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Flash flood risk management modeling in indian cities using IoT based reinforcement learning

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A B S T R A C T

Each year, flash floods in India have affected life, infrastructure and the economy of the country and there is a need for a systemic model of real-time flash flood management. So, to mitigate these losses, we proposed a flash flood management model focused on reinforcement learning. Based on their severity, the flash flood data is collected and rewards are distributed and this data is compared to the data collected from smart IoT devices deployed in the region impacted by the flood. We allocate the state-based reward values once the comparison is completed. The evacuation of flash flood water through the contour of the flash flood is carried out. This bypass has gates at different points that mean that, depending on the incentives, the gates are opened to remove flash flood water. The proposed solution was evaluated to be a faster, more effective and more accurate real-time flash flood management method.

1. Introduction

In India, in recent years, there are often flash floods during the year and flash floods due to heavy rainfall, torrential rainfall and lakes/rivers, and different pressure from coastal areas that bear precipitation [1]. This leads to major losses in terms of life, infrastructure and socio-economic conditions. Various factors lead to these inundations, including unplanned developments, urbanizations and geopolitical factors [2].

As per the UN report in 20 years the more than 50% of peoples migrate from rural to urban regions [3]. So the local government is not so resourceful to accommodate providing the infrastructures for them mainly drainage system and so on. The places near the sea are more prone to flash floods and the main reason is cyclones, storms, tsunamis, and so on [4]. Fig. 1 shows the typical views of flash floods and it commonly occurs in the urban region which is near to sea, river and near hilly region causing floods and also the blockage in the drainage is also corresponds to flash floods. The flash floods generally occur in the low lying areas and if the water is not evacuated for more than 6 h so this kind of floods comes under flash flood. These floods caused mainly due to one of the following [16].

- When the soil has the poor water-absorbing ability.
- The areas recently received precipitation has less ability to evacuate water.
- Blockage in the drainage system.
- Natural or manmade dam collapse.
- The runoff collects causes the obstruction to the flow of water and so on

These floods in recent years creating more challenges to the authorities by causing the large impact on the environment, causing damage to infrastructure, lives, cattle's, corps and so on [17]. So in this study we proposing a method based on Reinforcement Learning along with IoT devices. Also, we discussed related work from the available literature, research gap along with the method to fill the research gap in this study.

2. Literature review

The need for new techniques to minimize the losses during floods especially flash floods is in need. In general, the flash floods occur in urban regions and it is the economical hub of any state or

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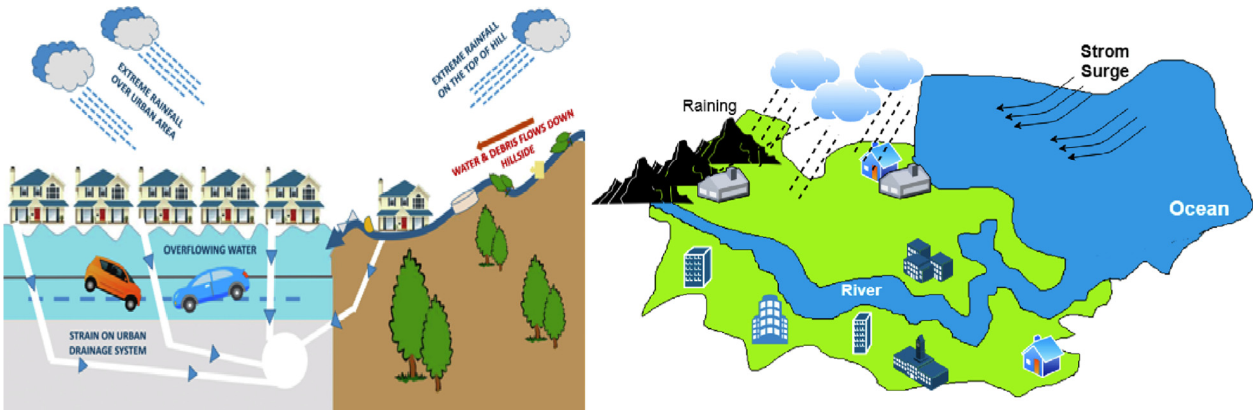

Fig. 1. Views of flash floods.

country and in particular in India. The following related works give an insight into the work carried out to date by the researchers.

S Yang, et al. explained in their work about maintaining the supply chain during urban floods using multi-agent Deep Reinforcement Learning (DRL). The large scale supply in the urban region is affected due to floods in these regions. To avoid the losses and to keep the supply chain on track the authors proposed a model that collects the data from different supply chain agents about flood intensity and so on. This data is used to train and to find effective and efficient solutions to continue the supply chain during and after floods [5].

Y Wang, et al. proposed a method based on IoT for storm surge floods using DRL. In recent years the storm surge floods near the coastal regions causing more losses. These models collect the data from IoT weather forecasting and urban flood data are used in DRL to analyse real-time forecasting to avoid losses to lives [6]. S M Saliba, et al. explained a method of storm water control to avoid flooding using Reinforcement Learning (RL). In this work, they used the real-time control system along with RL. Here the flood water controlled through the gate, values, and pump are generally used. But the older method is not having this kind of real-time control. The method explained will help to overcome this problem [7].

J C J H et al. explained a new method to analyse the uncertainty in flood risk assessment using Modern Portfolio Theory (MPT) this helps in deciding the flood management strategies. This model was adopted in the Netherlands and the others explained the extensively in this work [8]. A Mullapudi, et al. explained RL based storm water control. This model dynamically adopts the model according to the study the real-time control like a pump, gates; and so on in storm control is explained in detail [9]. In the above-related work, we only explained the positive aspects of RL used by the different researchers. In the next heading, we explain how the previous works lagging the present needs related to flash flood management are explained.

Jin-Hee Lee, et al. presented work on multi-reservoir control through reinforcement learning suing stochastic models along with AI in controlling two reservoirs in South Korea. The decision is made based on the continuous rewarding based on the parameters collected on the reservoirs and making a decision based on these rewards in managing the reservoirs simultaneously. The Monte carol simulation is also extensively used in this work [10].

A. Castelletti, et al. presented work on optimal reservoir operation management using tree-based reinforcement learning and here this approach is called Q-fitted iteration which combines principle of continuous approximation to calculate value function to while learning and decision making in the reservoir operation management [11].

A Mullapudi, et al. presented work on autonomous control of urban storm water using RL. Here the long urban storm water is through the storm water is passed through the channels connected with sensors and pump to storm water is evacuated based on the data collected from these sensors automatically using the RL based on weightage [12]. In the above review regarding the use of RL in flash flood management, the following key issues are observed.

- Most of the researchers focused on the floods and other related issues due to flood especially storm water control.
- The use of RL has not explained the situation where real-time continuous monitoring is necessary.
- The all proposed system is not automatic and with human interference will surely affect the rescue and other activates in that area.
- They used the only limited data in their study to get the final decision for the given situation.

So, in our work to overcome the above key issues we proposed IoT-based flash flood management with RL is explained under the following heads.

3. Role of RL in flash flood management

RL is a type of machine learning language which is used to make sequential decisions in uncertain and complex environment situations [15]. In this we apply the trial and error method to analyse the state of the given situation and rewards according to the state will decide the action plane for the given problem. Fig. 2 shows the working flow of RL; here for the given environment the state and rewards are set, based on the rewards the agent will take optimal actions. This process continues until it comes to a proper decision in our case the all-flash flood water evacuates through the gates of FFBW.

RL is extensively used in many applications in recent years and their roles in flash flood management are as follows:

- This model is generally used to make a sequential decision during an uncertain situation like flash floods.
- This model uses the trial and error method (iteration) in making the decision. The decision made is the optimal solution for the given problem.
- The training of this model is carried out based on rewarding and then the state, actions.

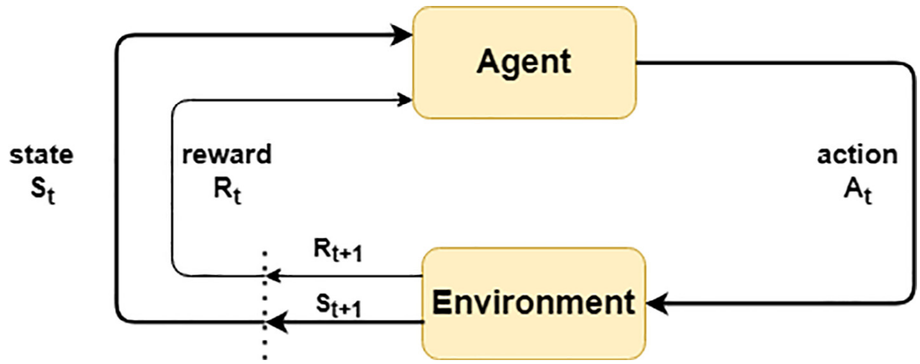

Fig. 2. Working flow of RL technique.

- Once it is trained then the prevention of flash floods is easy.
- It is used for real-time monitoring in a situation like flash floods or floods.

4. Proposed flash flood management model (FFMM)

The proposed model consists of three main important steps. The first is the workflow of the proposed model, its mathematical model, and algorithm. This is discussed under the following heads.

4.1. Workflow of FFMM

The workflow of FFMM is showed in Fig. 3. Once the flash floods occur due to heavy rains or overflow of a river or due to cyclone or torrential rains the FFMM initializes the modal parameters such as Total storage (T_s), Flood control storage (F_s), Crest elevation (C_e), Normal pool level (N_l), Flood control level (F_l), Historical flash flood data (H_{ff}), and so on [10,11].

In this step, the identification number of gates are opened (as action) for Flash Flood Bypass Waterways (FFBW) following the flash floods. Once the gates are opened we are finding the further actions required to evacuate the flood water to channels.

The reward is calculated based on the FFMM for each action is taken. Here the rewards are based on actions means the actions in anticipation of the severity of the flood are awarded high rewards. Similarly, the data coming from IoT devices are compared with the Flash flood severity rewards assigned. We are giving and choosing the highest or maximum reward after comparing and based on that best action plan decided. The number of gates opened according to the best action plan and the same is updated in FFMM [12].

For example, flash floods are common in the Kanpur district in Uttar Pradesh which is adjusted to river Ganga. (Map with flash flood evacuation channels with gates at different locations are shown under FFMM in Fig. 4). If the flash flood occurs, then the data from this flood is collected and rewards are assigned as per the severity and the data collected from IoT devices about the water level is compared with the data available. Both the data are compared then rewards are assigned. The higher the rewards critical is the situation than the gates are opened. If the action plan is satisfied or flash floods are under control based on real-time data comparison and rewarding based optimal action plan, then the process is stopped or else the process explained above continues till flash floods are under control.

4.2. Mathematical model

The problem solved by this algorithm is compared to that of the maze problem. Mainly there are two components in this algorithm that is action and state to the described problem. In our study, the number of gates is the state. In each time slot, the opened number of gates is changed, as an action, to simulate the flash flood in real-time [13,14].This algorithm is formulated for this works as follows

The 'state' is represented as S = S_0, S_1, S_2, S_3. . ...S_n and the action are represented as a = a_0,a_1, a_2, a_3. . . . . ..a_m (where the action refers to the number of the gate area to be opened for Optimal action).

The rewards are calculated iteratively and these three major parameters are proposed and are state transition probability matrix, the reward function, and the discount factor. The transition probability matrix T [s, s'] shows the possibility of state transfer from s to s'. Since the numbers of gates are known and the numbers of gates are to be opened can be estimated, the probability of the number of gates to be opened (normal distribution) as follows:

$$T[s, s'] = N(\mu_s, \sigma_s^2) \quad (1)$$

where $\mu_s$is expectation and σ_s is the deviation variances of the number of gates. The reward *R*[*s,a,s'*] is the anticipated benefit received by taking action *a* to transfer from the state *s* to the state *s'*. To adjust the weight of the "future benefit," *D* represents a discount parameter to control the "vision" of the algorithm.Note: The discount parameter is a value between 0 and 1. In the general MDP method, the policy of the action is defined as $\varphi\ (a|s)$ to represent the probability of taking action *a* and state *s* and is shown in Eq. (2).

$$\varnothing(a|s) = P(A = a|S = s) \quad (2)$$

In this work, we assume that every state and actions have the same probability. A total of five elements such as *S, A, T, W, and D* are necessary to build the MDP model. Agents Fig. 5, shows the states transfer from one to another according to the actions and the transition possibility matrix. The method for reward calculation is shown in Eq. (3).

$$W(t_0) = R_{t0,s} + D\sum_{j}^{j\in S_{t1,l}} R_{t1,j} + D^2\sum_{j}^{j\in S_{t2,l}} R_{t2,j} + \cdots \quad (3)$$

where, $S_{t,l}$ represents all the states at time interval *t*.

The D utilizes at this place reduces the confidence of the future by making this model more trustworthy and this equation is simplified and is shown in Eq (4).

$$W(t_0) = R(t_0, s) + DW(t_1) \quad (4)$$

The above equation shows the (total reward feedback) equals the current rewards and the corresponding discounted total reward in the next level is *t*. The current state $s_0$is shown in Eq. (5).

$$\beta(a) = E_{\varnothing}[W(t_0)|s_0] \quad (5)$$

Eqs. (4) and (5) are combined and are shown in Eq. (6).

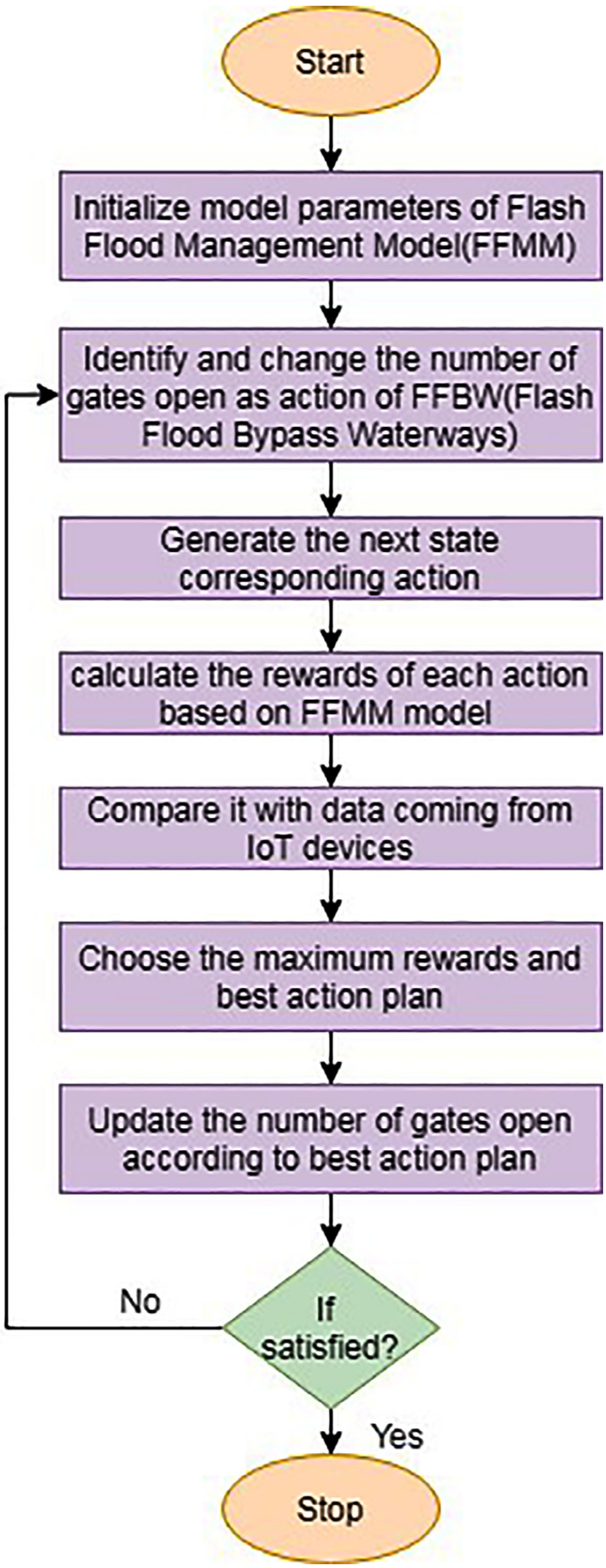

Fig. 3. Workflow of FFMM.

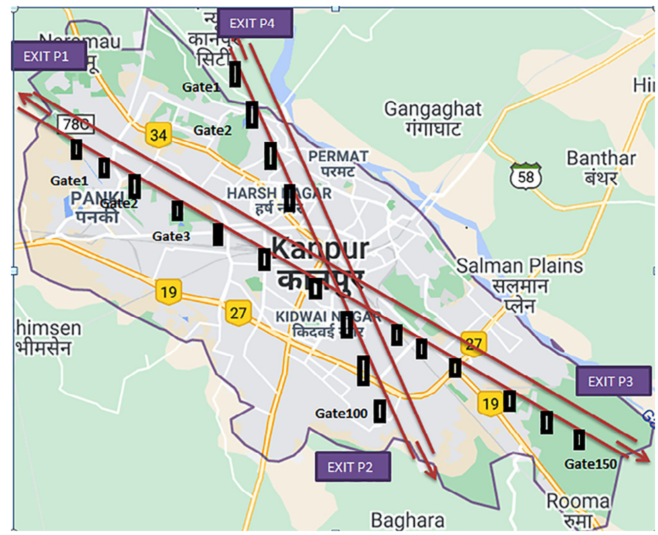

Fig. 4. Flash flood water evacuation channel under FFMM.

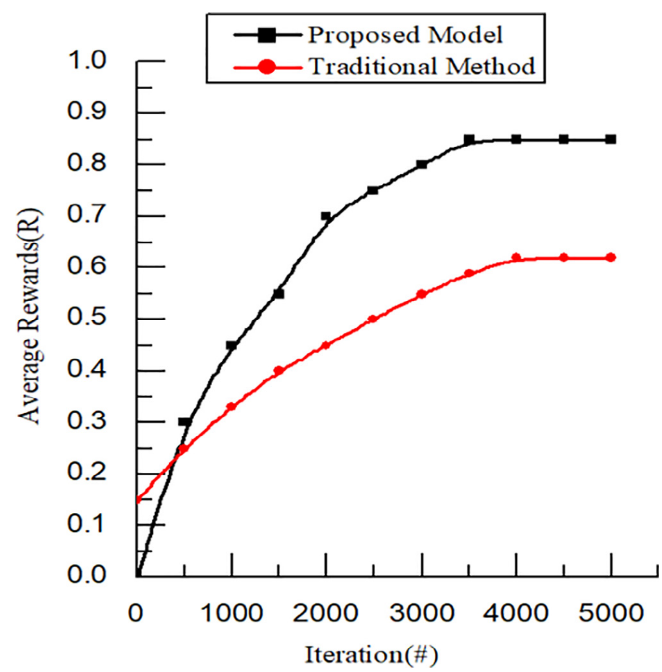

Fig. 5. Working process.

$$\beta_{\varnothing}(s_i) = E_{\varnothing}[W(t_i)|s_i] = E_{\varnothing}[\sum_{m=i} DR_{m+1}|s_i] \tag{6}$$

Eqs. (6) is modified (Bellman equation) into Eq (7)

$$\beta_{\varnothing}(s_i) = \sum_{aj} \varnothing(a_i|s_i) \sum_{S_{i+1,Ri}} T_{(S_{i+1,}} R_i|s_{i,}a_{i)} \times [R + D\beta_{\varnothing}(s_{i+1})] \tag{7}$$

The optimal action for the current state s_i is shown in Eq (8).

$$\beta^*(s_i) = max_{a\in A}(\beta_{\varnothing(a)}(s_i)) \quad (8)$$

The above equations are adopted in the following algorithm

Algorithm.

Input:-

FFBW:-
Number of gates (G)
Reservoir:-
Total storage (T_s), Flood control storage (F_s), Crest elevation (C_e), Normal pool level (N_l), Flood control level (F_l), Historical flash flood data (H_{ff})
Other sources: -
Drainage level (D_l), River level (R_l) (if any)
Others: -
Discount factor (D), Loop time (t)

1. Start **MDP**(G, T_s, C_e, D, t, D_l, R_l, H_{ff}, F_l, N_l, F_s)
2. Iteration ← 1
3. Based on current state s_1 generates the actions [a_1, a_2, ………..a_n]
4. Future states can be calculated as [$a_1 + s_1$, $a_2 + s_1$, ………..$a_n + s_1$]
5. X ← a, start loop
6. The input parameter will be fed into the FFMM model to obtain the flooding volume in urban city V_{ax} = [V_{x1}, V_{x2},… V_{xz}] for action a_x.
7. Compare the real flood volume V_{ax} with the calculated flood volume and then obtain rewards R
8. The calculated rewards will be fetched into the below equation
$\beta_{\varnothing}(s_i) = \sum_{aj}\varnothing(a_i|s_i)\sum_{S_{i+1,Ri}} T_{(S_{i+1,}} R_i|s_{i,}a_{i)} \times [R + D\beta_{\varnothing}(s_{i+1})]$
9. Modify the action x to another action and repeat till x become equivalent to a_n
10. The optimal action will be selected based on the result of the below equation
$\beta^*(s_i) = max_{a\in A}(\beta_{\varnothing(a)}(s_i))$
11. i ← i + 1
12. If i<=t repeat step1 to 9

5. Performance evaluation of the proposed model

FFMM is adopted is evaluated to understand how the proposed model works and this model is analysed using MATLAB and the results are shown in Fig. 6. In this figure, the rewards versus the number of the iteration are drawn. As we explained in the proposed model the rewards vary from 0.1 to 1 with an increment of 0.1 whereas the number of iteration is 5000.

The traditional model initial response is better as per flash flood is considered, but its response decreases as the iteration increases that is, its response for every action based on the rewards assigned for every action taken is not rewarded as the situation worsens, but our proposed model in the initial stage it is slower but as the rewards are assigned based on the actions and these rewards are compared with data acquired from IoT devices in real-time basis and then again the rewards are reassigned based on the severity of the floods. This process continues as long as flash flood water is evacuated. Also, it is observed that as the iteration increase the rewards based on action increase. This means we can save lives and minimize losses due to flash floods.

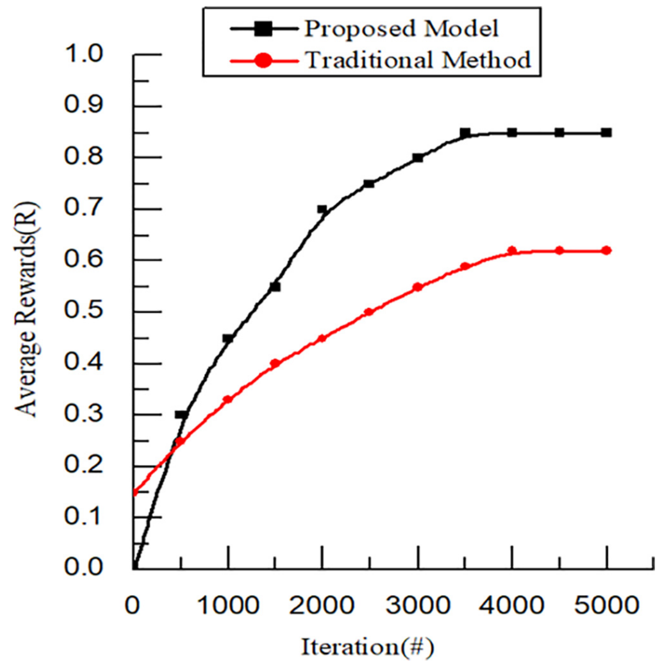

Fig. 6. Performance evaluation of FFMM versus traditional model.

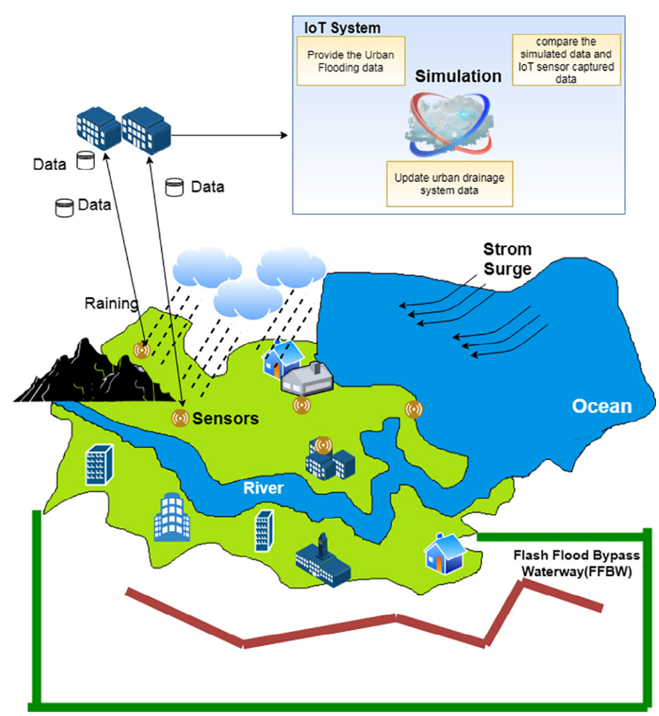

Fig. 7. Framework of FFMM.

Fig. 7 shows the framework of FFMM. The flash floods generally occur in the places like low lying near sea, river, hilly and urban regions where unplanned developments occurred. The flood data is available based on the weather forecast department and local information centres. This data is compared and verified with the data received from IoT smart devices in that area. Both the data are compared to the state of the gate is also obtained and rewards are assigned. Based on rewards the action is taken here the gates of FFBW opened near the flash flood zone. This process continues till the flash flood situation is under control.

6. Conclusion and future work

- Flash flooding has become frequent in India in recent years, usually due to growth factors that are geographic, socio-economic, geopolitical and unplanned. The areas near the river and sea are more vulnerable to these floods. The flash flood management model was proposed and tested based on improving learning in this study. The following conclusions have been drawn through this study. The FFMM model is suggested and the mathematics and algorithm are clarified for the proposed model.
- Since this strategy is focused on incentives and behaviour, we have found that this method is better in flash flood management. Increased benefits boost the course of action.
- The flash flood management system offers in real-time.
- The performance appraisal indicates that the proposed model at the beginning of the action plan is slower than the conventional Flash flood management models, but as data collection and reward-based comparisons are proceeding more successfully than the out coming models.
- We evaluated this model for 5000 iterations and we found the proposed model is better.

Instead of RL, this work can study the FFMM using Deep Learning or AI and such that we can explore the more possibility in minimizing or avoiding losses due to flash floods.

CRediT authorship contribution statement

Himanshu RaiGoyal: Formal analysis, Resources, Writing - original draft. **Kamal Kumar Ghanshala:** Conceptualization, Visualization, Supervision. **Sachin Sharma:** Writing - review & editing.

Declaration of Competing Interest

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

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