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Real-Time Multi-Agent Based Flood Forecasting and Warning System Model: A Malaysia Perspectives

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ABSTRACT

The development of a precise flood forecasting methodology necessitates the utilization of an automated data collection system for the examination of a comprehensive range of hydrographic catchment parameters that are continuously monitored. Monitoring river basins is a topic of significant strategic importance. In recent years, researchers have introduced several cutting-edge technologies to enhance this process, including the utilization of artificial intelligence (AI). Notably, AI has been applied in various techniques such as knowledge-based systems, agent-based modelling, and neural networks. These AI-based approaches have shown promise in improving the monitoring and management of river basins. The nationwide flood forecasting and warning system, known as 'NaFFWS', has been implemented in Malaysia through the PRAB program. The establishment was created with the purpose of facilitating the advancement of mitigation technologies aimed at minimizing the potential consequences of forthcoming flood events. The current utilization of modelling tools incorporates multiple factors that contribute to uncertainty, which can be attributed to the specific characteristics of the system. This review paper aims to explore the potential capabilities of an integrated multi-agent system specifically designed for the purpose of monitoring flood events. The proposed system is composed of logical agents and utilizes deep reinforcement learning (MADRL) techniques. This approach introduces a conceptual framework wherein a collection of intelligent agents collaborates to accomplish diverse tasks and effectively exchange information, ultimately facilitating the generation of timely alerts in the context of flood crises. The agents in question operate in collaboration with a hybrid approach that combines the DQN and TD3 algorithms. This combination is utilized to mitigate the various challenges arising from uncertainty. The proposed model's contribution is notable in enhancing flood forecasting accuracy amidst diverse sources of uncertainty.

1. Introduction

It is estimated that one-fifth of Malaysia's total population is at risk of flooding. Large parts of the country are regularly hit by severe and prolonged flooding. These events result in significant economic disruption, destruction of critical infrastructure, and often require the evacuation of entire

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communities from disaster-affected areas. Due to rapid urban growth and, in some cases, changes in rural land use, the impact of these floods has increased significantly over the past decade. This is because these developments have changed river runoff regimes and flood mechanisms [1]. According to the annual flood report by the Malaysian Ministry of Irrigation and Drainage (JPS) [2-6] for the five years from 2017 to 2021, a total of 4544 floods were recorded across the country, including flash floods, monsoon floods, mud flood and flood due to dam release. The breakdown of flood events by year is as follows; 2017 (1239 cases), 2018 (844 cases), 2019 (535 cases), 2020 (869 cases), 2021 (1057 cases). Two states with the most floods in the last five years are Sarawak with a total of 1371 and Selangor with a total of 689.

As a direct response to the devastating floods that struck eight different states in Malaysia in December 2014, the country's government established the National Flood Forecasting and Warning Program (PRAB). These states are Kelantan, Terengganu, Pahang, Perak, Perlis, Johor, Sabah, and Sarawak. More than half a million people were forced to evacuate their homes as a result of the flood, and the damage caused by the disaster exceeded RM 2.85 billion. PRAB's mission is to create and maintain an effective and efficient integrated flood forecasting and river monitoring system, complete with flood warning dissemination, by utilising national network data, telemetry data, radar data, and rainfall forecasts. However, the system will be implemented by phases [7].

Flood forecasting has become a significant topic of study for this reason; it is essential for national economic planning and saving lives. In recent years, computer science has been incorporated into flood forecasting technology, and flood forecasting capabilities have been considerably enhanced by database technology, artificial intelligence technology, and various Web-based decision support systems [8]. While it may be impossible to totally remove flood risks, their impact can be mitigated with the help of early warning systems and real-time flood forecast.

The purpose of flood forecasting is to anticipate potentially hazardous conditions as early as possible based on information about water supply and upcoming weather. Constraints such as data assimilation, minimal computation, and response time are essential for accurate real-time prediction [9]. Therefore, it is necessary to provide a real-time flood forecasting and warning system that considers all the above limitations. In this research, we propose a new multi-agent system (MAS) a real-time forecasting and alerting framework that acts as a guide for future development.

The remaining sections are organised as follows: Section 2 introduces the National Flood Forecasting and Warning System. In addition, Section 2 presents the previous research conducted by various scholars. Methods and techniques used in for the proposed conceptual model presented in the section 3. In Section 4, we introduce our real-time flood forecasting and warning system, which is based on multi-agent systems and the potential contribution of our proposed work. Section 5 concludes with a conclusion and recommendations for future work.

2. Preliminaries and Related Work

2.1 National Flood Forecasting and Warning System

Malaysia, through its PRAB had introduced new National Flood Forecasting and Warning System (NaFFWS) to serve as mitigation strategies to reduce the effects of future floods. NaFFWS forecasts river flows up to seven days in advance and issues flood alerts. NaFFWS Phase 1's flood forecasting system uses InfoWorks ICM for hydrological and hydrodynamic models and ICMLive for the shell. ICMLive loads real-time data, runs forecast simulations at predetermined times, analyses outcomes, and generates warnings [1].

ICMLive is a live modelling tool that was developed by Innonyze. It interfaces with hydraulic models, SCADA historians, and GIS applications in order to deliver updates on the operation of the system in a manner that is very close to real time. It is able to take radar data into account in order to estimate the influence that rainfall will have on collection system performance, floods, and the probability of overflow events occurring [10].

According to [11] ICMLive has been utilised in NaFFWS Phase 1 basins to generate flood forecasts based on real-time data. The created system automates the necessary processes by collecting and processing actual and forecast data and combining them with the ICM model (for simulating hydrologic and hydraulic processes) to produce flood forecasts:

i. Consolidate and validate real-time hydrometric data from river and rain gauges from JPS, radar data from Met Malaysia, and quantitative precipitation forecasts (QPFs) from Malaysia Meteorology Department (Met Malaysia). ICMLive's adaptable data connectivity permits the reading of a variety of real-time data formats
ii. Automatically initialize model simulations (using antecedent conditions and continuous tracking of the soil moisture content)
iii. Analyse and report on the observed data and the model forecasts
iv. Generate and disseminate alerts based on the data and/or model projections. Figure 1 shows the overview of NaFFWS.

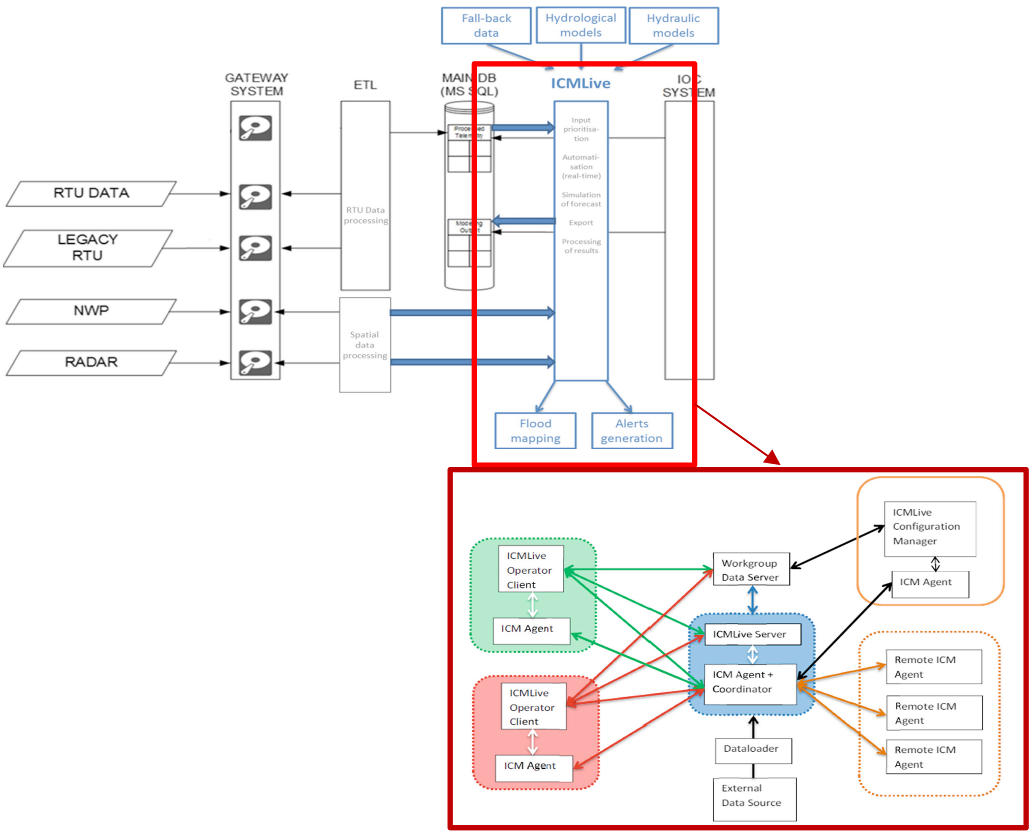

Fig. 1. Overview of NaFFWS

The NaFFWS system revolves around ICMLive as the primary hub. ICMLive automatically retrieves the input data (precipitation and water level) from the main database (main DB) and storage folders, and then imports this data into its own time series database (TSDB). Run the ICM hydrological and hydraulic flood models 7 days in advance, store the results in a database, and export the flood results to the main database. Additionally, it is set to send notifications when certain water levels are reached at rivers, towns, villages and other pre-selected points of interest (POIs).

ICMs, like every other modelling tool, have a variety of sources of uncertainty as a result of the characteristics that are inherent to the system. Complex processes are represented with minimal knowledge, relationships are calibrated using constrained data sets (which may lead to a poorly recognisable parameterisation), and linked simulations are carried out across a wide variety of spatiotemporal scales [12]. The step-by-step process of abstracting from the real world to represent it in a model, with all of the necessary simplifications and idealizations of the real systems that go along with it, inevitably results in the appearance of uncertainty [13]. These uncertainties include errors introduced by model parameterization, model-forcing data (such as precipitation), model input data (such as digital elevation models, soil or sewer conduit maps), model validation data (such as the use of incorrect water level rating curves), and model structures. For example, precipitation is an example of a model-forcing data (e.g. different mathematical representations)

2.2 Literature Review and Analysis

Priority areas and challenges, as well as gaps in the literature, are identified as a result of this review, which provided substantive directions for a new approach. Fourth steps were used to identify pertinent literature: First, a database search of Google Scholar was conducted using the search terms "Flood Forecasting" AND "Multi Agent System." Due to the nature and timeliness of the topic, Google was also searched for Flood Forecasting-related literature, including research results. Second, we conducted a search of academic databases (WoS and Scopus) for articles containing the terms "Flood Forecasting AND Multi Agent System." Thirdly, relevant papers were selected from the articles listed in the references of the key articles. Fourth, as a result of the literature review, related topics, such as machine learning and deep learning, have been selected as focal points. Moreover, based on the identified literature analysis, areas containing Multi Agent System Flood Forecasting challenges and issues were researched using keywords associated with these subjects.

George *et al.,* [14] presented a real-time simulator that forecasts floods using an adaptive model. The simulator is made up of two levels of self-organizing multi-agent systems. Each agent on the higher level has the responsibility of computing the change in water level over the course of a unitary period (usually an hour), and they accomplish this by using a weighted sum of the agents on the lower level. Enhancement of the real-time simulator from previous work on [14] have been implemented by integrating the Decision Support System with Adaptive MAS theory.

A combination of MAS theory and Decision Support System (DSS) for reservoir group's flood prevention optimizing schedule algorithm also has been introduced by [15]. In this research, a two-stage multi-joint reservoir scheduling model was designed based on Mobile Agent and Agent's cooperation. Meanwhile, De Roure *et al.,* [16] proposed a pervasive computing system that consists of stationary and mobile agents and an expert system to manage available sensors on the network and use their information to monitor the water level in a river, as well as feed data into a grid-based flood predictor model in order to generate an alert for the situation.

The role of MAS in monitoring and analysing potential flood events is utilize by [17] in a distributed system environment. The monitoring and analysing multi-agent system, often known as MASMA, is a decentralised system that consists of both central components (the dispatcher agent) and local components (the measuring agents). In contrast, Weerawardhana and Jayatilleke [18] proposed a distributed system by integrating Belief-Desire-Intention (BDI) based MAS with web services. This work built a web services inter-agent communication framework to share beliefs and aims. Using a service-based strategy let multi-agent systems interoperate in actual software environments like the Internet. The communication architecture uses a message broker service concept. The implemented multi agent system simulates Sri Lanka's flood forecasting system and employs the proposed communication infrastructure to share goals and beliefs.

Mabrouk *et al.,* [19] proposed a new optimal model based on multi-agent systems for treatment of dataset received from wireless sensors in order to classify data into two classes Valid and Invalid data to overcome the flood disaster. This model then gone through several enhancement on the implementation. In [20], Mabrouk *et al.,* had combining the roles of MAS and Wireless Sensor Network (WSN) with an expert system. The agents are responsible for making the processing in real-time proposed by the two levels of forecasting and they are also responsible for deciding about the flood occurrence by communicating with the knowledge base that contains the decision rules under decision tree format. Meanwhile in [21], they described an intelligent Pre-Processing model for classification and aggregation of real-time flood forecasting and warning data based on MAS and WSN. The suggested model comprises of multiple stages to monitor the wireless sensors and their proper operation, to give the most accurate real-time data from wireless sensor networks, and to produce historical data for future flood forecasting.

Linghu and Chen in their [22] study presents a case-based multi-agent approach for flood disaster forecasting. First, the suggested framework includes Front end user computer, Back-end server, and Flood disaster predicting servers. The suggested flood disaster predicting system consists of multiple agents, each of which implements a certain function. In the proposed algorithm, each agent has its own case base and cannot visit other agents' directly. Each case has a problem and a solution.

Meanwhile, [23] presents a distributed decision support system for flood management. This system uses Multi-Agent Systems and Anytime Algorithm and has two processing modes: Pre-Processing to test and control sensor data in real-time and Main Processing with three components. The first part, Trigger Mode, monitors rainfall and triggers the second part, Offline Mode, which anticipates floods based on past data without using a real-time decision support system. The online mode estimates the flood using real-time data, module communications, hydrodynamic data, GIS, decision support, and remote sensing.

An agent-based system that combines the capabilities of neural networks with those of intelligent logical agents to obtain a tool for real-time flood recognition, alert transmission and mobilisation of rescue activities, fire departments, and essentially all required authorities had been proposed by [24]. In contrast, [25] presents a tropical catchment modelling environment in which the multi-agent systems approach was used as a substitute for the conventional hydrologic model to construct a system that operates at the catchment level and is displayed with hydrometric stations, which use the data from hydrometric sensors networks (e.g., rainfall, river stage, river flow) captured, stored, and administered by an organisation of interacting agents whose primary objective is to perform flow forecasting.

Table 1 and Table 2 provide summary in yearly manner of the related research on flood forecasting/prediction based on MAS approaches and the parameter used to forecast the events. Based on the table, we could see how the flood forecasting using MAS has been evolved over the years.

Table 1
Summary on Previous Work

Authors	Year	Method	Use of MAS	Flood forecasting	Flood Control	Disseminate flood warning to third parties
George *et al.,*	2003	MAS + Adaptive MAS (AMAS) Theory	Real Time Simulation	/	x	x
De Roure *et al.,*	2005	MAS + Grid computing	agent-based pervasive computing simulator	/	x	x
Xie *et al.,*	2009	MAS + DSS + Agent Theory +scheduling	reservoir group's flood prevention optimizing schedule algorithm	x	/	x
George *et al.,*	2009	MAS+DSS+AMAS Theory	Real-Time Decision Support System	/	x	x
Matei	2011	MAS	monitoring and analysing of the parameters of the hydrographical basin	/	x	x
Weerawardhana *et al.,*	2011	MAS+BDI+Web services	monitoring and analysing of the parameters of the hydrographical basin	/	x	/ (general public and media)
Marouane *et al.,*	2014	MAS+WSN	Data Classifier	/	x	/ (Base Station)
Linghu *et al.,*	2014	MAS+Case Based Reasoning	Forecasting agent	/	x	x
El Mabrouk *et al.,*	2015	MAS + Expert System	Real-Time processor and communicator	/	x	/ (via email and SMS)
El Mabrouk *et al.,*	2017	MAS+WSN	Data classifier	/	/	x
Wahyu Satria Aji	2019	MAS + Particle Swarm Optimization	Rainfall point detector based on sensor	/	x	x
Marouane *et al.,*	2021	MAS+Ditributed DSS + Anytime Algorithm	Forecasting using anytime algorithm and communicating among modules	/	x	/ (within the system)
Rafanelli *et al.,*	2022	MAS+ML+ Neural Network	monitoring flood events	/	x	/(send alert to relevant authorities)
Simmonds *et al.,*	2022	MAS+BDI	stream-flow predictions	/	x	not stated

*MAS: Multi Agent System DSS: Decision Support System WSN: Wireless Sensor Network BDI: Belief-Desire-Intention ML: Machine Learning

Table 2
Summary of Input Parameter

Authors	Year	Input Parameter						Lead Time
		Water Level	Rainfall Level	Flow Level	River Velocity	Air Temperature	Runoff	
George *et al.,*	2003	/	/	x	x	x	x	Not Mention
De Roure *et al.,*	2005	/	x	x	x	x	x	Not mention
Xie *et al.,*	2009	/	/	x	x	x	x	Not Mention
George *et al.,*	2009	/	/	x	x	x	x	Not Mention
Matei	2011	/	/	/	/	/	x	Not Mention
Weerawardhana *et al.,*	2011	/	/	x	x	x	x	Not Mention
Marouane *et al.,*	2014	/	/	/	x	x	/	Not Mention
Linghu *et al.,*	2014	/	/	x	x	x	x	Not mention
El Mabrouk *et al.,*	2015	/	/	x	x	x	/	Short Term, Medium Term, Long Term
El Mabrouk *et al.,*	2017	/	/	x	x	x	/	Not Mention
Wahyu Satria Aji	2019		/	x	x	x	x	Not mention
Marouane *et al.,*	2021	/	/	x	x	x	/	Not Mention
Rafanelli *et al.,*	2022	/	/	x	x	x	x	Not Mention
Simmonds *et al.,*	2022	/	/	/	x	x	x	Not Mention

3. Methodology

This section presents the methods used in proposing our new multi-agent-based Flood Forecasting and Warning System Model (MFFWS). The development of this model is based on the *System, Model, Problem* guidelines introduced by [26]. In this study, the *System* was Hydrometeorological Monitoring System (HMS), Flood Forecasting and Warning System (FFWS) was the *Model* and the *Problem* was 'training the multi agent for forecasting flood and issuing early warning'. Figure 2 summarizes the methodology mapping in developing the MFFWS conceptual model.

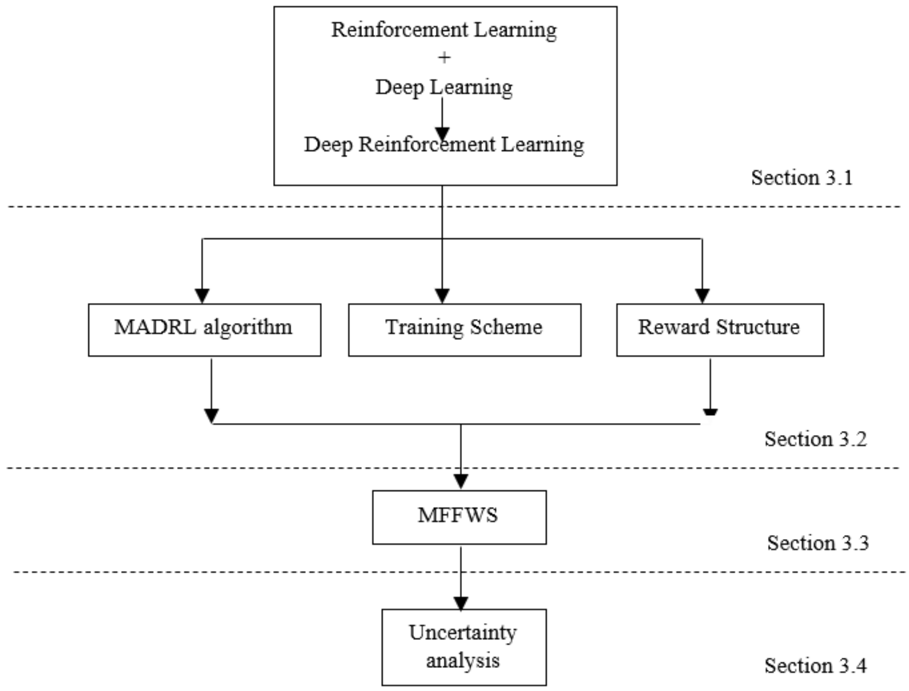

Fig. 2. Methodology Mapping

3.1 Multi-Agent Deep Reinforcement Learning Overview

The advancements in reinforcement learning have yielded phenomenal results in numerous fields. Despite the fact that the multi-agent domain has been overshadowed by its single-agent counterpart during this period of progress, multi-agent reinforcement learning is gaining rapid traction, and the most recent achievements target problems with real-world complexity [27].

As illustrated in Figure 3, there are two distinct types of solution methods: model-based and model-free. In model-based DRL, the model is either learned or known. A significant advantage of the model-based strategy is that it requires less learning examples. However, it becomes significantly more computationally complex when the model becomes unexpectedly difficult to master. On the contrary, model-free RL will be easier to work with. Effectiveness requires no accurate description of the environment, and it is also less computationally complex [28,29].

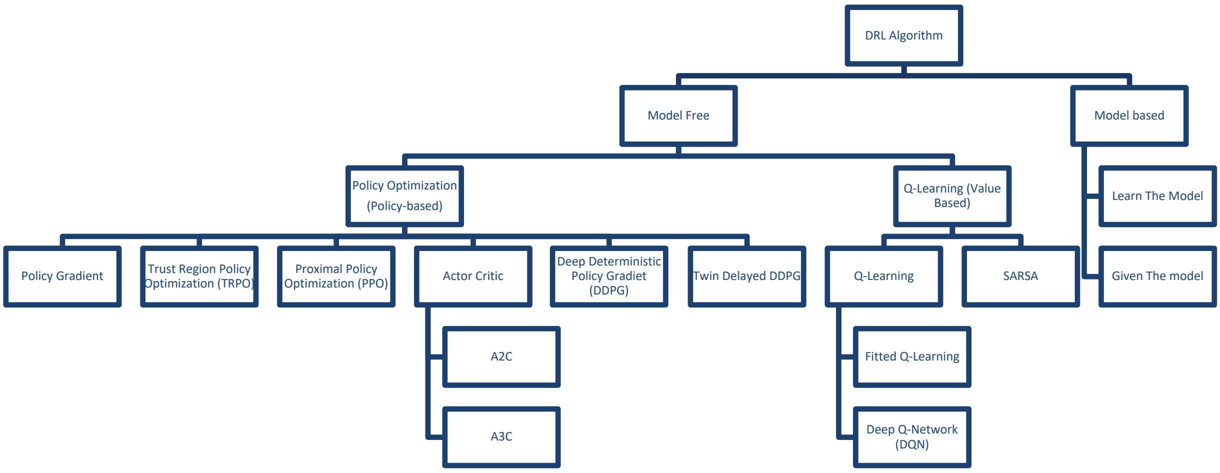

Fig. 3. Overview of Deep Reinforcement Learning Algorithm

In model-free DRL broadly classified into two types: value-based and policy-based. Using dynamic programming, value-based methods construct optimal policy by obtaining an approximation of the optimal function Q*(s, a). The Q-function in DRL is represented by a deep neural network. Policy-based algorithms use gradient approximate estimations relative to policy parameters to directly optimise policy π* without any additional information about MDP [27,30].

The framework of multi-agent reinforcement learning as shown in Figure 4 is a Markov Decision Process-based (MDP) stochastic game represented by the tuple $S, A_1 \ldots A_n, R_1 \ldots R_n, P$. Where n is the number of agents, $A = A_1 \times \ldots \times A_n$ is the joint action space of all agents, and $Rn : S \times A \times S \rightarrow R$ is the agent's reward function, and $P : S \times A \times S \rightarrow [0, 1]$ is the state transition function, assuming the reward function is constrained [31].

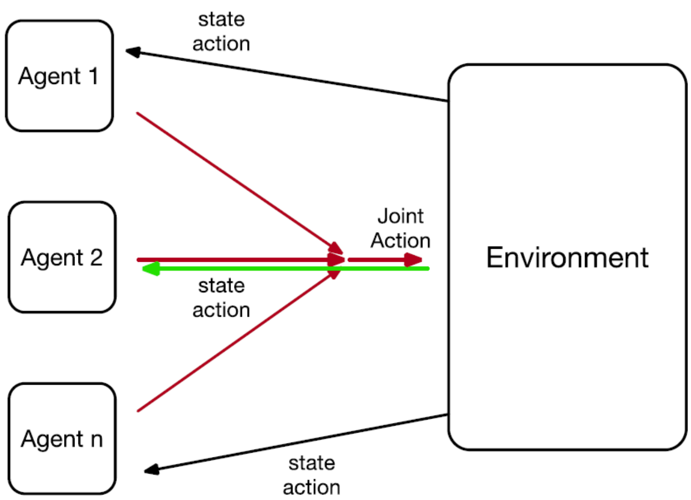

Fig. 4. Multi Agent Interaction with environment in MADRL [31]

3.2 Flood Related Deep Reinforcement Learning (DRL) Applications

In order to proceed with the designing our new proposed conceptual model. We did some research on DRL approach used on related flood areas. Table 3 summarizes the findings.

Table 3
DRL Approach on Related Flood Events

Author	Agent System	Algorithm/ RL Methods	Training and Execution Scheme	Input	Reward Structure
(Arakawa and Chun) [32]	Single agent	Twin Delayed DDPG (TD3)	-	Rainfall Flow rates	Deterministic
(Wang *et al.,*) [33]	Single Agent	Model-Free (Based on MDP)	-	Flood level	Deterministic
(Saliba *et al.,*) [34]	Single Agent	DDPG	Centralized Training	Rainfall	Deterministic
(Baldazo, Parras, and Zazo) [35]	Multi-Agent	DQN	CTDE	2D Map Water level	Independent reward Shared reward
(Rongtao *et al.,*) [36]	Multi-Agent	MADDPG	CTDE	Production time The bottom hole pressures The oil production rate Gas-oil ratio	Net present Value (NPV)
(Rajulapati, Nukavarapu, and Durbha) [37]	Multi-Agent	MADDPG	CTDE	Flood inundation Water inundation Road Blocked	Not Mention

[33] proposed the development of an IoT-enabled, MDP-based method for simulating storm surges using deep reinforcement learning. Utilizing the power of the IoT system, the suggested method is able to accurately evaluate the degradation of subterranean pipelines. Experiments are performed on a case study that initialises an urban IoT system for storm surge and gathers the volume of flooding. Meanwhile [32] develop a model for operating several dams for flood control using deep reinforcement learning. The developed model utilised Twin Delayed Deep Deterministic Policy Gradient (TD3) for the dam operating AI, and it was deployed to three different dams in a river basin. Flood control utilising an AI for dam operation for each dam was compared to flood control using dam operation guidelines. The performance of the dam operation AI was also tested based on the sort of reward.

Three Deep Deterministic Policy Gradient (DDPG) agents were trained through 10,000-time steps of interaction with a Storm Water Management Model simulation in [32]. Following training, the RL policies were tested on a series of rainfall events that had never been observed before. The researchers discovered that the DDPG techniques were able to tolerate unclear data, resulting in comparable flood mitigation capabilities for all three data circumstances. In multi agent environment, [35-37] adopt Deep Q-Network (DQN) and DDPG as the DRL algorithm to simulate the process of monitoring their specific flood event. Figure 5 illustrates the schematic diagram of single agent and multi-agent in the flood monitoring system with deep reinforcement learning control loop.

A technique for training through DRL using DDPG for guiding multiple fixed wing aircraft to monitor floods in a decentralized fashion was introduced by [35]. Agents are able to make judgements based on raw input data, which consists of a processed optical image and some information about the swarm's local state. The degree of decentralisation in training was compared across two incentive schemes. Simulation results indicate that planes are capable of monitoring floods in a coordinated manner with both incentive schemes. These controllers could be placed in actual UAVs to lower operational expenses. We trained on simulated floods caused by dam failures, but the training method should work well on all types of floods if the training material is sufficiently generic.

We simplified the DRL algorithm, training scheme, and reward structure in a schematic DRL learning control loop based on Flood Monitoring System (FMS) as the environment as in Figure 4. This schematic showing a clear distinction between the RL algorithm that currently used in FMS environment.

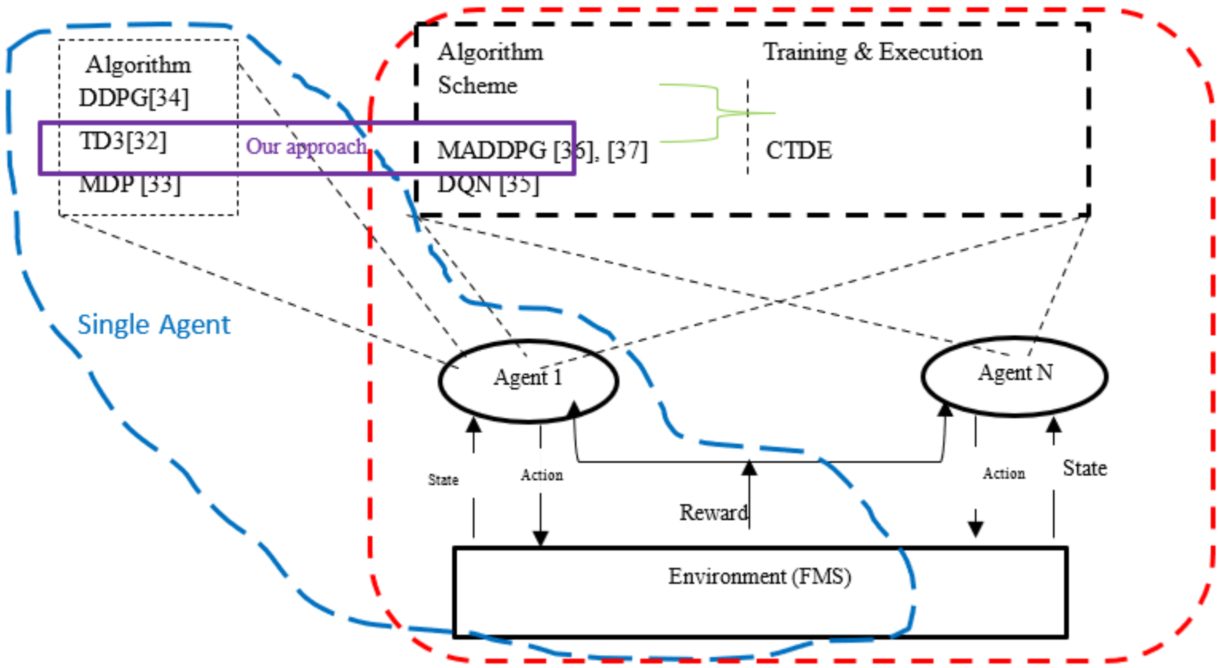

Fig. 5. Schematic showing a Flood Monitoring System Deep Reinforcement Learning Control Loop

3.3 Proposed Multi-Agent Based Flood Forecasting and Warning System Model (MFFWS)

This section describes the process of deriving new FFWS model by integrating the FMS and DRL control loop in one mechanism to monitor flood. Based on our literature findings, we constructed a new conceptual model for multi-agent-based flood forecasting and warning system. Our new conceptual model derived from the current forecasting system used by Malaysia known as NaFFWS as shown as in Figure 1. Figure 6 shows the enhancement area that we made on the current NaFFWS.

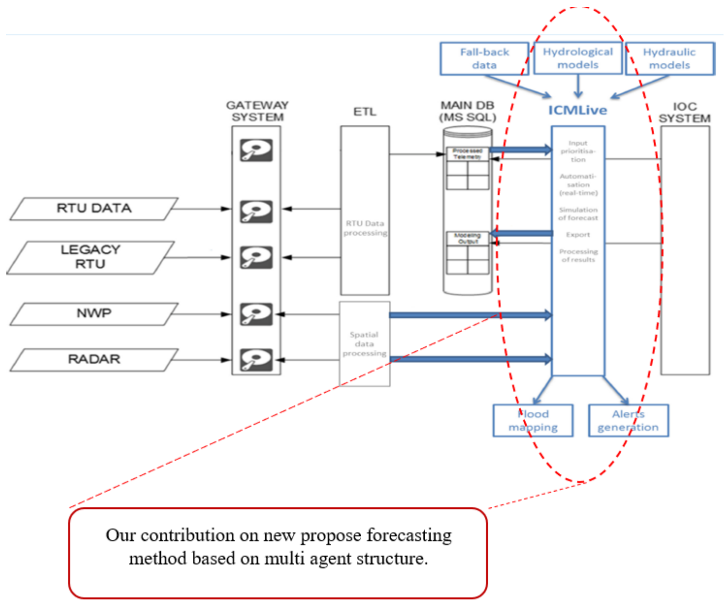

Fig. 6. Area of Research Contribution

3.3.1 Multi-agent system architecture

The proposed Multi-Agent System (MAS) framework is structured to efficiently handle the complexities of real-time flood monitoring and forecasting. It comprises several interdependent agents, each specializing in distinct tasks that contribute to the overall predictive capability of the system:

i. <u>Rainfall Agent (RA):</u> The RA is responsible for collecting real-time rain data from field rain gauge sensors. It then transmits this data to the Processor Agent for further processing and analysis.
ii. <u>Water Level Agent (WLA):</u> The WLA gathers real-time river surface water level data from field water level sensors. Similar to the RA, this data is sent to the Processor Agent for integration into the forecasting process.
iii. <u>Flow Level Agent (FLA):</u> The FLA focuses on obtaining real-time flow discharge data from field flow meter sensors. Like the RA and WLA, this data is relayed to the Processor Agent.
iv. <u>Processor Agent (PA):</u> The PA acts as a central hub for data processing. It receives data from the RA, WLA, and FLA, and then performs essential pre-processing tasks, including data treatment and imputation. These steps ensure that the incoming data is reliable and consistent for subsequent analysis.
v. <u>Historic Agent (HA):</u> The HA plays a vital role in data management and storage. It keeps a record of all data flowing through the MAS environment, logging communications and sensor readings. This stored information is available for reference and sharing among agents when needed.
vi. <u>Forecast Agents (FAs):</u> The FAs represent a collaborative group of agents designed to implement the Multi-Agent Deep Reinforcement Learning (MADRL) algorithm. These agents are trained to effectively interact with the environment and learn optimal control policies. During execution, they use their learned policies to make real-time decisions that contribute to the forecasting process.
vii. <u>Alert Agent (AA):</u> The AA holds the crucial responsibility of interpreting the forecast outputs generated by the FAs. It categorizes potential flood events based on severity,

generating alerts that are color-coded to indicate different levels of risk. The AA also communicates these alerts to relevant authorities and users through an intuitive user interface.

3.3.2 Data processing and integration

The integration of real-time data from the RA, WLA, and FLA into the framework is a critical step. Raw data obtained from these sensors may contain anomalies or missing values. The Processor Agent (PA) plays a pivotal role in rectifying these issues through data treatment and imputation. By ensuring the quality and consistency of the input data, the PA contributes to the accuracy of subsequent analyses.

3.3.3 Deep reinforcement learning algorithms

The core of the forecasting process involves the application of Deep Reinforcement Learning (DRL) algorithms. Specifically, the Twin Delayed Deep Deterministic Policy Gradient (TD3) and Deep Q Network (DQN) algorithms are employed. These algorithms enable agents to learn and optimize control policies that guide their decision-making in the face of uncertain and dynamic flood-related scenarios.

3.3.4 Environment and state representation

The MAS framework operates within an environment defined by the input data streams, including rainfall, river flow, and water level data. Agents interact with this environment by perceiving its state. The state representation is multidimensional and includes:

i. 24-hour rainfall forecast
ii. Water flow rate
iii. Water level rate
iv. Reservoir volume

This rich state representation empowers agents to make informed decisions by capturing relevant information about the current and predicted environmental conditions.

3.3.5 Actions and rewards

In response to the perceived state, agents take actions that influence the forecast outcomes. The central goal is to determine the probability of flood occurrence categorized into different levels of intensity. The actions taken by agents guide the decision-making process to mitigate potential flood risks. Rewards within the MAS framework is designed to incentivize desired behaviour. During flooding events, specific rewards are employed:

i. Positive reward based on flow rate: Encourages agents to respond effectively to changing flow conditions, facilitating optimal water management.
ii. Negative reward when reservoir capacity is reached: Discourages actions that may lead to the reservoir exceeding its maximum storage capacity, mitigating flood-related risks downstream.

3.4 Uncertainty Analysis

As part of the model evaluation, an uncertainty analysis will be carried out. We used two types of uncertainties in this study: (a) the diversity of rainfall events and (b) the RL agents' imperfect inputs [38]. Typically, the flooding and overflow volume of a given water reservoir are strongly influenced by rainfall conditions, making it difficult to assess the performance of the RL agents. Given this, we used the ratio of total flooding and overflow to total inflow (RSI) as an indicator of the RL agents' performance in the uncertainty analysis.

$$RSI = the\ sum\ of\ total\ overflow\ and\ total\ flooding/total\ inflow \quad (1)$$

This index ranges from 0 to 1. Therefore, it reduces the influence of the rainy conditions and offers a relatively objective evaluation of the RL agents' forecasting ability.

4. Result & Discussion

4.1 System Architecture and Agent Roles

The intricate architecture of the proposed Multi-Agent System (MAS) framework plays a pivotal role in the effectiveness of flood monitoring and forecasting. The distribution of roles among agents - Rainfall Agent (RA), Water Level Agent (WLA), Flow Level Agent (FLA), Processor Agent (PA), Historic Agent (HA), Forecast Agents (FAs), and Alert Agent (AA) - enables a seamless flow of information and a division of labour that is conducive to accurate predictions. The collaborative efforts of these agents ensure the efficient gathering, preprocessing, analysis, and dissemination of data, underscoring the system's robustness.

4.2 Data Integration and Quality Assurance

The success of any forecasting system hinges on the quality and reliability of input data. The Processor Agent (PA) acts as a crucial gatekeeper by conducting data treatment and imputation. The integration of data from various sensors, each susceptible to noise and errors, poses a challenge that the PA adeptly addresses. This data refinement process significantly contributes to the accuracy of subsequent analyses, highlighting the importance of proper data handling in real-world forecasting scenarios.

4.3 Deep Reinforcement Learning Algorithms

The utilization of Twin Delayed Deep Deterministic Policy Gradient (TD3) and Deep Q Network (DQN) algorithms represents a pivotal step towards enhancing flood forecasting accuracy. These algorithms provide agents with the ability to learn optimal control policies through interactions with the environment. The distinct algorithms cater to both continuous and discrete action spaces, allowing for a versatile approach to decision-making. This adaptation in algorithm selection showcases a well-thought-out strategy to cater to the inherent complexities of flood monitoring and forecasting.

4.4 Real-Time Decision-Making and Alert Generation

The Forecast Agents (FAs) are at the heart of real-time decision-making within the MAS framework. Through their training with DRL algorithms, these agents learn to act in a manner that maximizes the accuracy of flood predictions. The integration of forecast outputs into the Alert Agent's (AA) decision-making process leads to well-informed and timely alert generation. This fluid collaboration between forecast generation and alert dissemination minimizes response time, a critical factor in disaster preparedness.

4.5 Performance Metrics and Practical Implications

The framework's efficacy is evaluated through pertinent performance metrics, emphasizing accuracy, timeliness, and efficiency. The integration of intelligent agents and DRL algorithms results in heightened forecast accuracy, translating to actionable insights for stakeholders. Timely alerts, categorized by severity, enhance decision-makers' ability to assess risks and allocate resources effectively. The MAS framework's ability to adapt to changing conditions and its potential to revolutionize flood risk management underscore its practical implications for real-world disaster scenarios.

Our proposed conceptual model is comprised of the multi-agent architecture for flood forecasting and warning system integrated with Deep Reinforcement Learning for optimal flood forecast decision making. Figure 7 depicts our proposed conceptual model. The knowledge gained from the related literature review and related concepts resulted in the development of the proposed conceptual model to improve current flood forecasting within Malaysia's geographic boundaries. It is also meant to explain current MAS implementation in flood forecast areas and provide guidance for the next system implementation steps. Our overall contribution is the creation of a new model for the adoption and implementation of MADRL for flood forecasting, which is virtually non-existent in the literature. There have been a few theories proposed and models developed related to MAS-based flood forecasting, but this is the first to integrate the components of MAS and Deep Reinforcement Learning in a distributed forecasting system.

Uncertainty is one of the most challenging issues in current NaFFWS implementation due to the modelling tools and not to mention some cases in MAS modelling. Flood forecasting is one of the challenging decision-making issues with vast high-dimensional data [12,13,17] and uncertainty, hence an approach combining the multi-agent actor-critic algorithm with the deep deterministic policy gradient algorithm is suggested.

Multi-agent deep reinforcement learning (MADRL) is the learning technique of numerous agents attempting to maximise their projected total discounted reward while coexisting in a Markov game environment with transition and reward models that are typically uncertain or noisy. Formally, agents estimate their action values using neural networks with a large number of layers as a function approximator. In MADRL, an agent's optimal policy depends not just on the environment but also on the policies of other agents. Therefore, it minimizes the uncertainty factors that may occur during the agent decision making process [38-40].

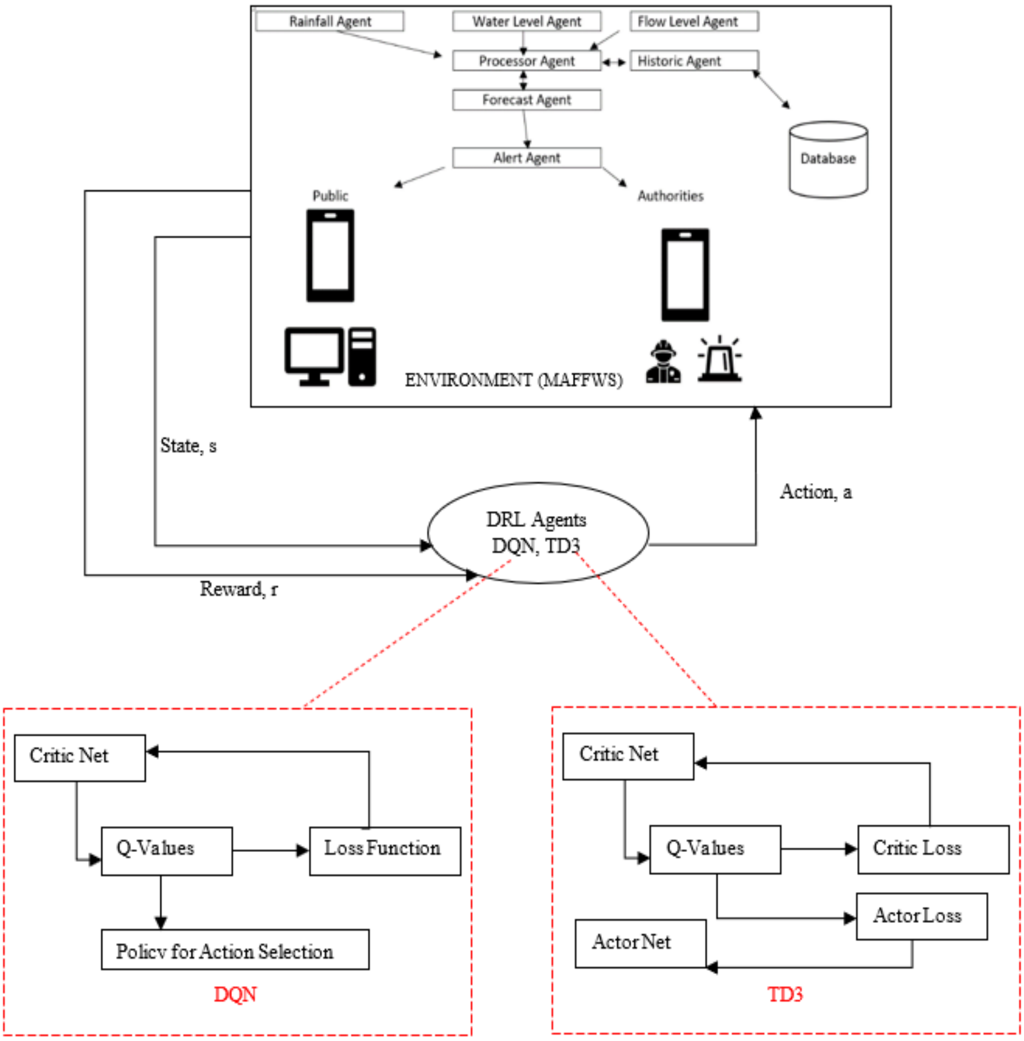

Fig. 7. MAFFWS Conceptual Model with Enlarge DRL Agent Algorithm

5. Conclusion

This idea is the first stage in the creation of an integrated system that can provide help and support during catastrophic weather occurrences, such as flooding. This concept arose from a desire to address the increasingly regular and severe problem of flood inundation. In light of this, we believe that artificial intelligence in general could provide a rapid and effective response to aid people in managing crises of this scale. We feel the success of the combination of multi-agent paradigms and Deep Reinforcement Learning could be the proposal's greatest strength.

Designing agents so that they can work efficiently and synergistically is crucial. This demands the identification of defined responsibilities for each agent, as well as the abstraction and formalisation of the multiagent system's organisational structure. In the future, we plan to develop each component of the suggested system in depth, especially the phase of forecast decision making into logical rules and the phase of flood warning distribution. We would also wish to integrate the system with external sources via APIs for data retrieval.

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