the environment. Diseases and lack of shelter due to flooding are other problems that affect animals. Sewage and solid waste that leak into homes and buildings degrade hygiene and increase the risk of disease transmission. Losing people and possessions has a profound psychological impact, and the healing process is difficult and time-consuming, which causes trauma in people that lasts a lifetime [22]. Direct and indirect causes of flooding fall into two categories. Examples of direct causes include man-made factors like the loss of natural drains and ongoing urban expansion as a result of population increase as well as natural ones like global climate change, changes in weather patterns, heavy rainfall, and so forth. An inadequate and flawed drainage system, on-street parking, and other indirect issues are among them [6]. Urban flooding is becoming more common, which emphasizes the need for effective flood mitigation measures that can reduce the loss of life and property. Globally, urban floodplains have embraced sustainable storm water management (SSM), an innovative storm water management method that reduces the problems associated with urban flooding. A few of the SSM techniques that have been implemented internationally are the Active, Beautiful, Clean (ABC) Waters Program in Singapore, Water Sensitive Urban Design (WSUD) in Australia, Low Impact Urban Design and Development (LIUDD) in New Zealand, and Sponge City (SC) in China [1].

Studies on flood forecasting have frequently employed predictive data mining techniques. These studies, however, fall short in their ability to correctly forecast (few) severe occurrences. These methods explore datasets for occult patterns and discover predictive data that goes beyond what is anticipated by experts[2].

The most popular computational (CI) methods in hydrology are based on ANNs, fuzzy sets, wavelet models (W-CI), support vector machines (SVMs), and evolutionary computing (EC), as well as hybrid methods that combine the aforementioned methods used for flood forecasting using various parameters such as temperature, water level, rain data etc.[2]. The water level monitoring and flood alerting system based on IoT-based sensor network was designed and tested in 2021 by O. Mendoza-Cano et al. In order to monitor and issue alerts on urban floods in the Mexican city of Colima-Villa de Alvarez, the project utilized IoT and a wireless sensor network [3].

Citizens can feel secure realizing that essential services, such as public transportation, communications, distribution of water and electricity, hospitals, schools etc. A combination of physical and IT systems and infrastructure, smart cities has the ability to boost cognitive abilities, ensure social cohesiveness, and tackle and deploy innovation. These factors are closely related to the newly developed idea of urban resilience, which is altering the conception of smart cities. In fact, resilience depends on complex interactions between people, communities, institutions, and infrastructures [16].

IoT and computational models such as the fuzzy model, Artificial Neural Networks (ANNs), Machine Learning (ML), and hybrid models have opened up new pathways that have made it possible to develop new hardware and software for flood monitoring and forecasting. Even if the accuracy of a few computational models is high and is based on real-time or past hydrological data, such models or systems are only used to alert people. Therefore, it is necessary to create a smart system that can effectively control flood water.

The objective of this research paper is to design water sensitive Storm Water Control Network Model (SWCNM) for efficient control of surface urban flood water and a smart flood water control algorithm for controlling of urban flood water based on SWCNM.

## II. RELATED WORK

A prototype device was created by Mochammad Hannats Hanafi Ichsan et al. (2019) to monitor water on waterways that may cause floods. The water channel in the prototype can be used to depict rivers, culverts, drains, etc. To measure speed and water level, a sensor is attached to the node. These readings' findings are evaluated using fuzzy logic to

classify the information regarding possible flooding or not. The outcome of fuzzy logic is then communicated to the master node so that it may show information about the state of the water flow via LEDs [5].

With the installation of controllers at Urban Drainage Systems (UDS), Real-Time Control (RTC) has recently gained popularity as an adaptable method of solving flooding challenges caused by urban drainage. RTC is a dynamic, heuristic, and affordable approach that may be used from three angles, including improving the eco-system, optimizing operating strategy, and adjusting UDSs to changing situations [8].

Jiada Li (2020) developed a co-simulation of fuzzy logic control and urban flooding using the SWMM FLC tool, and also trained the relationship between the inputs and outputs of the fuzzy inference system using data-driven methodology. SWMM FLC can decrease overall flooding volume at urban drainage systems downstream [7].

In 2018, Riyanto Wibisono et al. proposed a concept for a fuzzy logic control system to combine the controlling of water level on two water gates. The system, which comprises of a water gate and a control system element, was created on a prototype scale. Two fuzzy logic controllers were employed in the control system. The active time of the water gate motor (between 0 and 2 seconds) was used as the control output to modify the sluice gate's opening size. The fuzzy logic controller's inputs were error signal and water level delta error. The input and output values were divided into five membership functions and the Centre of Area (COA) approach was used to defuzzify the system [10].

As mentioned in Dharamniwas, Aziz, Redhu, and Gupta's review of fluid level control strategies utilizing fuzzy logic, research on the application of fuzzy logic algorithms for water level management has also been conducted [11]. Additionally, studies on fluid level control systems using fuzzy logic and Matlab simulation have been given by Farooq, Rafiq, F., Abbas, G., and Asad and Mushtaq, Tayyaba, and Ashraf [12][13].

An Artificial Neural Network method for real-time flood prediction utilising IoT sensors on edge computing was presented by Eric Samikwa et al. in 2020. Low power edge devices are used to process the sensor data. The system keeps track of rainfall and water level time series in real-time and uses the temporal correlation data to estimate flood water levels in advance utilizing long short-term memory (LSTM). A form of ANN that works well with time series data is the LSTM. Regression statistical error measurements were used by Eric Samikwa et al. to test the model on a real dataset [14].

Yves Abou Rjeily and colleagues concentrate on creating a flooding forecast system (FFS) that can notify the Urban Drainage System authority in advance of potential floods in 2017. The model calculates the depth of water fluctuation in the crucial manholes for the anticipated storm events. Proposed FFS and Nonlinear Auto Regressive with eXogenous Inputs neural network are used in the strategy to predict flooding episodes [18].

In order to forecast the flood in Kerala state, Saiesh Naik et al. (2020) adopted and examined the logistic regression approach. In this work, a flood model was trained and projected using rainfall data for Kerala state over the last 115 years. Rainfall data broken down by month is used, and it ema-

nates from data.gov.in. Only 75% of the model's accuracy was discovered [19].

A proposed Artificial Intelligence-based Urban Flood Warning System utilising IoT-based Flood Depth Sensors was made by Li-Chiu Chang et al. in 2020. The method includes an online correction algorithm with a regional flooding prediction system for continuously learning and updating model parameters [20].

Numerous researchers have suggested different computational intelligence techniques, including fuzzy systems, artificial neural networks, machine learning, and IoT-based systems, for managing floods. It is determined that most research over the past two decades has been on flood predicting and monitoring and has suggested solutions based on historical data and real-time data from hydraulic models to flood forecasting. The majority of the current work focuses on flood preparedness using forecast, monitoring, and alerting models. These systems can only be used for flood predictions, real-time flood monitoring, and warning; they cannot be used for real-time flood water control or as a system for flood resistance. Therefore, the need arises to develop an automatic flood resilience model for the urban city.

### III. PROBLEM IDENTIFICATION

Flood control refers to any methods used to reduce or stop the harmful impacts of flood waters. In addition to the flood prediction, monitoring, and alerting techniques mentioned in section II, common flood control techniques include the installation of sandbags, rock rip-raps, maintaining normal slopes with vegetation, rock berms or applying soil cements to steeper slopes, as well as the construction or enlargement of drainage channels.

As all of the aforementioned strategies emphasize, flooding can be prevented by building infrastructure that is flood-resistant. However, many municipal authorities employed the water pumps to move the water from the catchment to the drainage line when the city was flooded. Since the method of pumping water is entirely manual and only effective after a flood, it is not suitable.

The main reason of the rainwater accumulation is dirty and insufficient drainage. Uncertainty exists regarding the condition of much of the drainage and sewage system. They're overflowing with rubbish and non-biodegradable plastic bags, or they can't handle the volume of water. Unauthorized connections cause sewers to overflow, and the sewage system is unable to handle the growing volume. In cases of heavy rainfall, storms, and high tide for the coastal cities, the drainage network is overloaded. The city drainage system is only designed to transport sewage and is constructed taking into account factors such as land area and population density.

Due to the aforementioned factors, we recommend a separate storm water line that runs parallel to the drainage system and automatically reduce the flood water. The only goal of the storm water line network is to manage the flooding rainwater, while it can also be utilized to provide solution to water problem.

### IV. PROPOSED URBAN FLOOD CONTROL METHODOLOGY

The water-sensitive Storm Water Control Network Model serves as the foundation for the intelligent flood control sys-

tem based on IoT and Fuzzy inference. The goal of the Storm Water Control Network Model (SWCNM) is to manage storm water, not sewage or waste water. Figures 1.0 show a satellite map of a city area for Storm Water Control pipeline Network design for illustration purpose.

We utilized the Google Maps tool and the EPA SWMM 5.2 simulation tool to access the satellite picture of the research region.

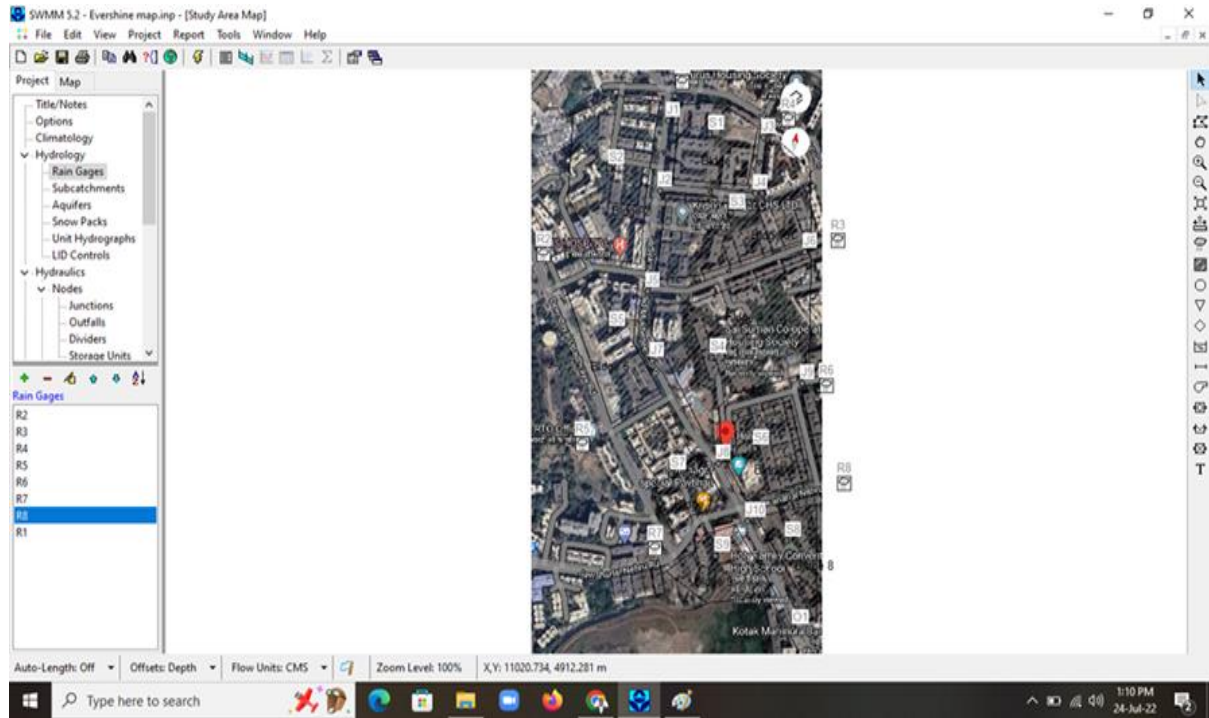


Figure 1: Satellite map of study area

The study area is divided into  $n$  number of sub-catchments based on frequently flooding part of study area. Water level sensors are used throughout the network's several catchments to gather flood data in real-time. On the Storm water network line and the existing drainage line, the one-way check valve is installed which act as non-power mechanical actuators based on real time flood level to prevent back-flow. The number of check valves is variable and depends on sub-catchment area and length of storm water line. If the sub-catchment area is vast and water logging occurs more frequently then the number of check valves may be 8-10 on at some considerable locations. Installing the check valves may be effective and reduces load of the actuators (pumps). For each sub-catchment, the pumps can be installed which will act as actuator and perform the action of sucking the flood water from sub-catchment to storm water pipeline. The number of pumps depends on sub-catchment area and length of storm water line. The flood water level is monitored and controlled using a flood fuzzy inference system employing time-series data on surface water levels.

#### A. System Block Diagram

The system block diagram is shown in Figure 2, it includes the parts for computing the flood water level and water volume for each sub-catchment, reading input sensor values, and actuator control. The parameters used in the system block diagram are  $WL_{Ci}$  (Water level sensor values of  $i^{th}$  sub-catchment) and  $Wv_{Ci}$  is the water volume in  $i^{th}$  sub-catchment. A microcontroller in each sub-catchment trans-

mits the readings of the water level sensors periodically to a server by utilizing transmitter-receiver devices.

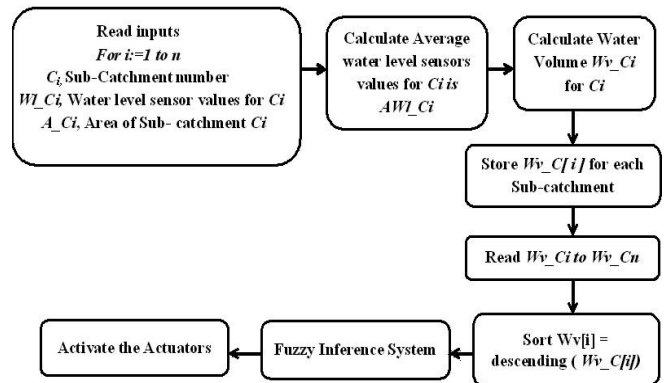


Figure 2: System Block Diagram

The water volume of each sub-catchment is computed at the server side using the real time series data values from water level sensors. The sub-catchment with the highest flood water is chosen to carry out the actuator action in terms of controlling the flood water on top priority by comparing the water volumes of the sub-catchments. On the basis of the membership function and fuzzy inference rules, the fuzzy inference system selects and manages actuators like pumps. The calculations for water level and volume are done on the server, and the server sends the command to turn on or off the pump to the appropriate microcontroller in each sub-catchment.

### B. Pseudo Algorithm for Sub-catchment Water Volume

**Input:** C:  $C_1 \dots C_n$ ,  
*// Number of Sub-catchments in study area*  
 $Wl_1\_C_1, Wl_2\_C_2 \dots Wl_n\_C_n$   
*// Water level sensor values for C*  
 $A\_C_n$  *// Area of sub-catchments*

**Output:** Water Volume  $Wv\_C_n$

**Procedure** WATER\_VOLUME ( $A\_C_n, Wl_n$ )  
**begin**  
**for each**  $i:=1$  **to**  $n$  **do**  
 $Wl\_C_n = \sum_{k=0}^n Wlk/n$  *// calculate average*  
*water level for the current sub-catchment*  
 $Wv\_cn\ i[] = A\_C_n * Wl\_C_n$   
**end for**  
**For each**  $i:=1$  **to**  $n$  **do**  
 $Wv\_C[i] = \text{descending}(Wv\_cn)$  *// Sort the sub-*  
*catchments according to highest to lowest water volume*  
*value.*  
**end for**  
**end procedure**

In order to determine the water volume ( $Wv$ ) for the sub-catchments based on sub-catchment area ( $A\_C$ ), water level sensors are placed and spaced apart, forming geometric shapes like rectangles, triangles, and hexagons, among others.

For instance, Sub-catchment Area  $A\_C$  has a rectangular form due to the positioning of its four water level sensors.  $A\_C$  is therefore determined as follows.

$$A\_C = \text{dist}(Wl_1\_C, Wl_2\_C) * \text{dist}(Wl_2\_C, Wl_3\_C)$$

Where  $Wl_1\_C$ ,  $Wl_2\_C$  and  $Wl_3\_C$  are the water level sensors installed at Sub-catchment C.

According to the following calculation, the water level in sub-catchment C is the average of all the readings of the water level sensors gives the depth of water in the sub-catchment.

$$Wl\_C = \sum_{k=0}^n Wlk/n$$

, Where n is total number of water level sensors in the sub-catchments

Water Volume  $Wv\_C$  in the given sub-catchment is calculated by

$$Wv\_C = A\_C * Wl\_C$$

### C. Data Collection

In this proposed methodology, sensors and IoT technology may be used to collect real-time flood data. The information from the water level sensors may be utilized to calculate the water volume of each sub-catchment. The average water depth at each sub-catchment is calculated using these readings from the water level sensor. Stainless steel probe sen-

sors are the ideal sensor to use in a water level indication. Due to bad water quality, stainless steel sensors don't rust, foul, or deteriorate. Figure 3 shows a stainless steel ultrasonic water level sensor and its working principle. The ultrasonic sensor, often known as a transducer, operates similarly to a radar system. Electrical energy can be transformed into acoustic waves by an ultrasonic sensor, and the other way around. An ultrasonic wave moving at a frequency over 18 kHz is the acoustic wave signal. The well-known HC SR04 ultrasonic sensor produces ultrasonic waves at a frequency of 40 kHz. With a minimal tolerance of 3 mm, ultrasonic sensors like the HC-SR04 can accurately measure distances up to 400 cm.

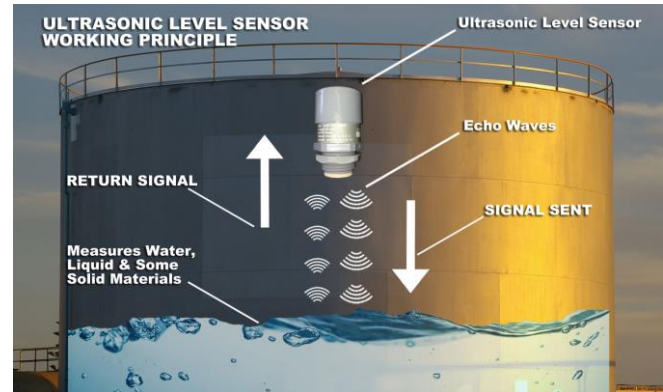


Figure 3: Water level sensor (Ultrasonic), Image Source [21]

The water level sensors linked to the Arduino will use a Wi-Fi model to transmit the time series sensor readings to the server or to the cloud.

### D. Fuzzy Inference System

The fuzzy Inference controller can be different types but there are two main types are Mamdani and Sugeno. Sugeno fuzzy inference employs singleton output membership functions that are either constant or a linear function of the input values, also known as Takagi-Sugeno-Kang fuzzy inference. Mamdani fuzzy inference was initially developed as a technique for developing a control system by combining a collection of linguistic control rules that were acquired from skilled human operators. Mamdani systems are particularly suited to expert system applications where the rules are developed from human expert knowledge because they have more logical and understandable rule bases. Using fuzzy logic to create a mapping from an input to an output is known as fuzzy inference in Mamdani. The mapping then serves as the basis on which decisions may be made or patterns can be found. All the components that are discussed in Membership Functions, Logical Operations, and If-Then Rules are used in the fuzzy inference process. Due to the aforementioned benefits, we propose the Mamdani fuzzy system in this work.

The linguistic input variables are used in this study is according to different rules which can be synthesized in the Table 1.

Linguistic parameter for the fuzzy system is as given below:

Input parameter: Sub- Catchment Water Volume ( $Wv\_C$ )

Output parameter: Sub-Catchment pumps ( $P\_C$ ).

The table 1 shows the fuzzy inference rules for the sub-catchment type. The sub-catchments can be classified in terms of Low, Medium and High flood prone sub-area.

TABLE 1: FUZZY INFERENCE RULES FOR SUB-CATCHMENT TYPE  $C_1$ ,  $C_2$ , AND  $C_3$

| Sub-Catchment type | $WV\_C$ Low<br>0-1 ft | $WV\_C$ Medium<br>1-2 ft | $WV\_C$ High<br>2-3 ft | $WV\_C$ Extreme<br>$\geq 3$ ft | Pump ( $P\_C$ )<br>ON/OFF         |
|--------------------|-----------------------|--------------------------|------------------------|--------------------------------|-----------------------------------|
| $C_1$              | 0                     | 0                        | 0                      | 0                              | $P1: OFF$                         |
|                    | 0                     | 0                        | 1                      | 0                              | $P1: ON$                          |
|                    | 0                     | 0                        | 1                      | 1                              | $P1: ON$<br>$P2: ON$              |
| $C_2$              | 0                     | 0                        | 1                      | 0                              | $P1: ON$<br>$P2: OFF$             |
|                    | 0                     | 0                        | 1                      | 1                              | $P1: ON$<br>$P2: ON$              |
| $C_3$              | 0                     | 0                        | 1                      | 0                              | $P1: ON$<br>$P2: ON$<br>$P3: OFF$ |
|                    | 0                     | 0                        | 1                      | 1                              | $P1: ON$<br>$P2: ON$<br>$P3: OFF$ |

If water volume is High at  $C_1$  then we use only pump to control the flood water. If water volume is High at  $C_1$  is extreme then we activate both pumps to control the flood water. Similarly, the flood is controlled for sub-catchment area  $C_2$  and  $C_3$ , according to given rules and parameter values. The activation command *ON/OFF* sends from the server to the actuator nodes through transmitter / receiver model via Wi-Fi.

#### E. Resource Optimization

Unlike the research in flood monitoring and controlling the water using pumps based on the water level only and makes decision by local node, where pump turns ON/OFF depending upon the water level Low, Medium and High. In the present design of algorithm, the system makes collective decision by considering real time flooding data of all sub-catchments. The system decides which sub-catchment area needed highest service in terms of reduces the water level. The priority to control the flood depends on water volume (low, medium, high, extremely high) of sub-catchment. For example, while controlling the actuators of one sub-catchment, the actuators of other sub-catchments may be inactive. As a result, the usage of actuators can optimize resource allocation process and minimize power consumption.

For example: For sub-catchment type is  $C_1$

If  $WV\_C_1$  is low then  $P_1=OFF$

It means that when water level is less than 1feet, the system uses only the one-way check valves to control the flood water and did not use any actuators.

If  $WV\_C_1$  is high then  $P1=ON$  and  $P2=OFF$

In such a situation, we use only one actuator to control the flood water and one way check valve.

If  $WV\_C_1$  is extreme then  $P1=ON$  and  $P2=ON$

And if the sub-catchment type is extreme then flood is controlled using both actuators along with one way check valves.

#### V. CONCLUSION

For managing floods, several researchers have proposed various computational intelligence methods, such as fuzzy systems, artificial neural networks, machine learning, and IoT-based systems. It is determined that over last two decades, most research has concentrated on flood monitoring and forecasting, and has suggest solutions based on real-time and historical data. The majority of recent research has been directed at developing forecast, monitoring, and alerting models for flood preparedness. These systems are only effective for real-time flood monitoring, warning, and prediction; they cannot be used to control floodwaters in real-time or as a system for flood resistance.

This research paper proposes a method for real time controlling the urban surface flood water. In order to prevent the overflow and insufficiency of the current drainage water network, this research recommends a water-sensitive Storm Water Control Network Model (SWCNM) that will serve as the framework for an intelligent flood control system. As a foundational infrastructure for a smart flood water control system, the SWCNM may be used to capture rainwater and use for solving water problem. Utilizing IOT and water level sensors, the suggested methodology may be implemented for the smart city. The proposed methodology can be used to reduce surface flood water using a fuzzy system and Internet of Things. However, in this study the storm water capacity, water pressure, water flow, and rain intensity are not considered to design an efficient flood control methodology.

#### REFERENCES

- [1] Wenchao Qi, Chao Ma1, Hongshi Xu, Zifan Chen, Kai Zhao1, Hao Han, "A review on applications of urban flood models in flood mitigation strategies", Springer, Natural Hazards, March 2021, <https://doi.org/10.1007/s11069-021-04715-8>
- [2] Farnaz Fotovatikhah, Manuel Herrera, Shahaboddin Shamshirband, Kwokwing Chau, Sina Faizollahzadeh Ardabili & Md. Jalil Piran, "Survey of computational intelligence as basis to big flood management: challenges, research directions and future work", Engineering Applications of Computational Fluid Mechanics, March 2018, 12:1, 411-437, DOI: 10.1080/19942060.2018. 1448896
- [3] O. Mendoza-Cano, R. Aquino-Santos, J. López-de la Cruz, R. M. Edwards, A. Khouakhi, I. Pattison, V. Rangel-Licea, E. Castellanos-Berjan, M. A. Martinez- Preciado, P. Rincón-Avalos, P. Lepper, A. Gutiérrez-Gómez, J. M. Uribe-Ramos, J. Ibarreche and I. Perez, "Experiments of an IoT-based wireless sensor network for flood monitoring in Colima, Mexico", Journal of Hydroinformatics 23.3 | 2021 page no.385, doi: 10.2166/hydro.2021.126
- [4] Wenting Zhang , Xiang Wang, Yongzhi Liu ,Tao Zhang," Simulation of Rainstorm Waterlogging Based on SWMM and Visualization Module Research", IEEE, 2016 International Conference on Smart City and Systems Engineering, DOI 10.1109/ICSCSE.2016.28.
- [5] Mochammad Hannats Hanafi Ichsan, Wijaya Kurniawan, Aulia Tri Wulandari, "Fuzzy Logic for Flood Detection System in an Embedded System", IEEE, 2019 International Conference on Sustainable In-

formation Engineering and Technology (SIET),  
10.1109/SIET48054.2019.8986051

- [6] Anil Hingmire, Dr. Pawan Bhalldhare, "A Review on Urban Flood Management techniques for smart city and future research", Springer, International conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI 2022) proceedings, August 2022, pg.319-336
- [7] Jiada Li, "A data-driven improved fuzzy logic control optimization-simulation tool for reducing flooding volume at downstream urban drainage systems", Elsevier, Science of the Total Environment, 2020, <https://doi.org/10.1016/j.scitotenv.2020.138931>
- [8] García, L., Barreiro-Gomez, J., Escobar, E., Téllez, D., Quijano, N., Ocampo-Martínez, C., 2015. Modeling and real-time control of urban drainage systems: a review. *Adv. Water Resour.* 85, 120–132. <https://doi.org/10.1016/j.advwatres.2015.08.007>.
- [9] Shahirah Binti Zahir, Phaklen Ehkan, Thennarasan Sabapathy, Muzammil Jusoh, Mohd Nasrun Osman, Mohd Najib Yasin, Yasmin Abdul Wahab, N.A.M Hambali, N.Ali, A.S.Bakhit, F.Husin, M.K.Md.Kamil, R.Jamaludin13, "Smart IoT Flood Monitoring System", International Conference Computer Science and Engineering 2019, Journal of Physics: Conference Series, doi:10.1088/1742-6596/1339/1/012043
- [10] Riyanto Wibisono, "Integrated Water Level Control System Using Fuzzy Logic", European Union Digital Library, EAI, 2018, ISBN 978-1-63190-171-3, <https://eudl.eu/pdf/10.4108/eai.20-1-2018.2281872>
- [11] Dharamniwas, A. Aziz, V. Redhu, and U. Gupta, "Liquid Level Control By Using Fuzzy Logic Controller," International Journal of Advances in Engineering & Technology, ISSN: 2231-1963, July 2012., vol. 4, no. 1, pp. 537–549, 2012.
- [12] U. Farooq, Rafiq, F., Abbas, G., Asad, "A Simplified Fuzzy Logic Liquid Level Control System," J. Intell. Comput., vol. 7, no. 4, pp. 135–144, 2016.
- [13] Z. Mushtaq, S. Tayyaba, and M. W. Ashraf, "Liquid Level Controlling by Fuzzy Logic Technique," Int. J. Innov. Sci. Res., vol. 12, no. 2, pp. 372–379, 2014.
- [14] Eric Samikwa, Thiemo Voigt, Joakim Eriksson, "Flood Prediction Using IoT and Artificial Neural Networks with Edge Computing", 2020 International Conferences on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (Smart Data), DOI 10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics50389.2020.00053.
- [15] Wenting Zhang, Xiang Wang, Yongzhi Liu, Tao Zhang, "Simulation of Rainstorm Waterlogging Based on SWMM and Visualization Module Research", 2016 International Conference on Smart City and Systems Engineering, 978-1-5090-5530-2/16, 2016 IEEE, DOI 10.1109/ICSCSE.2016.28
- [16] Luís B. Elvas, Bruno Miguel Mataloto, Ana Lúcia Martins and João C. Ferreira, "Disaster Management in Smart Cities", Smart Cities 2021, 4, 819–839. <https://doi.org/10.3390/smartcities4020042>, <https://www.mdpi.com/journal/smartcities>
- [17] Zening Wu, Yihong Zhou, Huiliang Wang, Zihao Jiang, "Depth prediction of urban flood under different rainfall return periods based on deep learning and data warehouse", Science of the Total Environment, 2020, <https://doi.org/10.1016/j.scitotenv.2020.137077>
- [18] Yves Abou Rjeily, Oras Abbas, Marwan Sadek, Isam Shahrour and Fadi Hage Chehade, "Flood forecasting within urban drainage systems using NARX neural network", Water Science & Technology, 2017, doi: 10.2166/wst.2017.409
- [19] Saiesh Naik, Srushti Ashok Patil, Anang Verma, Anil Hingmire, "Flood Prediction using Logistic Regression for Kerala State", International Journal of Engineering Research & Technology (IJERT), NTASU - 2020 (Vol. 09 – Issue.03)
- [20] Li-Chiu Chang and Fi-John Chang, "IoT-based Flood Depth Sensors in Artificial Intelligent Urban Flood Warning Systems", EGU General Assembly 2020, <https://doi.org/10.5194/egusphere-egu2020-12523>
- [21] <https://waterlevelcontrols.com/water-level-indicator/>
- [22] <https://www.clearias.com/urban-flooding/>