International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6s
DOI: https://doi.org/10.17762/ijritcc.v11i6s.6952
***Article Received**: 28 March 2023 **Revised**: 18 May 2023 **Accepted**: 26 May 2023*

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

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Abstract— City flood control is a significant concern everywhere due to the constantly changing environment. The modern world needs smart cities with smart infrastructure to manage or control floodwaters. The research objective of this study is to design real time urban flood control methodology, develop the working model and testing the model with result analysis in controlled environment. This research paper proposes a smart water control model based on fuzzy inference system. The research is advancement in the Water Sensitive Storm Water Management System by creating a prototype model and then evaluating it in real-world scenarios using input parameters as rainfall intensity, water flow rate, and water level. The method relies on water catchment flooding data that was collected in real-time using sensors and an autonomous smart controller. The system considers the real-time sensor data from all catchments to make collective decision, which also optimize the use of actuators by conserving the power used by the actuators. In terms of early floodwater control, the recommended approach optimizes the use of actuators with utilizing the existing drainage system. The average water reduction rate at the medium level is 34.8%. At high levels, the average water reduction rate is 61.43%, and at extremely high levels, it 73.63%. A significant reduction of water level achieved in the most inundated area by 73.9 % in high and extreme input parameter value.

Keywords- Smart City, Fuzzy logic, Internet of Things, Urban Flood, Storm Water Control Network.

I. INTRODUCTION

Cities all around the world are employing smart technologies enabled by the Internet of Things (IoT) to streamline local operations, spur economic growth, and enhance citizen quality of life. Key services including public transportation, communications, water and electricity distribution, hospitals, and schools will continue to be provided without interruption to residents of safe and resilient cities with smart city critical infrastructure [1]. Smart cities should have basic infrastructure, a good standard of living for its residents, a healthy environment, and the use of "smart" solutions. Urbanization and climate change are mutually dependent, although in different ways. Climate change is primarily characterized by variations in temperature and precipitation. With regard to industrial output, societal infrastructure, and public services, these variances have an impact on the metropolitan city's economic index. The planning of a smart city might be complicated by climate change. With the development of technology, a smart city must be developed as a safe and environmentally friendly place to live. Mitigating natural calamities like urban floods should be required in the planning [3].

One of the most frequent and destructive natural catastrophes, floods cause massive property, infrastructural, and agricultural damage while displacing millions of people worldwide. Floods are typically caused by lengthy, intense rain, high snowmelt, tropical storms, tsunamis in coastal areas etc. Urban flooding occurs whenever rainfall exceeds the ability of drainage systems, such as storm sewers, and floods lands or property inside a built environment, especially in areas that are more densely inhabited. Urban planners and local governments have a significant issue as urban flooding occurs increasingly often across the world.

Floods in metropolitan areas are caused on by the rapid, unforeseen release of water from dams and lakes, which happen without giving the public the time to react. The majority of urban drainage systems were designed to manage lower runoff volumes than those found today, making them vulnerable to collapse during storms with high rainfall intensities. Natural and man-made factors can contribute to urban flooding. Natural causes like global warming, changing weather patterns, heavy rains, etc., as well as artificial ones like the loss of natural drains and ongoing urban expansion due to population increase.

According to a report from the United Nations Development Program (UNDP), urbanization is still one of the major trends of the twenty-first century. By 2050, 68 percent of the world's population will live in urban areas. However, many cities all across the world are struggling with issues including rising inequality and the ongoing problems of creating sustainable and habitable environments [2].

As storm water runoff increases due to cementitious infrastructure, Urban engineers are integrating green infrastructure, such as avenue trees to lessen flood-related landslides, permeable-paved roads, retention and detention ponds, green roofs, and rain gardens to absorb rainwater to improve flood protection, as storm water runoff increases due to cementitious infrastructure. The Internet of Things (IoT) and computational models like hybrid models,, fuzzy models, artificial neural networks (ANNs) have opened up new avenues for the creation of new hardware and software for flood monitoring and forecasting [4].

The Internet of Things (IoT) is now used in a variety of industries, including manufacturing, disaster management, healthcare, smart cities, safety, and asset monitoring and inventory control. By using real-time data, IoT aids disaster management by monitoring, managing, sensing, and tracking the environment. The development of smart cities has relied heavily on Internet of Things technologies.

Urban pluvial floods are caused by an imbalance between the capacity of storm water drainage systems and the intensity of rainfall and runoff. The fundamental elements of managing flood risk in urban areas are storm water drainage systems; different drainage facilities can be built to lower the risk. Better hydrological modelling has become practicable because of technological development and the creation of various significant software applications, which will help solve the problem.

The objective of this research is to design an effective real-time urban flood control algorithm, build a real-time urban flood control hydrological using fuzzy system and the Internet of Things (IoT) with result analysis. The system is the enhancement of real time flood control system based on Storm Water Control Network Model (SWCNM) and Internet of Things, described in section 3.

II. RELATED WORK

Urban drainage systems (UDSs) are often under additional pressure due to the combination of climate change and urbanization especially precipitates rainfall frequency and amplifies peak runoff rate. Among the storm water facilities that can be managed in real-time to reduce urban floods downstream are UDSs. Jiada Li (2020) created an enhanced data-driven fuzzy logic control optimization employing fuzzy logic control and genetic algorithms for smart decision making concerning flooding mitigation in terms of lowering flooding volume at downstream urban drainage systems. Under eight simulated rainfall scenarios; the cumulative flooding volume is decreased by up to 4.55% based on the simulation results of the Storm Water Management Model (SWMM). At the downstream site of urban drainage networks, only one storage unit and one fuzzy logic controlled gate (orifice) were conceptually built and simulated. Focusing on spreading numerous Fuzzy Logic Controlled gates among various storage sites and looking at how data-driven fuzzy logic control strategy may increase system-level fuzzy logic control strategy can improve the rate of lowering flood volume [5].

A method for assessing flood risk those Binh Thai Pham et al. [2021] presented uses a deep learning algorithm in conjunction with Multi-Criteria Decision Analysis. Three primary elements comprise the flood risk assessment considered as hazard, exposure, and vulnerability. Data from the 847 previous flood locations is utilized to train and test the model. The methodology includes flood vulnerability evaluation, flood susceptibility analysis, flood exposure assessment and flood risk map analysis. Models for flood susceptibility were created using training data, and their effectiveness was verified using testing data. Flood susceptibility models includes Deep Neural Networks (DNNs) and Forest by Penalizing Attributes (FPA). The flood hazards map is produced using the best flood susceptibility map along with maps of flood depth and duration. The model access the flood susceptibility, flood depth, flood duration, distance to river, road density etc. [6]. The model's goal is to forecast flood danger based on sparse historical data, not to control floods in real time.

In order to lower the risk of urban flooding, W. Shepherd et al. (2017) presented a sewer flow control system that is locally autonomous and data-driven. The system consists of a wireless local water level monitoring, a flow control device and control system. A data-driven algorithm analyses the water level data and gives directions to the flow control device in order to reduce the threat of flooding at the downstream flooding point. A SWMM model has been connected to a fuzzy logic control algorithm to permit virtual testing and to serve as the foundation for a genetic algorithm that will optimize the fuzzy logic membership functions. Additionally, techniques for producing the initial starting membership functions used as input by the genetic algorithm have been studied. In simulated testing, the enhanced Fuzzy Logic membership functions lead to an average 25% reduction in flood volume only [7].

A system for real-time flood prediction that makes use of IoT sensing and Artificial Neural Networks (ANN) was presented by Eric Samikwa et al. in 2020. On a low power edge device, the sensor data is processed. 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). The information is displayed as a time series of time stamps with associated values for rainfall and water level [8]. The

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model is better suited for flood prediction and early warning than for controlling the floodwaters in real time.

To estimate flood depth, Weijun Dai et al. (2021) suggested an ensemble learning method based on Bayesian model combination (BMC-EL). The models comprise backpropagation neural networks, random forests, support vector machines, linear regression, and BMC-EL models. The model was evaluated using actual flood data collected from Macao, China, and experimental findings demonstrate its ability to anticipate flood depth one hour in advance. The accuracy ratio of the various flood intensity levels used as a measure of the models' dependability. The model is appropriate for warning the public, not for flood control [9].

In order to commence rescue operations as soon as possible, Hafiz Suliman Munawar et al. (2021) suggest real-time flood management technologies that could rapidly detect flooded locations. Unmanned aerial vehicles (UAVs) are used in the system to create an autonomous imaging system that can detect flooded regions from aerial photographs. To build an automated imaging system that can recognise inundated regions from aerial photographs, the system uses unmanned aerial vehicles (UAVs). The aerial images taken by UAVs were used to both identify flooded regions and to identify features like roads and houses. A deep learning system is trained using a training dataset that includes the extracted landmarks. Roads and buildings are detected from photos with 91% and 94% accuracy, respectively, according to trial results. In categorizing the input into flooded and non-flooded zones, an overall accuracy of 91% was observed [10].

In order to control the urban flood water in real time situation, Anil Hingmire eta al. proposed the conceptual approach that incorporates the water-sensitive Storm Water Control Network Model as the foundation for the intelligent flood control system based on IoT and Fuzzy inference in order to regulate the urban flood water in real-time situations. By optimally activating the activators, the system will be able to regulate flood water utilizing time series data on water volume and water level in the sub-catchments [12].

III. EXISTING SYSTEM

Existing authors, Anil Hingmire et al. [11] have proposed the real time flood control system based on Storm Water Control Network Model (SWCNM) and Internet of Things on primary storm water channel network instead of drainage network. The Urban Flood Resilience System uses a fuzzy logic controller to analyze the most impacted region and take into account the best usage of actuators to control the surface flood water. The time series data of every 15 minutes time interval is considered for the controlling of the flood in the sub-catchments by activating or deactivating the sub-catchment actuators (pumps). The simulation result shows that the reduction of water level in the most flooded sub-catchment is 47.07 % in high and extreme input water level parameter value. The technique is based on real-time flood data for water catchments that was acquired with the use of sensors and an autonomous smart controller. The system is only based on water volume of sub-catchments and the storm water network model.

IV. PROPOSED METHODOLOGY

The proposed research is a continuation of the system proposed by us in [11], in which we proposed an IoT and fuzzy based Storm Water Control Network Model to control the flood water. However, the findings of the existing system show that the flood water reduction rate is only 47.7% and only takes into account the sub-catchment water level parameter. The data set generated was small and number of sub-catchments was only three. It takes into account time series real-time data with a 15-minute time interval. In case of heavy rainfall, the system cannot control flood water as time interval to get real time data is long and the system does not consider the intensity of rain fall.

To improve the performance of system and able to work in heavy rainfall, in the proposed study the parameters including rain intensity, water flow, water level for each sub-catchment and utilizes the existing drainage network for controlling the flood water efficiently has been considered. The number of sub-catchments has also been increased to four and implementation of the actual prototype of the system has been done. Instead of every 15 minutes, real-time flood data from each catchment is retrieved every 1 minute. In case of heavy rainfall and extreme water level, the system reduced the overload of Storm Water Control Network by using the existing drainage system.

A. System Block Diagram

As shown in figure 1, the abstract view of the system includes four Internet of Things (IoT) nodes which transmit the real-time series data of sensors after every 1 minute to the Storm Water Control system. The Storm Water Control System calculates the Water Volume (*Wv*) of each sub-catchment and decides which sub-catchment is on higher risk and need to control the flood water immediately. Based on Water Volume (*Wv*), Water level (*Wl*), Rain Intensity (*Ri*), and Water Flow (*Wf*) in the sub-catchment area the fuzzy based controller algorithms utilizes the fuzzy inference rules and sends command to the respective IoT node for controlling of flood water.

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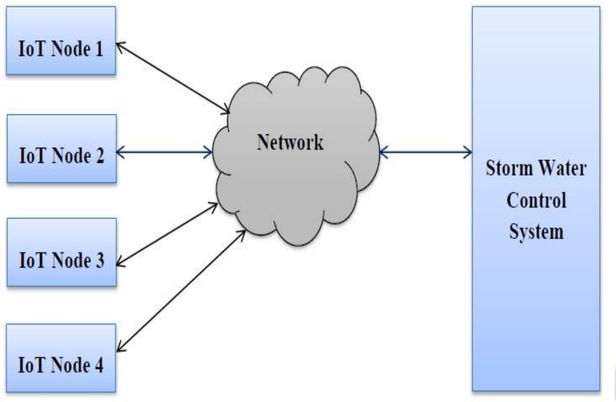

Figure 1: System Block Diagram

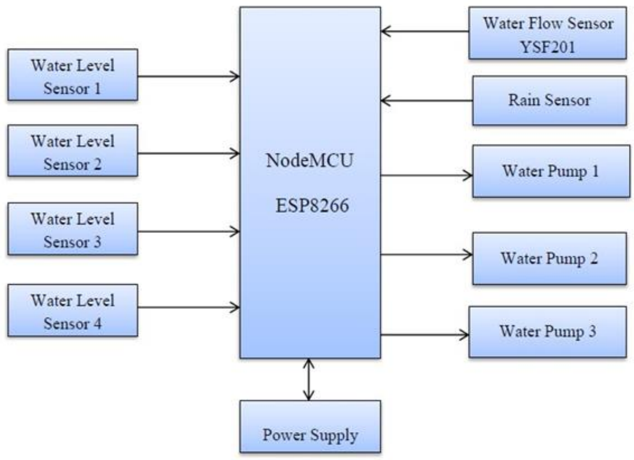

Figure 2: IoT Node Architecture

B. IoT Node Diagram

Figure 2 shows the Internet of Things (IoT) node components, Arduino UNO microcontroller and the six sensors and the three actuators. In this prototype model we used Water level sensor, 1/2 inch Water flow sensor YSF201, Rain Drop Sensor Module (EC-0569) and three Submersible Mini Water Pumps as actuators which controls the flood by reducing the water level in the sub-catchments. A set of parallel exposed traces on the water level sensor module are used to measure the volume of the water in order to calculate the water level. The output to analogue signal is precisely proportional to the water level, making water level monitoring very simple. The Analog to Digital Converter (ADC) may read the output analogue values directly, and the analogue input pins of the microcontroller can also be directly linked to the output analogue values. A NodeMCU ESP 8266 wi-fi equipped microcontroller communicates the real-time sensor readings obtained from the Aurdino Uno microcontroller to the Storm Water Control System server. As instructed by the Storm Water Control System Server, the ATmega32 sends commands through NodeMCU to the actuator pump. The capacity of submersible pump is 120 liter per hour and operates on 3-6 volts and maximum water lift is 40 ~ 110 mm. the flow rate of YF-S201 Water Flow Sensor is 1 to 30 Liters/Minute with maximum water pressure 2.0 MPa.

C. Experimental Setup

The four sub-catchment regions with storm water pipeline networks built parallel to drainage networks were taken into account for this research study. Four water level sensors are positioned at predetermined distances for each sub-catchment. Distance between water level sensors in the sub-catchment used to calculate the area of sub-catchment. The submersible pumps are installed on storm water channel and the drainage network. Each sub-catchment has one pump put on the drainage network line and two pumps installed on the network of storm water channels. To measure the water flow rate and detect rain in real time, one rain drop and one water flow sensor are employed for each catchment.

Figure 3 shows the experimental setup and the prototype model of the system, which includes the four sub-catchments named C_1, C_2, C_3 and C_4. The water level sensors installed in sub-catchment C_1 is $C_1\_Wl_1$, $C_1\_Wl_2$, $C_1\_Wl_3$ and $C_1\_Wl_4$. For sub-catchment C_2, the water level sensors used namely is $C_2\_Wl_1$, $C_2\_Wl_2$, $C_2\_Wl_3$ and $C_2\_Wl_4$. For sub-catchment C_3, the water level sensors used namely *is* $C_3\_Wl_1$, $C_3\_Wl_2$, $C_3\_Wl_3$ *and* $C_3\_Wl_4$. And for C_4, the water level sensors used namely *is* $C_4\_Wl_1$, $C_4\_Wl_2$, $C_4\_Wl_3$ *and* $C_4\_Wl_4$.

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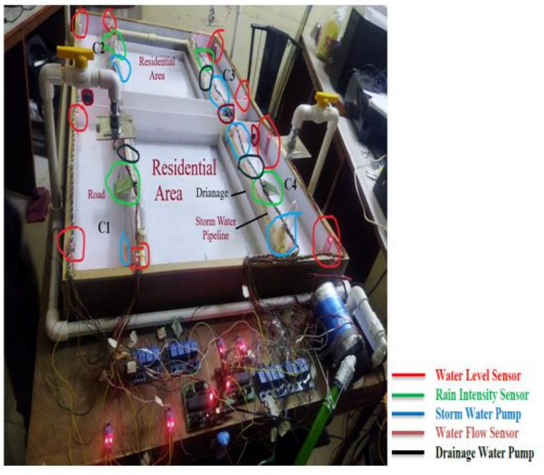

Figure 3: Experimental Setup of prototype model

D. *System Working*

The Storm Water Control System reads water level values of each sub-catchment and calculates the water volume of each sub-catchment. For determining the water volume, the system averages the values of all water level sensors and predefined area of present sub-catchment. The system selects the sub-catchment/s which has highest water volume value and applies fuzzy logic inference rules to control the flood water in the respective sub-catchment. Figure 4 shows the system flow to select the sub-catchments and activates the actuators.

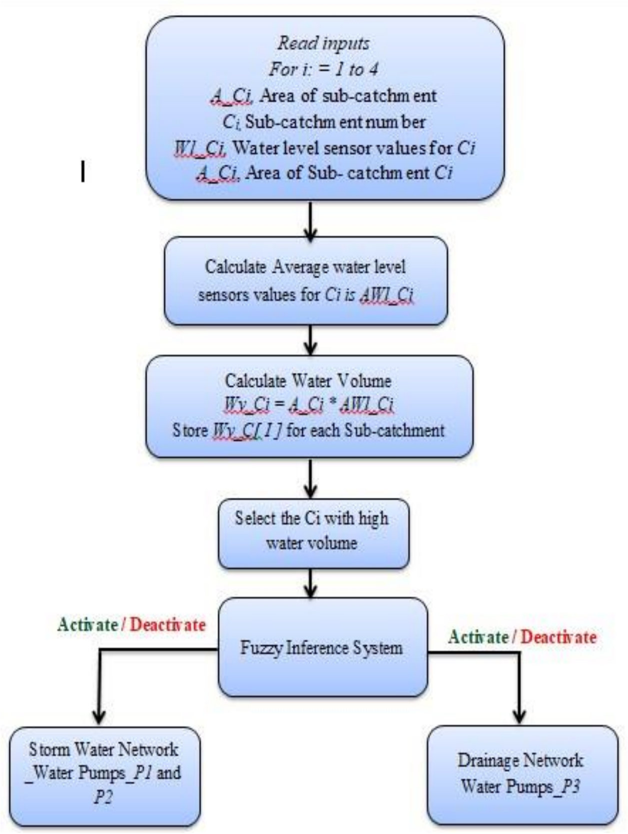

Figure 4: System Flow Diagram

E. *Fuzzy Logic System*

Based on the water volume *Wv*, the catchment is chosen to regulate the flood water as shown in the system block diagram in figure 3. The input and output parameters for the fuzzy controller system are provided in Table 1. The rain drop sensor module is used to measure the rain intensity parameter (EC-0569).

Table 1: Linguistic input and output parameters

Linguistic Parameter	Value	Description
Input Parameter: Water level (*AVWl*)	Millimeter (*mm*)	Average water level of all sensors in the sub-catchment at time instance *t*.
Input Parameter: Rain Intensity (*RI*)	Millimeter (*mm*)	Measures the intensity of rain fall in the sub-catchment in digital at time instance *t*.
Input Parameter: Water flow Rate (*WFR*)	Sq.mm	Determines the water flow rate in the sub-catchment at time instance *t*.
Output Parameter: Water Pump (*WP*)	*ON / OFF*	Action of Pump in the sub-catchment at time instance *t*.

Table 2 shows the rain sensor value range and its respective rain intensity.

Table 2: Rain Intensity range

RI values (mm)	Rain Intensity
0 to 25	low
25 to 50	Medium
50 to 100	High
100 to 150	Very High

Figure 5 shows a graphical representation of membership function for the input parameter Rain Intensity *(RI)*, the input to 4-level fuzzifier varies from 0 to 150mm. The fuzzy subset configuration for input parameter *RI* is Low, Medium, High, and Very High.

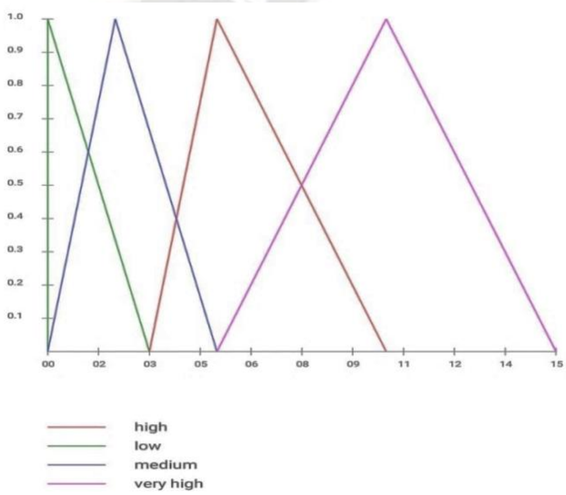

Figure 5: Fuzzy Membership Function for input Rain Intensity (*RI*)

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Figure 6 shows a graphical representation of membership function for the input parameter Water Flow Rate (WFR), the input to 4-level fuzzifier varies from 0 to 200sq.mm. The fuzzy subset configuration for input parameter WFR is Low, Medium, High, and Very High as shown in table 3.

Table 3: Water Flow Rate range

WFR values (Sq.mm)	Water Flow Rate
0 to 50	low
50 to 100	Medium
100 to 150	High
150 to 200	Very High

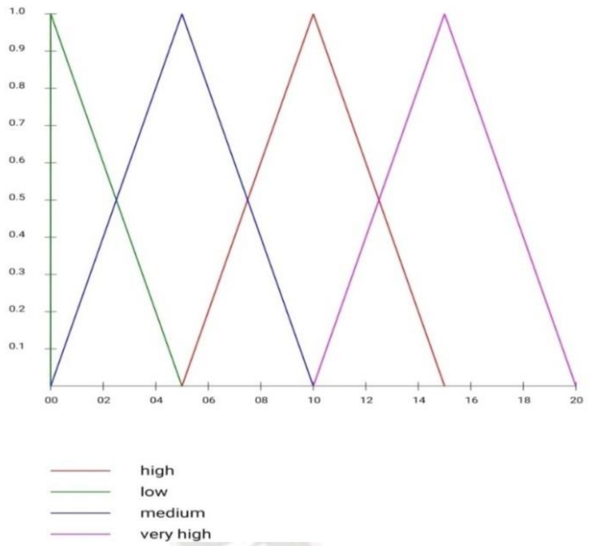

Figure 6: Fuzzy Membership Function for input Water Flow Rate (*WFR*)

Figure 7 shows a graphical representation of membership function for the input parameter Average Water level (AWl), the input to 4-level fuzzifier varies from 0 to 350mm. The fuzzy subset configuration for input parameter *WFR* is Low, Medium, High, and Very High as shown in table 4.

Table 4: Average Water level range

AWl values (mm)	Average Water level
0 to 50	low
50 to 150	Medium
150 to 250	High
250 to 350	Very High

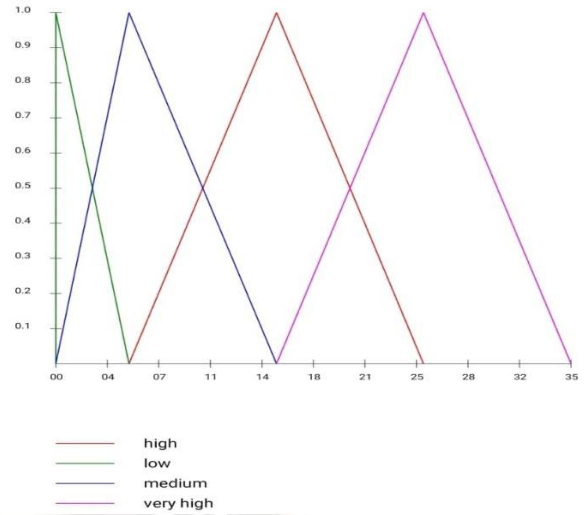

Figure 7: Fuzzy Membership Function for input Average Water level (*AWl*)

Table 5 shows fuzzy inference rules for the fuzzy system with input parameters as Average Water level at sub-catchment (*AWl_Ci*), Water Flor Rate at sub-catchment (*WFR_Ci*), Rain Intensity (RI) and output controllers Storm Water Pipe Network Pump (*SWPN_P*), Drainage Water Pipe Network (DWPN_P1). The system uses two water pumps namely *SWPN_P1*, *SWPN_P2* on storm water pipe network in each sub-catchment, so that the more rain water can be preserved and one water pump (*DWPN_P1*) on drainage water pipe network of each sub-catchment for early reduction of flood water.

Table 5: Fuzzy inference rules

No	*AWl_Ci*	*WFR_Ci*	Rain Intensity *(RI)*	*SWPN_P1*	*SWPN_P2*	*DWPN_P1*
1	Low	Low	Low	Off	Off	Off
2	Low	Medium	Low	Off	Off	Off
3	Low	High	Low	Off	Off	Off
4	Low	V. High	Low	Off	Off	Off
5	Low	Low	Medium	Off	Off	Off
6	Low	Low	High	Off	Off	Off
7	Low	Low	V. High	Off	Off	Off
8	Low	Medium	Medium	Off	Off	Off
9	Low	High	High	Off	Off	Off
10	Low	V. High	V. High	Off	Off	Off
11	Medium	Low	Low	Off	Off	Off
12	Medium	Medium	Low	Off	Off	Off
13	Medium	High	Low	Off	Off	Off
14	Medium	V. High	Low	Off	Off	Off
15	Medium	Low	Medium	Off	Off	Off
16	Mediu	Low	High	On	Off	Off

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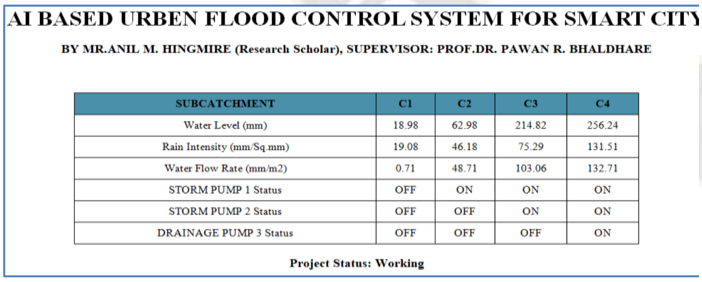
	m					
17	Medium	Low	V. High	On	Off	Off
18	Medium	Medium	Medium	Off	Off	Off
19	Medium	High	High	Off	Off	Off
20	Medium	V. High	V. High	Off	Off	Off
21	High	Low	Low	On	On	Off
22	High	Medium	Low	On	On	Off
23	High	High	Low	On	Off	Off
24	High	V. High	Low	On	Off	Off
25	High	Low	Medium	On	On	Off
26	High	Low	High	On	On	Off
27	High	Low	V. High	On	On	Off
28	High	Medium	Medium	On	On	Off
29	High	High	High	On	On	Off
30	High	V. High	V. High	On	On	Off
31	V. High	Low	Low	On	On	On
32	V. High	Medium	Low	On	On	On
33	V. High	High	Low	On	On	On
34	V. High	V. High	Low	On	On	On
35	V. High	Low	Medium	On	On	On
36	V. High	Low	High	On	On	On
37	V. High	Low	V. High	On	On	On
38	V. High	Medium	Medium	On	On	On
39	V. High	High	High	On	On	On
40	V. High	V. High	V. High	On	On	On

V. RESULT ANALYSIS AND DISCUSSION

This section presents the system testing findings, including an analysis based on time series data collected from sensor nodes and actions taken by actuators in response to server commands.



AI BASED URBEN FLOOD CONTROL SYSTEM FOR SMART CITY

BY MR.ANIL M. HINGMIRE (Research Scholar), SUPERVISOR: PROF.DR. PAWAN R. BHALDHARE

SUBCATCHMENT	C1	C2	C3	C4
Water Level (mm)	18.98	62.98	214.82	256.24
Rain Intensity (mm/Sq.mm)	19.08	46.18	75.29	131.51
Water Flow Rate (mm/m2)	0.71	48.71	103.06	132.71
STORM PUMP 1 Status	OFF	ON	ON	ON
STORM PUMP 2 Status	OFF	OFF	ON	ON
DRAINAGE PUMP 3 Status	OFF	OFF	OFF	ON

Project Status: Working

Figure 8: Real time Server display for Sub catchments

Figure 8 depicts real-time sensor values received on the server from an IoT node through NodeMCU, as well as the activation or deactivation of water pumps in all four sub-catchments by the controller system.

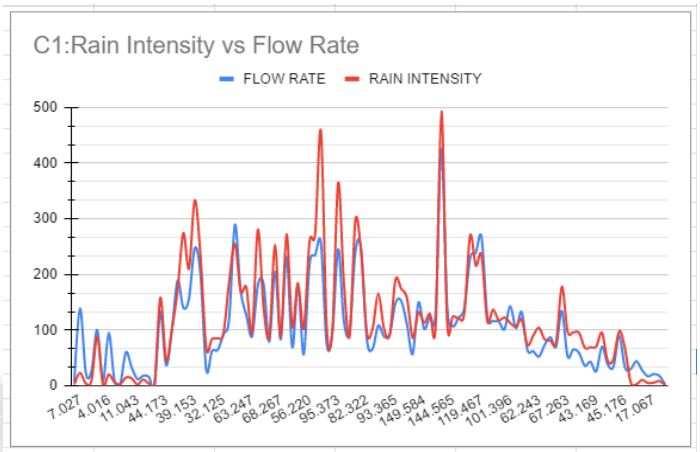


Figure 9: Graph of Rain Intensity and Water Flow Rate of Sub catchments *C1*

Based on real-time data values, Figure 9 illustrates a graph of rain intensity and water flow rate. Water flow rate increases as rain intensity increases, as indicated in the graph, at low, medium, high, and extremely high levels.

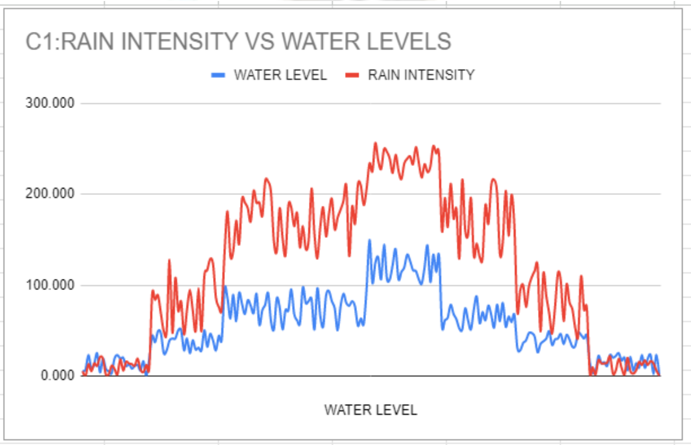


Figure 10: Graph of Rain Intensity and Water level of Sub catchments *C1*

The graph in figure 10 clearly shows the relationship between the intensity of the rain and the water level. As the intensity of the rain increases, we can observe that there is a corresponding increase in the water level. This indicates that higher levels of precipitation can lead to higher water levels in areas where there are no other factors influencing it.

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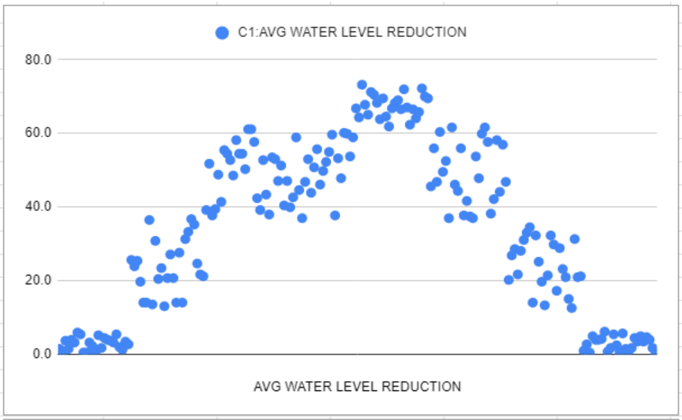

Figure 11: Average Water Level Reduction of *C1*

As shown in figure 11 of sub-catchment C1, the average water level in the sub-catchment is significantly reduced from high to medium and very high to low as the result of pumps activation from pump 1 to 3. When the rain intensity, water level, and water flow rate are all at medium levels and only one storm water network pump is started, the water level drops from 37% to 13% on average. When both storm water network pumps are active, the water level drops from 61% to 37% on average. At extremely high levels, two pumps on the storm water network and a drainage pump are operated, the water level in the sub-catchment is gradually decreased from an average of 73% to 62%, and two pumps are triggered again when the water level rises.

Similarly the average water level reduction for the sub-catchments C2, C3 and C4 is shown in figure 13, 14, 15 and 16 respectively.

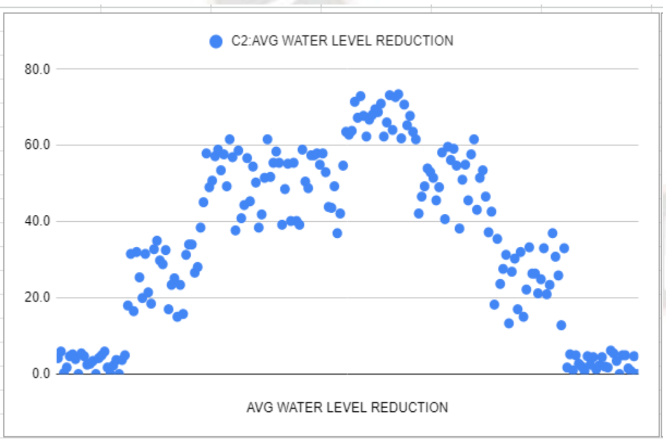

Figure 12: Average Water Level Reduction of *C2*

As shown in Figure 12, when the rain intensity, water level, and water flow rate are all at medium levels and only one storm water network pump is started, the water level drops from 34% to 15% on average. When both storm water network pumps are active, the water level drops from 62% to 37% on average. At extremely high levels, two pumps on the storm water network and a drainage pump are operated, and the water level in the sub-catchment is gradually lowered from an average of 74% to 62%, and two pumps are triggered again when the water level rises.

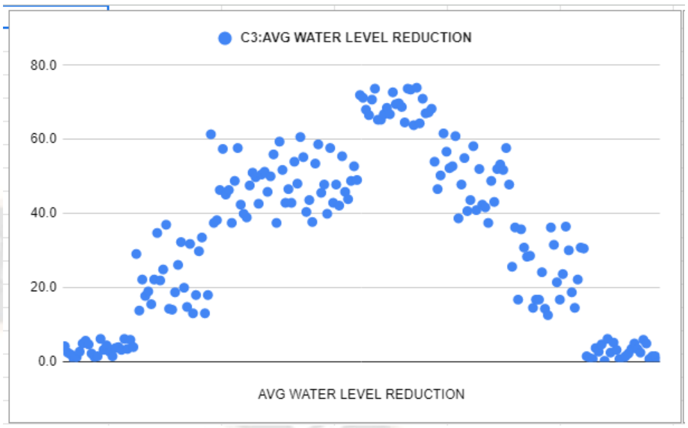

Figure 13: Average Water Level Reduction of *C3*

Figure 13 shows that when the rain intensity, water level, and water flow rate are all at medium levels and only one storm water network pump is active, the water level drops from 34% to 13% on average. When both storm water network pumps are active, the water level drops from 61% to 38% on average. At extremely high levels, two pumps on the storm water network and a drainage pump are operated, the water level in the sub-catchment is gradually decreased from an average of 74% to 64%, and two pumps are triggered again when the water level rises.

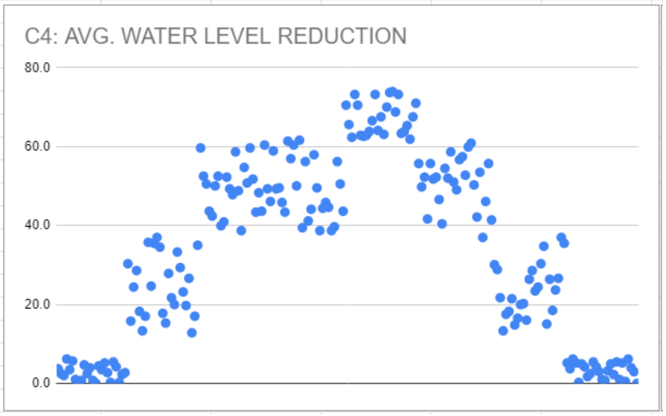

Figure 14: Average Water Level Reduction of *C4*

Figure 14 shows that when the rain intensity, water level, and water flow rate are all at medium levels and only one storm water network pump is active, the water level drops from 35% to 13% on average. When both storm water network pumps are active, the water level drops from 62% to 39% on average. At extremely high levels, two pumps on the storm water network and a drainage pump are operated, the water level in the sub-catchment is gradually decreased from an average of

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6s
DOI: https://doi.org/10.17762/ijritcc.v11i6s.6952
Article Received: 28 March 2023 Revised: 18 May 2023 Accepted: 26 May 2023

74% to 62%, and two pumps are triggered again when the water level rises.

Table 6: Average Water level Reduction analysis for C1 to C4 sub-catchments

Sub-Catchment	Medium (P1=On, P2=Off, P3=Off)	High (P1=On, P2=On, P3=Off)	Very High (P1=On, P2=On, P3=On)	Average Water level Reduction in Sub-catchment
C1	13.1% to 36.7%	37.0 % to 61.1%	61.9 % to 73.2%	11.3 % to 54.4 %
C2	15.0% to 34.0%	37.0 % to 61.6%	61.6 % to 73.5%	16.1 % to 50.0 %
C3	13.1% to 33.5%	37.5 % to 61.4%	63.8 % to 73.9%	11.1 % to 64.8 %
C4	12.8% to 35.0%	38.7 % to 61.6%	61.9 % to 73.9%	19.4 % to 65.3 %
Average	13.5% to 34.8 %	37.55 % to 61.43%	62.3 % to 73.63%	14.48 % to 58.63%

Table 6 depicts the average reduction in water level in sub-catchments *C1*, *C2*, *C3*, and *C4*. As can be seen, the average water reduction rate at the medium level ranges from 13.5% to 34.8%. At high levels, the average water reduction rate ranges from 37.55% to 61.43%, and at extremely high levels, it ranges from 62.3 to 73.63%. In all four sub-catchments, the overall flood water decrease ranges from 14.8% to 58.63%. The most significant decrease in water level is 73.9%.

VI. CONCLUSION

City flood control refers to the many steps taken by a city or urban region to avoid or minimize the damage caused by floods. Cities are especially sensitive to flooding owing to the large population of buildings, infrastructure, and people in a limited area, which increases the danger of damage and loss of life. To manage or control flooding, the contemporary world requires smart cities with smart infrastructure.

We present an enhanced smart urban flood control technique in this study that is based on the water-sensitive Storm Water Control Network Model (SWCNM) and takes use of IoT infrastructure. The urban flood control approach is based on fuzzy logic and takes into consideration factors such as rainfall intensity, water level, and water flow rate in the sub-catchment region. In terms of effective flood water control, the system makes collaborative decisions by taking into account real-time conditions in all sub-catchments.

The results of the prototype model of approach implemented demonstrate a large reduction of water in the sub-catchments through the optimal use of actuators to control the flood. At the medium level, the average water level reduction rate ranges from 13.5% to 34.8%. The average water reduction rate at high levels ranges from 37.55% to 61.43%, and at extremely high levels, it ranges from 62.3 to 73.63%. The overall percentage of flood water drop ranges from 14.8% to 58.63% in all four sub-catchments. The greatest reduction in water level is 73.9%. However, the rate of water reduction in the sub-catchments depends on the capacity of the drainage, storm water pipeline network, and water pump capacity. A method for developing an autonomous flood management system that avoids surface flood water has been described and can be implemented in a smart city.

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