# Urban Flood Control System using Fuzzy Logic and Internet of Things (IoT) for Smart City

***Anil M. Hingmire, Pawan R. Bhaladhare***

## Abstract

Urban flood disaster losses have increased in recent decades as a result of climate change's worsening of meteorological disasters worldwide. Numerous approaches have been put forth in related research to improve urban flood resilience infrastructure, flood forecasting, flood monitoring, and flood warning based on computational methodology like machine learning, fuzzy logic, Artificial Neural Network and green infrastructure. This research paper proposes a real time flood control system based on Storm Water Control Network Model (SWCNM) based on Internet of Things. The proposed urban flood resilience model is based on fuzzy logic controller to controls the surface water by analyzing the most affected area by considering the optimum use of actuators. The approach is based on real time flood data for water catchments that were gathered using sensors and an autonomous smart controller. The water sensitive storm water network was designed using EPA SWMM tool and the flood control system was simulated for three sub-catchment area. A significant reduction of water level in the most flooded sub-catchment by 47.07 % in high and extreme input parameter value. The methodology for urban flood control that has been suggested can be built for the smart city and is useful to researchers in enhancing the efficiency of the model.

**Keywords:**
Urban Flood, Water Level, Fuzzy Logic, Smart City, Internet of Things.

## Introduction

Cities' land surface is rapidly decreasing as a result of urbanization's rapid development. The frequency of catastrophic floods tends to be higher as a result of global climate change, and the loss of life and property is certainly rising. A successful flood management strategy is essential to reducing the effects of floods. A lot of inconveniences are brought to people's everyday lives and jobs as a result of the water logging issue that is being produced by an increasingly impermeable land surface, decreased surface flow concentration time, and an aged drainage pipe network [1]. Urban climate change is currently a significant issue for all nations around the globe. Urban flood resilience was described in the Engineering and Physical Sciences Research Council (EPSRC) project as a city's ability to maintain future flood risk at tolerable levels by preventing fatalities and injuries, minimizing damage and disruption during floods, and recovering quickly afterward, while ensuring social equity, protecting the city's cultural identity, and maintaining its economic vitality[2].

The use of information technology (IT) to aid in flood control has grown during the past several years. For instance, it has become standard practice in many countries around the world to utilize sensors to collect hydrological data, such as water level, and then send that data over the network. The same is true for gathering and disseminating flood-related geological and meteorological data. This infrastructure comes together to create the Internet of Things (IoT) [6].

The Internet of Things (IoT) is a key enabler for a wide range of intelligent applications that need enormous data gathering and precise decision. The Internet of Things serves as a connecting element between sensing devices and the data plane in the implementation of smart cities [7].
The most widely used computational (CI) approaches in hydrology are based on Artificial Neural Network (ANN), fuzzy inference systems, Support Vector Machines (SVMs), and evolutionary computing (EC), as well as hybrid approaches that combine the aforementioned approaches and are used for flood forecasting using different parameters like temperature, water level, rain data, etc. [8].

***Corresponding Author: -** Anil M. HIngmire
**Address: -** 1* Research Scholar, School of Computer Science & Engineering, Sandip University, Nashik, Maharashtra, India.
E-mail: - anilhingmire@yahoo.com
2 Professor, School of Computer Science & Engineering, Sandip University, Nashik, Maharashtra, India.
E-mail:- pawan_bh1@yahoo.com

Development of new technology and software for flood monitoring and forecasting has become possible due to the Internet of Things (IoT) and computational models like the fuzzy model, Artificial Neural Networks (ANNs), Machine Learning, and hybrid models. Even though certain computational models have a high degree of accuracy and are based on current or historical hydrological data, these models or systems are solely used to warn people.

Due to climate change and development, urban pluvial flooding is becoming increasingly significant. However, the numerical models employed for flood forecasting and risk reduction suffer from a significant shortage of monitoring data, which impacts model accuracy. Monitoring data are required so that models with undetermined parameters may be calibrated and verified against real flood occurrences.

The aim of this research study is to design water sensitive Storm Water Control Network Model (SWCNM) based on IoT for efficient control of surface urban flood water. To develop the flood water control algorithm based on fuzzy inference system and evaluation of the developed model.

## Related Work

Wireless sensor networks can be used for flood monitoring and detection. Uldo et al. described a technique for tracking water level and flood detection utilizing humidity levels, water level, temperature and precipitation amount. To monitor the rate of rainfall, humidity level and temperature variables are employed. To predict the water level, rainfall values are used. The flood's intensity will be classified as low, medium, or high depending on the water level. This will improve flood early detection. Residents in the flood-prone area receive the flood status straight from the surveillance center [4].

Mochammad Hannats Hanafi Ichsan et al. (2019) developed a prototype system to monitor water on streams that may trigger floods. The prototype's water channel may be used to represent rivers, culverts, drains, etc. A sensor is fastened to the node to gauge speed and water level. Fuzzy logic is used to analyse the results of these readings and categorize the information regarding potential flooding or not. The output of fuzzy logic is then transmitted to the master node so that it may use LEDs to display information about the water flow's status [5].

In order to evaluate flood resilience, Zongmin Lia and colleagues created a method that takes into account the whole catastrophe cycle, including the capacity for resistance before to a flood, the capacity for coping with and recovering during a flood, and the ability for adaptation following a flood. The hesitant fuzziness is used to characterize professional language words in order to deal with the subjective uncertainty. So the assessment method includes hybrid crisp, random, and reluctant fuzzy values [9].

B Nair et al. propose a deep learning-based computer vision and crowdsourcing approach for identifying and estimating flood levels. Modern flood detection systems depend on radar or satellite images. This research looks at random images obtained using smartphones or digital cameras in flood-damaged regions. The crowdsourcing photography collection of flood situations provides improved exposure and a range of angles for assessing flood devastation. By analyzing crowdsourced photographs, a fuzzy logic-based algorithm and color-based image segmentation are used to determine the degree of flooding. Flooded areas can be classified as having a high, medium, or low degree of flooding using these methodologies, enabling for more efficient and immediate rescue attempts. [10]

Shi-Wei Lo et al. (2021) developed the system based on visual sensing for flood detection and incident mapping using deep neural networks and communication and information technologies. The use of a deep sensing system during the monsoon season in Taiwan was shown, and waterlogging events on an island-wide scale were forecasted. Through an internet of video things architecture, the system was able to detect roughly 2379 vision sources and relay event-location information in 5 minutes.[11]

Jiada Li (2020) used the SWMM FLC tool to create a co-simulation of data driven fuzzy logic controller for urban flooding. SWMM FLC has the potential to decrease overall flooding volume in urban drainage systems downstream. [12].

In 2018, Riyanto Wibisono et al. presented a concept of a fuzzy based control system on two water doors to water level management. The prototype system, which consists of a water gate and two fuzzy logic controllers were used. The working time of the water gate motor is between 0 and 2 seconds used to control water gate output. The error signal and water level delta error were the inputs to the fuzzy logic controller. The input and output values were separated into five membership functions and the

system was defuzzified using the Centre of Area (COA) technique. [14].

Eric Samikwa et al. demonstrated an Artificial Neural Network technique for real-time flood prediction utilizing IoT sensors on edge computing in 2020. Sensor data is processed using edges devices which consume less power for processing data. The system continuously checks the real time rainfall, water level and analyses temporal correlation data to forecast flood water levels in advance using long short-term memory (LSTM). The LSTM is a kind of ANN that works well with time series data. Eric Samikwa et al. employed regression statistical error measures to evaluate the model on a real dataset [15].

## Need for Water Sensitive Flood Control Model

Flood control refers to any approach utilized to reduce or eliminate the detrimental consequences of flood waters. In addition to flood prediction, monitoring, and alerting methods, common flood management techniques include the placement of sandbags ,rock pathway, rock rubble, maintaining normal slopes with vegetation or applying soil cements to steeper slopes, and the construction or enlargement of drainage channels. When the city was inundated, however, several local authorities used water pumps to transport the water from the catchment to the drainage line. It is not ideal since the process of pumping water is totally manual and only useful after a flood. The primary cause of rainfall collection is clogged and inadequate drainage. The drainage network for coastal communities is overburdened during heavy rains, storms, and high tide. The city drainage system is solely intended to carry sewage and is built with considerations such as land area and population density in mind. Rainfall during the non-monsoon season, cyclones in coastal regions, tsunamis, man-made floods caused by dams, and land slide causing the flow of the river to change direction are the main factors that cause flooding in Indian cities and towns.

Because of the aforementioned issues, we propose a separate storm water line that runs parallel to the drainage system and reduces overload on existing drainage network to reduce the flood water. The storm water line network's only purpose is to control flooding precipitation, but it may also be used to solve water problems for drinking, agriculture and industry purpose. However, it may increase infrastructure costs, although this is only an initial cost, and the storm water line network model can only be utilized on large roads to control the surface flood water. We may use the current drainage system on narrow roadways.

## Proposed Methodology

### A. Design of Storm Water Control Network Model (SWCNM)

The proposed system encompasses the Storm Water Control Network Model (SWCNM) which serves as the basic infrastructure for smart flood control system. The aim of SWCNM is to control the urban surface flood water and not the drainage water. The SWCNM can be used at urban flood prone area of the city. The urban flood prone area taken into consideration for this study is Evershine city vasai, a suburb of Mumbai. The EPA SWMM 5.2 simulation tool is used to design the water-sensitive Storm Water Control Network Model

(SWCNM). Figures 1 shows a Storm Water Control pipeline Network design for the research study area. In figure 1 shows water flow direction along with the Storm Water Control Pipeline laid both side of road. In each sub-catchment the water level sensors are placed and the water level values are used to calculate the water volume of the catchment.

The study area is divided into a three sub-catchments based on frequently flooding part of study area. The network's multiple catchments employ water level sensors to collect real-time flood data. On the Storm water network line, the one way check valve is installed which act as actuators based on real time flood level to prevent backflow. The number of check valves is variable and depends on sub-catchment area and length of storm water line. For each sub-catchment, we installed the pumps which 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.

The study area is splitted into a three sub-catchments $C_1$, $C_2$, and $C_3$. However the automated valves can be used and can be operated using microcontroller for opening and closing based on water level sensor values. But to reduce the cost of automated valves with microcontroller we proposed the use of check valves. The sub-catchment $C_2$ is employed, together with two actuator pumps $P_1\_C_2$ and $P_2\_C_2$ and three water level sensors ($WL_1\_C_2$, $WL_2\_C_2$, and $WL_3\_C_2$). And the sub-catchment $C_3$, two actuator pumps $P_1\_C_3$, $P_2\_C_3$, and six water level sensors $WL_1\_C_3$, $WL_2\_C_3$, $WL_3\_C_3$, $WL_4\_C_3$, $WL_5\_C_3$, and $WL_6\_C_3$ are employed.

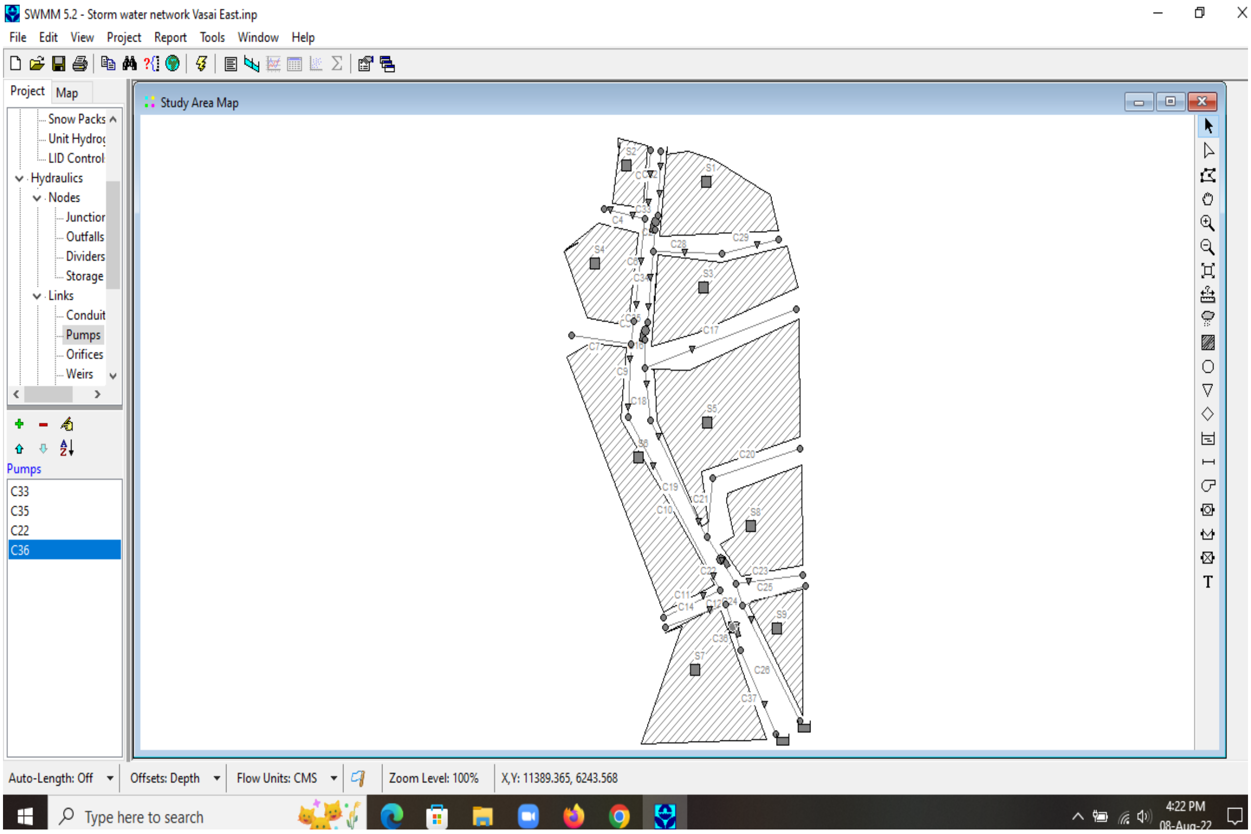


Figure 1: Storm Water Control pipeline Network of study area

Sensors monitoring water levels are located at a fixed distance. Figure 2 shows a schematic diagram of a sub-catchment $C_1$ which includes four water level sensors and two pumps which acts as actuators based on fuzzy inference rules. The sub-catchment $C_1$ uses four water level Ultrasonic sensors $WL_1\_C_1$, $WL_2\_C_1$, $WL_3\_C_1$, $WL_4\_C_1$ and two actuators pumps $P_1\_C_1$ and $P_2\_C_1$. In order to manage surface flood water, the algorithm calculates the water volume (Wv) parameter for each catchment, then it selects the catchment that needs flood water control immediately.

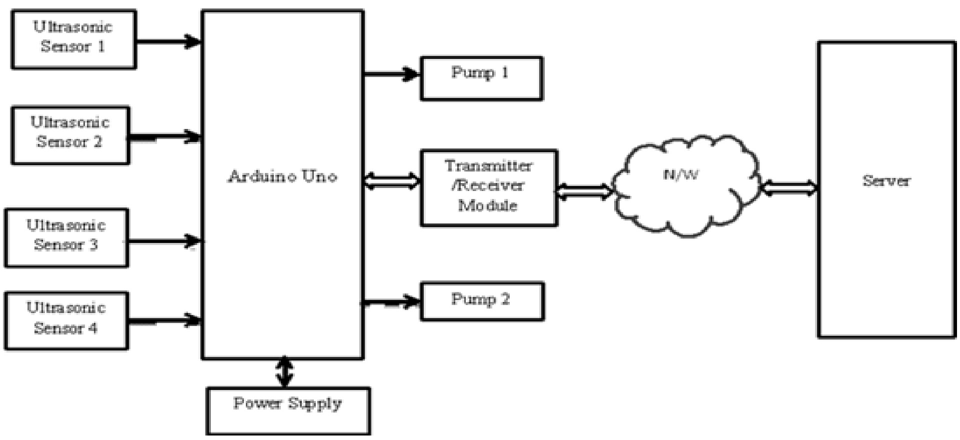


Figure 2: Schematic diagram of catchment $C_1$

To calculate the water volume (*Wv*) for the sub-catchments based on sub-catchment area (*A_C*) based on placements and distance between water level sensors which creates a geometrical shape like rectangle, triangle, hexagon etc. Based on distance between water level sensors and the average of water level values the water volume of the sub-catchment is calculated. In order to manage surface flood water, the algorithm calculates the water volume (*Wv*) parameter for each catchment, then it selects the

For example, Sub-catchment Area $A\_C_1$ for $C_1$ is rectangle as the placements of four water level sensors create rectangle shape. So $A\_C_1$ for $C_1$ is calculated as below

$$A\_C_1 = dist\ (Wl_1\_C_1,\ Wl_2\_C_1) * dist\ (Wl_2\_C_1,\ Wl_3\_C_1)$$

Water level in sub-catchment *C* is Average of all values of water level sensors, as given by following formula,

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

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

## B. System Block Diagram

catchment that needs flood water control immediately.

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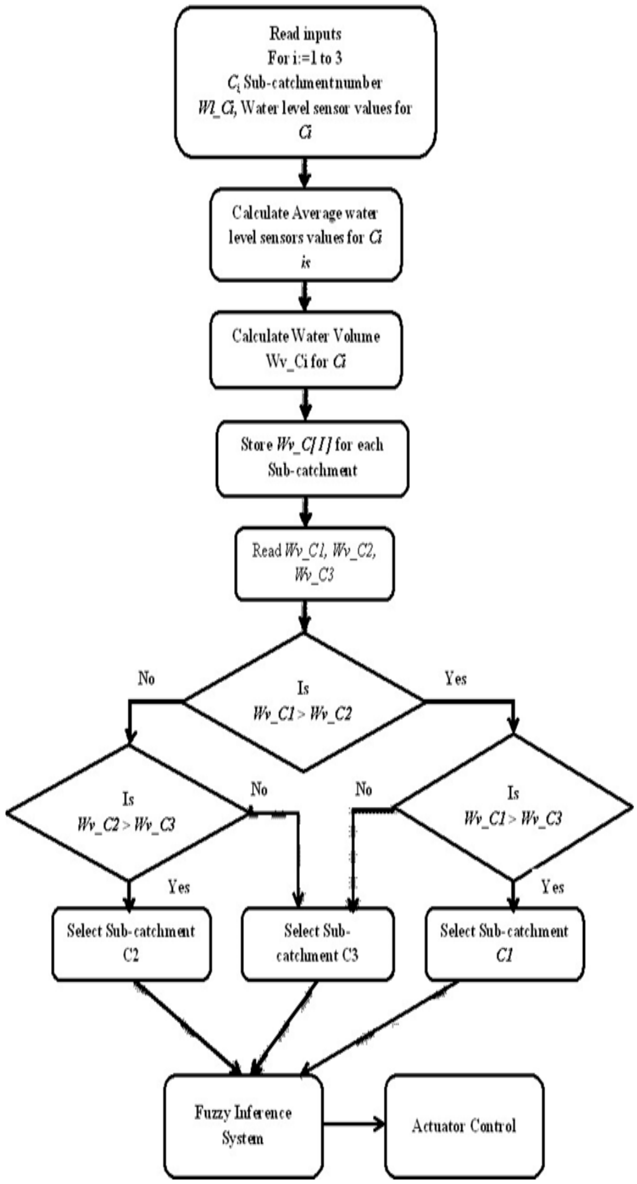


Figure 3: System Block Diagram

The system block diagram is shown in Figure 3. It includes the parts for computing the flood water level and water volume for each sub-catchment, reading input sensor values, and actuator control. A microcontroller in each sub-catchment transmits the readings of the water level sensors periodically to a server by utilizing transmitter-receiver devices. 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.

## C. Data Collection

In this study, an ultrasonic sensor is employed to determine the state of the water level. The water level values sensed by Ultrasonic sensor installed in the catchments are transmitted to the server and used for computations of water volume in the catchments. The microcontroller of each catchment reads real time water level sensor values after every 15 minutes of three sub-catchments and transmits to server. The water level values from the sensors are in mm. Table 1 shows the actual water level sensor data for the given sub catchments.

Table 1: Water level sensor values in mm

| **Date** | **Time** | **wtr_lvl_1A** | **wtr_lvl_1B** | **wtr_lvl_1C** | **wtr_lvl_1D** | **wtr_lvl_2A** | **wtr_lvl_2B** | **wtr_lvl_2C** | **wtr_lvl_3A** | **wtr_lvl_3B** | **wtr_lvl_3C** | **wtr_lvl_3D** | **wtr_lvl_3E** | **wtr_lvl_3F** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 20-08-22 | 1:00 PM | 95 | 98 | 93 | 97 | 150 | 152 | 158 | 104 | 100 | 105 | 102 | 106 | 101 |
| 20-08-22 | 1:15 PM | 200 | 195 | 197 | 201 | 368 | 370 | 381 | 249 | 243 | 250 | 248 | 254 | 253 |
| 20-08-22 | 1:30 PM | 550 | 505 | 509 | 524 | 597 | 594 | 600 | 375 | 372 | 378 | 370 | 374 | 376 |
| 20-08-22 | 1:45 PM | 944 | 964 | 961 | 957 | 872 | 865 | 876 | 608 | 607 | 610 | 611 | 609 | 601 |
| 20-08-22 | 2:00 PM | 1024 | 1011 | 1019 | 1021 | 1080 | 1086 | 1099 | 1035 | 1033 | 1035 | 1031 | 1038 | 1039 |
| 20-08-22 | 2:15 PM | 1358 | 1355 | 1360 | 1362 | 1399 | 1405 | 1420 | 1547 | 1544 | 1546 | 1544 | 1550 | 1558 |
| 20-08-22 | 2:30 PM | 1203 | 1229 | 1232 | 1218 | 1680 | 1669 | 1675 | 1869 | 1873 | 1874 | 1863 | 1869 | 1877 |
| 20-08-22 | 2:45 PM | 1101 | 1107 | 1110 | 1106 | 1533 | 1534 | 1540 | 1755 | 1758 | 1749 | 1751 | 1759 | 1756 |
| 20-08-22 | 3:00 PM | 896 | 894 | 900 | 901 | 1601 | 1598 | 1608 | 1508 | 1506 | 1504 | 1501 | 1498 | 1506 |
| 20-08-22 | 3:15 PM | 573 | 568 | 560 | 559 | 1479 | 1479 | 1485 | 1086 | 1081 | 1089 | 1087 | 1086 | 1083 |
| 20-08-22 | 3:30 PM | 429 | 471 | 467 | 459 | 1118 | 1111 | 1123 | 929 | 920 | 927 | 925 | 927 | 923 |
| 20-08-22 | 3:45 PM | 351 | 313 | 333 | 329 | 893 | 890 | 901 | 785 | 782 | 786 | 781 | 780 | 783 |
| 20-08-22 | 4:00 PM | 264 | 256 | 260 | 259 | 621 | 623 | 635 | 407 | 408 | 411 | 409 | 403 | 401 |
| 20-08-22 | 4:15 PM | 108 | 100 | 98 | 102 | 321 | 320 | 334 | 296 | 294 | 293 | 295 | 289 | 291 |

## D. Fuzzy Logic System

The catchment is selected to control the flood water based on the water volume *Wv* as described in system block diagram in figure 3. To design the fuzzy controller system the input and output parameter shown in Table 2.

Table 2: Linguistic input and output parameters

| **Linguistic Parameter** | **Value** | **Description** |
|---|---|---|
| Input Parameter: Water Level *(AWl)* | feet | Average water level of all sensors in the sub-catchment |
| Output Parameter: Pump (*P*) | ON / OFF | Action of Pump in the sub-catchment |

Figure 4 shows a graphical representation of membership function for the input parameter *AWl*, the input to 4-level fuzzifier varies from 0 feet to 3 or more than 3. Hence the corresponding output also changes.

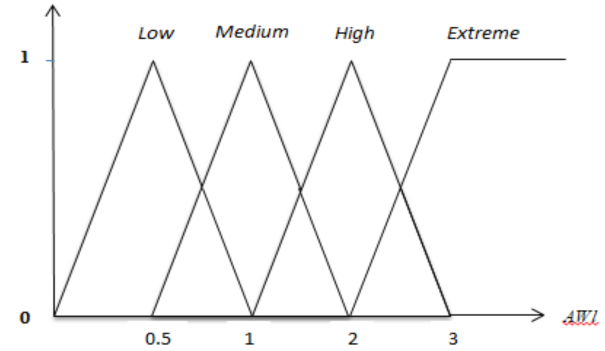


Figure 4: Fuzzy Membership Function for input Water level

The fuzzy subset configuration for input parameter AWl is Low, Medium, High, Extreme and for output parameter Pump (P) is ON / OFF.

In Table 3 shows the fuzzy inference rule sets for input parameter value and the output action of pumps for the sub-catchments $C_1$, $C_2$ and $C_3$.

Table 3: Fuzzy Inference rules for Sub-catchment *C1*, *C2*, and *C3*

| **Sub-Catchment** | ***AWl* Low (0-1 ft )** | ***AWl* Medium 1-2 ft** | ***AWl* High 2-3 ft** | ***AWl* Extreme** | ***Pump (P)* ON/OFF** |
|---|---|---|---|---|---|
| *C1* (Area 1) | 0 | 0 | 1 | | |
| | 0 | 0 | 1 | | |
| *C2* (Area 2) | 0 | 0 | 1 | | |
| | 0 | 0 | 1 | | |
| *C3* (Area 3) | 0 | 0 | 1 | | |
| | 0 | 0 | 1 | | |

```
======== RESTART: C:\Users\student\Desktop\Water  Drain\Drain_script.py =

['Area code: 3, Sensors : 6, Vol: 8500.0', 0.34]
['Area code: 1, Sensors : 4, Vol: 620.0', 0.31]
['Area code: 2, Sensors : 3, Vol: 400.0', 0.5]

['Area code: 3, Sensors : 6, Vol: 20500.0', 0.82]
['Area code: 1, Sensors : 4, Vol: 1300.0', 0.65]
['Area code: 2, Sensors : 3, Vol: 976.0', 1.22]

['Area code: 3, Sensors : 6, Vol: 30750.0', 1.23]
['Area code: 1, Sensors : 4, Vol: 3420.0', 1.71]
['Area code: 2, Sensors : 3, Vol: 1568.0', 1.96]

['Area code: 3, Sensors : 6, Vol: 49750.0', 1.99]
['Area code: 1, Sensors : 4, Vol: 6280.0', 3.14]
['Area code: 2, Sensors : 3, Vol: 2288.0', 2.86]

['Area code: 3, Sensors : 6, Vol: 84750.0', 3.39]
['Area code: 1, Sensors : 4, Vol: 6680.0', 3.34]
['Area code: 2, Sensors : 3, Vol: 2856.0', 3.57]

['Area code: 3, Sensors : 6, Vol: 127000.0', 5.08]
['Area code: 1, Sensors : 4, Vol: 8900.0', 4.45]
['Area code: 2, Sensors : 3, Vol: 3696.0', 4.62]
```

Figure 5: Water volume and water level of Sub-catchments

## Results Analysis and Discussion

Figure 5 shows the result of calculation of water volume and water level in the sub-catchment area at the instance of fetched sensor data and sorted in descending order. The water level values are converted from mm to ft. Each row in the table contains the record of sub-catchment number, number of water level used in sub-catchment, the calculated water volume in the sub-catchment and the water level in the sub-catchment in given time series data.

Figure 6, 7, 8 shows the graph of water level of outputs of actions taken by pumps for the sub-catchment area $C_1$, $C_2$, and $C_3$ respectively. As shown in Figure 6, the average water raising rate is around 2.18 times at each time interval of 15 minutes till 656.5mm before the pump P1is activated.

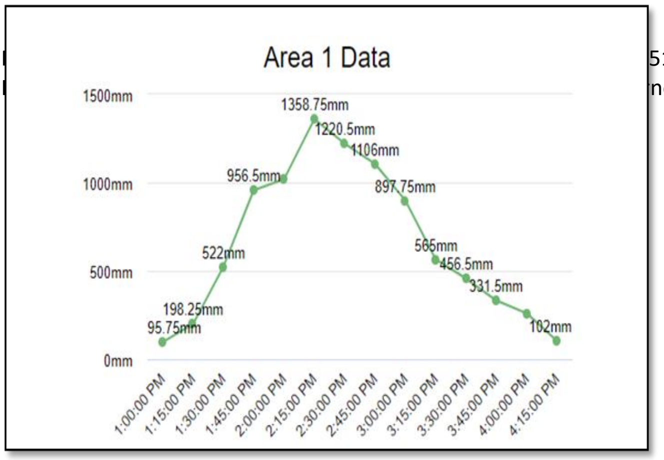


Figure 6: Water level of sub-catchment *C1*

*P1* becomes *ON* at water level 956.5 mm as the water level is *High* and remains ON till water level becomes 586mm. The water level is reduced by 20% when the *P1* is only activated. The pump *P2* starts at water level 956mm and remains *ON* till 897.75mm according to the fuzzy rule set for the catchment *C1*. Based on the graph of *C1*, the water level of the sub-catchment reduces when $P_1$ and $P_2$ both are *ON* for extreme level by 47.068 % on average.

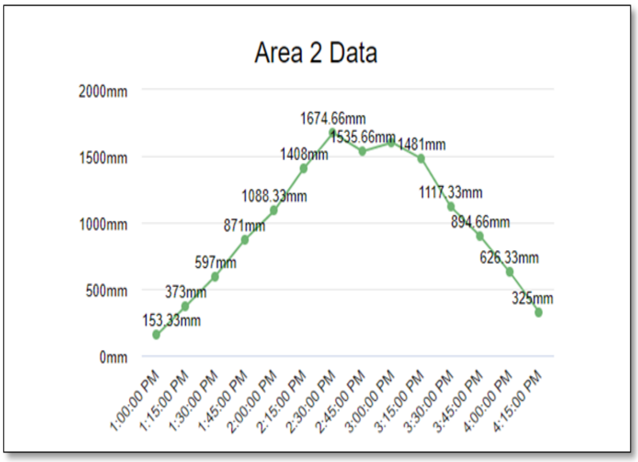


Figure 7: Water level of sub-catchment $C_2$

Based on the graph depicted in Figure 7 the average water level raising rate is 34.12% till 871mm before the pump P1is activated. P1 becomes ON at water level 956.5 mm as the water level is High and remains ON till water level becomes 325mm. The water level is reduced by 24.95% when the P1 is only activated. The pump P2 starts at water level 1088.33mm and remains ON till 894.66mm according to the fuzzy rule set for the catchment C2. Based on the graph of C2, the water level of the sub-catchment reduces when P1 and P2 both are ON for extreme level by 16.42% on average.

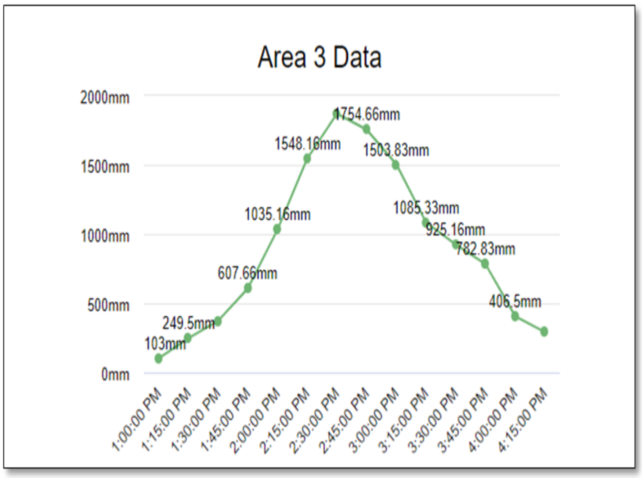


Figure 8: Water level of sub-catchment C3

Based on the graph depicted in Figure 8 the average water level raising rate is 42.19% till 607.66 mm before the pump P1 and P2 is activated. P1 and P2 becomes ON at water level 607.66 mm as the water level is High and remains ON till water level becomes 406.5mm. The pump P3 starts at water level 1035.16mm and remains ON till 782.83mm according to the fuzzy rule set for the catchment C3. Based on the graph of C3, the water level of the sub-catchment reduces when P1, P2 and P3 are ON for extreme level by 20.48% on average.

## Conclusion

Losses from urban flood catastrophes have risen in recent decades as a result of climate change's worsening of meteorological disasters across the world. Based on computational techniques and IoT, several ways have been proposed by the researchers in related studies to improve urban flood resilience infrastructure, flood forecasting, flood monitoring, and flood warning.

In this study, we propose a water-sensitive Storm Water Control Network Model (SWCNM) that makes use of IoT infrastructure. The urban flood control methodology implemented using fuzzy logic and the simulated results are shown in this research article. The water sensitive storm water network is designed using EPA SWMM tool and the flood control system is simulated for three sub-catchment area. The result shows that the most flooded catchment the water level reduces by 47.07 % for high and extreme input parameter value when more than one pump is activated. However the water level reduction rate is 20% for a single pump. The increasing rate of water level in the catchments is more may be because of high intensity of rainfall during the period. The water reducing rate is depending on water volume in the catchment, rain intensity, water flow, pump capacity and the density of SWCNM pipeline.

## References

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, IEEE, DOI 10.1109/ICSCSE.2016.28

Meiyan Gao , Zongmin Wang, Haibo Yang, "Review of Urban Flood Resilience: Insights from Scientometric and Systematic Analysis", International Journal of Environmental Research and Public Health", 2022, 19, 8837. https://doi.org/10.3390/ijerph19148837

M Salunke, N Korade. Survey on Flooding Detection System using Internet of Things. International Journal of Computer Applications. 2017; 165

EN Udo, EB Isong. Flood Monitoring and Detection System using Wireless Sensor Network. Asian Journal of Computer and Information Systems. 2013; 1(04): 108-113.

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

Azimah Abdul Ghapar, Salman Yussof and Asmidar Abu Bakar, "Internet of Things (IoT) Architecture for Flood Data Management", International Journal of Future Generation Communication and Networking, Vol. 11, No. 1 (2018), pp.55-62, http://dx.doi.org/10.14257/ijfgcn.2018.11.1.06

B. Hammi, R. Khatoun, S. Zeadally, A. Fayad, L. Khoukhi, "IoT Technologies for Smart Cities", IET Networks 7 (1) (2018), 1–13. doi:10.1049/iet-net.2017.0163.

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

Zongmin Lia, Xinxin Zhanga, Yanfang Mab, Cuiying Feng, Asaf Hajiyevd, "A multi-criteria decision making method for urban flood resilience evaluation with hybrid uncertainties", International Journal of Disaster Risk Reduction 36 (2019), https://doi.org/10.1016/j.ijdrr.2019.101140

B Nair, Bhavanaa; Krishnamoorthy, Shivsubramanib M, Geethab N Rao, Sethuramana, "Machine vision based flood monitoring system using deep learning techniques and fuzzy logic on crowdsourced image data", Intelligent Decision Technologies, vol. 15, no. 3, pp. 357-370, 2021, 10.3233/IDT-200133

Shi-Wei Lo , Jyh-Horng Wu, Jo-Yu Chang, Chien-Hao Tseng, Meng-Wei Lin, and Fang-Pang Lin, "Deep Sensing of Urban Waterlogging", IEEE Access, VOLUME 9, 2021, 10.1109/ACCESS.2021.3111623

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

Himanshu Rai Goyal , Kamal Kumar Ghanshala, Sachin Sharma, "Post flood management system based on smart IoT devices using AI approach ", Materials Today: Proceedings, www.elsevier.com/locate/matpr, https://doi.org/10.1016/j.matpr.2020.12.947

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

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.

Li-Chiu Chang and Fi-John Chang, "IoT-based Flood Depth Sensors in Artificial Intelligent Urban Flood Warning Systems", EGU2020-12523, EGU General Assembly 2020, https://doi.org/10.5194/egusphere-egu2020-12523

A. E. Alabi, O. S. Ayoola, O. A. Fakolujo, "Fuzzy Logic-based Data Controlled Wireless Sensor Network Routing Protocol for Flood Early Warning", Nigerian Journal of Technological Development, VOL. 18, NO. 3, SEPTEMBER 2021, doi: http://dx.doi.org/10.4314/njtd.v18i3.