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AI-Enhanced Adaptive Flood Management: Integrating Multi-Objective Evolutionary Optimization and Real-Time SCADA for the Muda River Basin

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ABSTRACT

Mainly during the monsoon season, the Muda River Basin in northern Malaysia faces significant flood risks, threatening community safety, local infrastructure, and agricultural activities. Traditional flood management methods, which often rely on simplified empirical models, fall short in addressing the complex and dynamic nature of flood events in this region which prevents the hydromechanical infrastructure from being operated optimally. This study introduces an innovative AI-powered framework designed to enhance mechanical flood gates optimally in the Muda River Basin by integrating advanced machine learning techniques, real-time hydrological data, and automation technologies within an intelligent control system. The system features mechanical improvements such as automated hydraulic gate control for optimized discharge management and dynamic flood routing, all facilitated by a sophisticated SCADA architecture. These mechanical automation enhancements, combined with AI-driven models, improve the accuracy of flood predictions, enabling more effective, data-driven decision-making and adaptive flood control strategies. The results of this research demonstrate that AI-based flood management systems can significantly enhance operational resilience through optimal hydromechanical operation, improve flood prediction accuracy, and optimize water flow management, providing a scalable solution for mitigating flood risks in tropical river basins.

Keywords: AI-driven flood management; flood forecasting; machine learning; Muda River Basin; SCADA integration

Nomenclature (Greek symbols towards the end)

A	River storage volume (m^3)
L_1	River length (m)
W_1	River width (m)
D_1	River depth (m)
Q	Flow rate through the gate
C_d	Discharge coefficient
A	Area of gate opening
g	Gravitational acceleration
h	Height of water above gate opening

Abbreviations

AI	Artificial intelligence
LSTM	Long Term-Short Memory
SCADA	Supervisory Control and Data Acquisition
CFD	Computational Fluid Dynamics
MOE	Multi Objective Evolutionary
SL	Shadow Logic
PLC	Programmable Logic Control
HMI	Human Machine Interface
ANN	Artificial Neural Network
PtP	Point to Point
PtMP	Point to Multi Point
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
DEAP	Distributed Evolutionary Algorithms in Python

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1.0 INTRODUCTION

Flooding is one of the most devastating natural hazards worldwide, posing significant risks to human lives, infrastructure, and ecosystems [1]. The 2005 Taum Sauk Pumped Storage Powerplant failure in Missouri, USA, stands as a striking example of how a combination of design and construction flaws, instrumentation programming errors and human mistakes can align to create catastrophic consequences [2]. When the Upper Reservoir failes, it released an estimated peak discharge of 289,000 cubic feet per second (8,184 m^3/s), devastating Johnson Shut-ins State Park; although remarkably, only five people were injured. In Canada's Cleveland Dam incident on October 1, 2020, the unexpected lowering of the drum gate unleashed a sudden surge into the Capilano River, trapping four fishermen and prompting a redesign of the control system from mechanical to electronic automation [3]. Similarly, the 2010 Niedów Dam failure in Poland illustrates the perils of inadequate gate control during extreme water levels. A simultaneous malfunction and manual over-adjustment caused the accelerated opening of a gate, ultimately washing away the earth-type dam and releasing approximately 8.5 million cubic meters of water, leading to substantial downstream flooding and economic loss [4]. Collectively, these cases underscore how mechanical vulnerabilities, human error, and insufficient system safeguards can converge to produce severe hydromechanical disasters, reinforcing the need for robust design, redundant control systems, and stringent operational protocols in dam safety management.

As noted by [5], tropical regions such as Southeast Asia are particularly vulnerable to seasonal monsoon floods, a risk further exacerbated by rapid urbanisation, deforestation, and climate change. The Muda River Basin in northern Malaysia is especially prone to these floods, with factors such as intense rainfall, urban development, and inadequate drainage infrastructure worsening the situation [6]. According to [7], conventional hydrological models have been used for flood prediction and management in this region. However, these models often fail to accurately account for the complex interactions between environmental variables, human activities, and flood dynamics. Integrating these flood predictions with automated flood gates can lead to major mismanagement of the flood basin. This occurred during the Sungai Muda Barrage Gate failure on May 14, 2023, which caused an unplanned loss of fresh water in the Muda River.

This study proposes integrating Artificial Intelligence (AI) techniques into an advanced flood management system for the Muda River Basin. Unlike conventional methods, which rely on static data and simplified assumptions, AI-driven approaches can dynamically adapt to changing environmental conditions, thereby improving predictive accuracy [8], [9]. Machine learning algorithms, particularly Long Short-Term Memory (LSTM) networks, forecast flood events with higher precision. This is supported by a study conducted by [10], which demonstrated that LSTM networks enhance flood predictions by learning from historical hydrological data and adapting to real-time inputs. Integrating AI into a Supervisory Control and Data Acquisition (SCADA) system enhances automation for hydraulic gate control, enabling more responsive flood mitigation during extreme weather events. [11] highlighted that AI-driven approaches, particularly ensemble deep learning models, significantly improve flood forecasting accuracy and system responsiveness in such dynamic conditions. This research explores the application of AI in flood management through a holistic framework that incorporates real-time monitoring, predictive flood forecasting, and automated infrastructure management. Specifically, the integration of LSTM networks for flood prediction, automated gate control for discharge management, and SCADA for system-wide coordination and communication form the foundation of the proposed approach. This AI-powered system seeks to reduce the destructive impacts of floods, improve the effectiveness of water flow management, and offer a scalable solution for Southeast Asian flood-prone areas by increasing the accuracy of flood forecasts and optimising response techniques. The primary objective of this study is to develop an intelligent, adaptive flood management framework that can be applied to the Muda River Basin, leveraging the power of AI to optimise flood management through optimal hydromechanical flood gates by improving forecasting, water discharge regulation, and overall flood resilience.

1.1 Study Area

The Muda River Basin, located in northern Malaysia, spans an area of 4,111 km^2 with an approximate river length of 180 kilometres [12]. The region experiences significant seasonal rainfall, especially during the monsoon periods from April to November, which increases flood risks, as observed by [13]. The basin is influenced by major hydrological features, including the Muda Dam and the Beris Dam, which play essential roles in water storage and flood control. Figure 1 shows the topography and spatial distribution of hydro-climatic monitoring stations across the Muda River Basin. These stations provide real-time data on critical hydrological parameters such as water levels, rainfall intensity, and discharge rates, which are vital for flood forecasting and management.

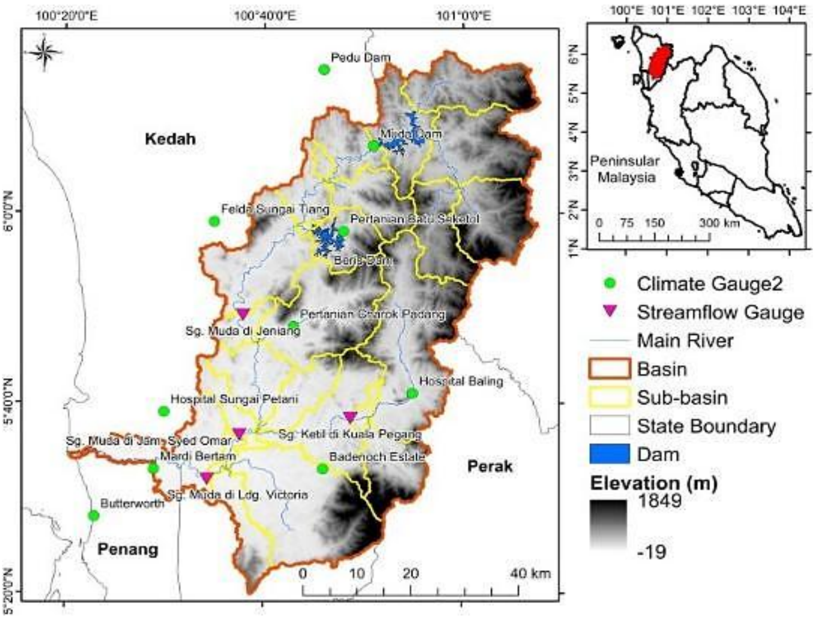

Figure 1. The topography and spatial distribution of hydro-climatic monitoring stations in the Muda River Basin, Malaysia (Source: Luhaim et al., 2021)

In addition, the Sg Muda Basin is managed by hydromechanical infrastructures scattered approximately 20 kilometres from the river mouth, beginning with a 14-gate barrage, over 30 pumping stations for irrigation/potable water and 102 flood sluice gates in combination with 2, 3 or 4 gates each. As shown in Figure 2(a) and 2(b), the failure of Gate 14 at the Sungai Muda Barrage caused a significant disruption. The study uses AI techniques to enhance control over the hydromechanical infrastructure to prevent a hydrological catastrophe that occurred on 14 May 2023, which was published in all news media. Figure 3 illustrates the equipment failure that caused the river level to drop drastically during this event. The AI techniques would prevent such incidents by utilising supervised learning (k-means) for fault detection in the hydromechanical sensors. The study also looks at the optimisation of the industrial engineering field through AI automation by utilising Multi-Objective Evolutionary Optimisation.

(a) (b)

Figure 2. (a) Failure of Gate 14 at the Sungai Muda Barrage, (b) Low water level at Sungai Muda on 14 May 2023

Figure 3. Equipment failure that causes the river level to drop

2.0 METHODOLOGY

Data collection was performed using a combination of flow stations, ultrasonic level sensors, and weather monitoring stations strategically placed across the Sg Muda Basin. These sensors measure water levels, velocity, and discharge at key locations, feeding real-time data into the PRIME SCADA system. Ultrasonic sensors were deployed at both the upstream and downstream of each gate to monitor localised stage measurements, which inform the operation of the gates. In addition to real-time monitoring, data from the Sungai Muda Barrage gates and the Sluice gates are crucial for understanding the water flow dynamics within the system. The operation of these gates is influenced by several factors, including upstream water levels, discharge rates, rainfall intensity, catchment changes, SCADA Alarms, Mechanical Actuators and Automation Data.

2.1 Hydraulic Modelling and Simulation

Computational Fluid Dynamics (CFD) is particularly effective for modelling complex hydraulic processes that are difficult to simulate using conventional methods [14]. It plays a crucial role in simulating flow conditions during flood events [15], assessing the performance of flood control infrastructure [16], and predicting the impacts of environmental factors [17]. The integration of CFD with real-time monitoring data enables dynamic adjustments to flood control measures, ensuring more effective management and decision-making during flood events in the Muda River Basin. By modelling water flow and interactions within the basin, CFD provides a comprehensive framework for simulating fluid dynamics, including turbulent flow, and evaluating the performance of flood control structures like barrages, sluice gates, and pump stations. A CFD model was developed using Python which applied the RANS equations to simulate water flow in the Muda River Basin. This model incorporated a Multi-Objective Evolutionary (MOE) algorithm to optimise gate operations and discharge rates, providing an accurate representation of non-uniform flow conditions, turbulence, and sediment interactions. Boundary conditions were established using real-time upstream water level data from Jeniang and downstream tidal measurements from Sidam, which governed the inflow and outflow dynamics. This allows the model to realistically capture the effects of backwater and flow resistance.

2.2 Integration of PRIME SCADA

The integration of PRIME SCADA is designed to improve the efficiency of existing flood management systems by upgrading the monitoring capabilities and enabling smarter decision-making through AI models [18]. With modules such as AI Flood Routing, Real-Time Website interfaces, Barrages, and Flow Stations, the system ensures a holistic approach to flood control. Real-time data from INFOBANJIR, Flow Stations, and Tidal Gates are continually fed into the system, enabling predictive flood forecasting and dynamic control of hydraulic infrastructure, such as gates and pumps. Figure 4 shows the SCADA conceptual architecture.

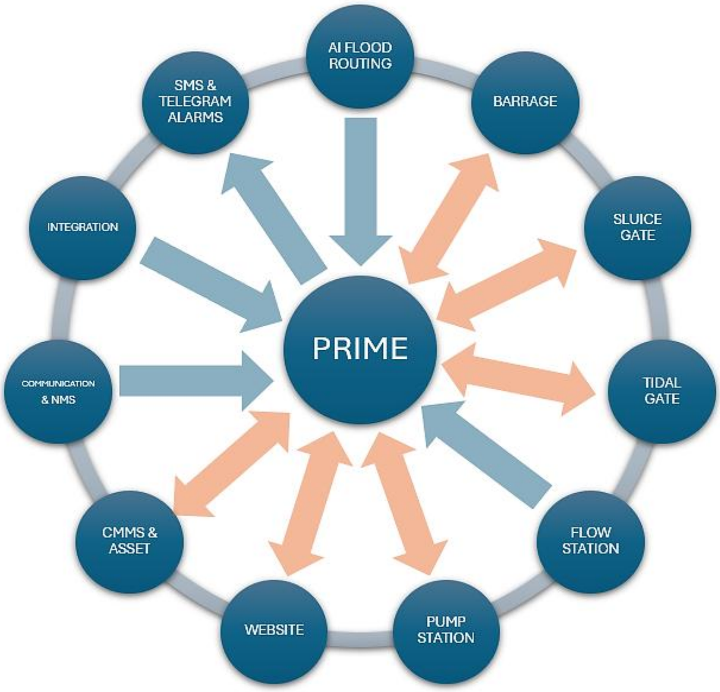

Figure 4. SCADA conceptual architecture

As shown in Figure 4, the SCADA Conceptual Architecture of the PRIME SCADA system outlines the various modules and components that work together to manage and control the Sg Muda River Basin. It demonstrates the interconnection between AI Flood Routing, Barrages, Sluice Gates, Pump Stations, Flow Stations, and Tidal Gates, each contributing to a real-time, automated system that can predict and control flood risks dynamically. The architecture also incorporates communication networks, SMS and Telegram alerts, and integrated systems for seamless data exchange across all system components, ensuring optimal flood management. This comprehensive structure enables the PRIME SCADA system to enhance flood prediction, water management, and control, providing a scalable solution for regions facing similar flood risks.

A new function block of "Shadow Logic" (SL) has been developed to supervise all algorithms running at the Programmable Logic Controller (PLC). The SL function block runs in parallel and has its algorithm at the SCADA server level to determine if the PLC is performing the automatic mode as it is supposed to. If an error or unexpected condition occurs at the PLC, SL shall override the automatic mode and provide a severe alarm to the operator for manual intervention. SL shall ensure the override is in a fail-safe mode so as not to damage the hydromechanical infrastructure or the gate operation modes. The SL has also been developed to monitor the gate position sensor to prevent the 14 May 2023 event from reoccurring. The SCADA system design has been made in compliance with IEC 62682, which specifies general principles and processes for the management of alarm systems based on control systems and human-machine interfaces (HMI) for facilities in the process industries. It covers all alarms to be presented to the operator through the control system, which includes alarms from basic process control.

2.3 Flood Routing and Machine Learning Integration

Flood routing utilises both translation and storage effects to model the movement of flood waves downstream. The translation effect involves the flood wave maintaining its shape as it moves, while the storage effect refers to the attenuation of the wave due to valley storage, which modifies the peak flow and hydrograph shape. To model these effects accurately, the conservation of mass and momentum equations are employed, allowing for precise predictions of flood levels and peak discharges. Additionally, machine learning models, such as Long Short-Term Memory (LSTM) networks, Artificial Neural Networks (ANN), and Decision Trees, are increasingly used to enhance the prediction of flood dynamics. These models can process large datasets and capture complex, nonlinear relationships within hydrological systems, improving forecasting accuracy. According to [19], integrating machine learning algorithms into flood forecasting significantly increases the accuracy and responsiveness of predictive models, making them more effective for real-time flood management. The project segments the river into 11 sections to better monitor the water based on the segments as shown in Table 1. Each segment is monitored with a flow sensor at the start of the segment and another flow sensor at the exit. The flow in and flow out are derived from the subtraction of the flow out from the flow in.

Table 1: Muda River Volume Calculation in Million Cubic Meters (MCM)

Segment	Length (m)	River Width (m)	Remarks	Depth (m)	Area (m^2)	Total A (m^3)	Total B (m^3)	Total Volume (m^3)	MCM
Segment 1	14,986	7.82	Google	3.00	23.46	175,785.78	840,714.60	1,016,500.38	1.02
Segment 2	21,769	34.00	CS	3.30	112.2	1,221,240.90	864,566.72	2,085,807.62	2.09
Segment 3	4,231	24.07	Google	3.30	79.431	168,036.28	761,580.00	929,616.28	0.93
Segment 4	11,980	60.00	Report	6.00	360	2,156,400.00	1,260,595.50	3,416,995.50	3.42
Segment 5	21,453	34.50	CS	6.10	210.45		3,965,812.31	6,223,204.23	6.22
Segment 6	25,172	60.61	Google	6.10	369.721	4,653,308.51	6,505,879.60	11,159,188.11	11.16
Segment 7	2,596	84.74	Google	6.10	516.914	670,954.37	542,290.12	1,213,244.49	1.21
Segment 8	16,692	68.49	Google	6.10	417.789	3,486,866.99	5,515,272.16	9,002,139.15	9.00
Segment 9	8,775	86.27	cs	7.66	660.8282	2,899,383.73	3,721,105.44	6,620,489.17	6.62
Segment 10	5,128	110.72	Google	7.66	848.1152	2,174,567.37	1,338,285.95	3,512,853.33	3.51
Segment 11	11,262	68.14	Google	7.66	521.9524	2,939,113.96	5,313,211.70	8,252,325.66	8.25

In Table 1, the river storage area is calculated for each segment by using the river width and the depth of the river. The river width is either from "Google", which means it was obtained from Google Earth Platform or Cross-section (CS), which was obtained from the actual river cross-section. The storage volume, Total A, for Segment 1 uses the following equation:

$$A = W_1 \; X \; D_1 \; X \; L_1 \qquad (m^3) \qquad (1)$$

Total A Segment 1:

River Width at Flow Start	= 7.82m	
River Depth at Flow Start	= 3.00m	
50% of Segment 1 Length	= 14,986m x 0.5	= 7,493m
Total A	= 7.82m x 3.00m x 7,493	= 175,785 m³

Total B:

River Width at Flow End	= 34.0m	
River Depth at Flow End	= 3.30m	
50% of Segment 1 Length	= 14,986m x 0.5	= 7,493m
Total B	= 34.0m x 3.30m x 7,493	= 840,714 m³

Total A + Total B = 1,016,500 m3 /1,000,000
= 1.02 Million Cubic Meter Cube (MCM)

The calculation was made based on the actual levels during high flow and the total MCM derived was 53.43 MCM. The scenarios were also made based on normal and drought conditions by varying the depths of the calculation by 50% for the Normal level and 10% for the drought condition.

Drought (10%) = 5.34 MCM

Normal (50%) = 26.72 MCM

Flood (Max capacity) = 53.43MCM

2.4 Communication Network Design for PRIME SCADA

An integral part of the flood management system is the communication infrastructure that supports the real-time operation of the gates and flow stations, as stated by [20]. A hybrid wireless network, consisting of Point-to-Point (PtP) and Point-to-Multipoint (PtMP) technologies, is proposed for the Sg Muda Basin. This network design ensures reliable communication across the large and remote regions of the basin, enabling effective coordination between the different components of the flood management system. The communication network is designed to be fault-tolerant, with self-healing mechanisms that ensure continuous operation even in the event of a network failure.

2.5 Discharge Rate Calculation

To calculate the discharge rates through the gates, the following equation is used:

$$Q = C_d A\sqrt{2gh} \qquad (\mathrm{m}^3) \qquad (2)$$

In this equation, Q represents the flow rate in cubic meters per second (m³/s), while Cd is the discharge coefficient, which accounts for factors such as the shape and roughness of the gate. The area of the gate opening is denoted by A and is measured in square meters (m²). The symbol g refers to the gravitational acceleration, with a standard value of 9.81 meters per second squared (m/s²), and h represents the effective head, which is the height of the water above the gate opening and is measured in meters.

This equation is applied for each gate, considering various headwater elevations and the gate positions to determine the flow rate at different discharge scenarios. The system continuously adjusts the gates based on real-time measurements, ensuring that the discharge rate is maintained within safe limits during flood events.

2.6 Google Earth

Previous CFD and hydraulic modelling implemented for River basins produce significant errors, which are amplified when integrating with the automation of the hydromechanical infrastructures. Such errors occur over time due to the catchment changes and land use. In this study, an analysis was done on historical satellite images obtained from Google Earth Engine. This approach also considers the impact of human activities, such as land use changes and sand mining, which can significantly alter the catchment area and affect water flow. By continuously updating the system with new data, the SCADA system can adapt to these changes and maintain accurate predictions.

The land use and topographic changes were analysed from 2011 to 2020 by using Google Earth Engine (GEE). GEE is a cloud-based geospatial processing platform that enables large-scale analysis of satellite imagery and geospatial datasets. Satellite historical images were obtained from GEE and analysed using a developed script to compare images from 2011 to 2020. Figure 5 shows vegetation losses that impact the automation of Hydromechanical Infrastructure throughout the study area.

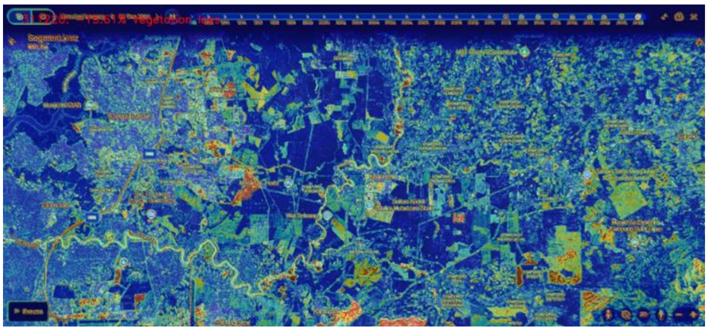

Figure 5. Vegetation losses that impact automation of hydromechanical infrastructure

3.0 RESULTS AND DISCUSSION

The data analysis for this study involves processing, evaluating, and comparing the results from the integrated models such as CFD, LSTM and PRIME SCADA system, against observed field data. Key performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2) are used to assess the accuracy of the model predictions compared to observed data collected from the Muda River Basin's hydrological monitoring stations.

3.1 Optimization for CFD using Google Earth

The forecasted vegetation loss for 2025 is based on the trend observed in the previous years and a linear trend computation is used. Most traditional flood forecasting systems rely on static models and historical data, often fail to account for the dynamic nature of land use and topographical changes. Over time, activities such as sand mining and urban development can significantly alter the landscape, leading to discrepancies between the predicted and actual water flow patterns. These discrepancies result in errors in the system's forecasts, making it less reliable for real-time water management. Figure 6 illustrates the Python script used to calculate the vegetation loss in the Sungai Muda Catchment while Table 2 presents the historical vegetation loss data, which serve as the basis for the forecast. The table shows the vegetation loss percentages from 2011 to 2025, with the forecast for 2025 indicating a loss of 20.34%.

```
def calculate_vegetation_loss(base_img, current_img):  1 usage
    """Calculate vegetation loss based on green pixel reduction."""
    hsv_base = cv2.cvtColor(base_img, cv2.COLOR_BGR2HSV)
    hsv_current = cv2.cvtColor(current_img, cv2.COLOR_BGR2HSV)

    # Define green color range
    lower_green = np.array([35, 50, 50])
    upper_green = np.array([85, 255, 255])

    base_mask = cv2.inRange(hsv_base, lower_green, upper_green)
    current_mask = cv2.inRange(hsv_current, lower_green, upper_green)

    base_vegetation = np.sum(base_mask > 0)
    current_vegetation = np.sum(current_mask > 0)

    loss_percentage = 100 * (base_vegetation - current_vegetation) / base_vegetation if base_vegetation > 0 else 0
    return loss_percentage


def overlay_changes(base_image, accumulated_changes, alpha=0.5):  1 usage
    """Overlay detected changes onto the original image with transparency."""
    changes_colored = cv2.applyColorMap(accumulated_changes, cv2.COLORMAP_JET)
    changes_colored_resized = cv2.resize(changes_colored, dsize: (base_image.shape[1], base_image.shape[0]))
    blended = cv2.addWeighted(base_image, 1 - alpha, changes_colored_resized, alpha, gamma: 0)
    return blended


def process_image_changes(folder):  1 usage
    """Process all images in the folder and create a time-lapse video of significant changes."""
    image_filenames = sorted([f for f in os.listdir(folder) if f.endswith(".bmp")])

    if len(image_filenames) < 2:
        print("Error: Not enough images to create time-lapse.")
        return

    base_image = load_images(folder, filenames: ["311211.bmp"]).get("311211.bmp")
    if base_image is None:
        print("Error: Could not load baseline image 311211.bmp")
        return
```

Figure 6. Python script to determine the vegetation loss of the Sungai Muda catchment

Table 2: Historical GEE satellite images of vegetation loss

Year	2011	2012	2013	2015	2020	2025
Vegetation Loss (%)	0.00 (baseline assumption)	-1.12	-2.38	-10.43	-15.61	-20.34 (forecasted)

In contrast, the New SCADA design incorporates real-time data and advanced machine learning algorithms to update and refine its models continuously. This approach allows the system to adapt to changes in land use and topography, ensuring that these changes do not contribute to forecast errors.

In the analysis, the data file from the last flood event was utilised. The data file of Titi Beris and Jambatan Sidam from 1 November 2024 to 30 November 2024 was obtained and used in this simulation. As a control file, the raw data were analysed to determine the flood routing time from Titi Beris until Jambatan Sidam. The distance between these two points is about 127 kilometres, and it takes about 42 hours and 45 minutes of travel time. Python programming was used as a tool to produce the results. The analysis below is only a conceptual simulation as the other conditions of water extraction are not considered in this simulation. Figure 7 displays the raw comparison of the actual hydrograph peaks at SIDAM and Titi Beris, while Figure 8 presents the predicted discharge at SIDAM based on the Committee Machine Learning Models.

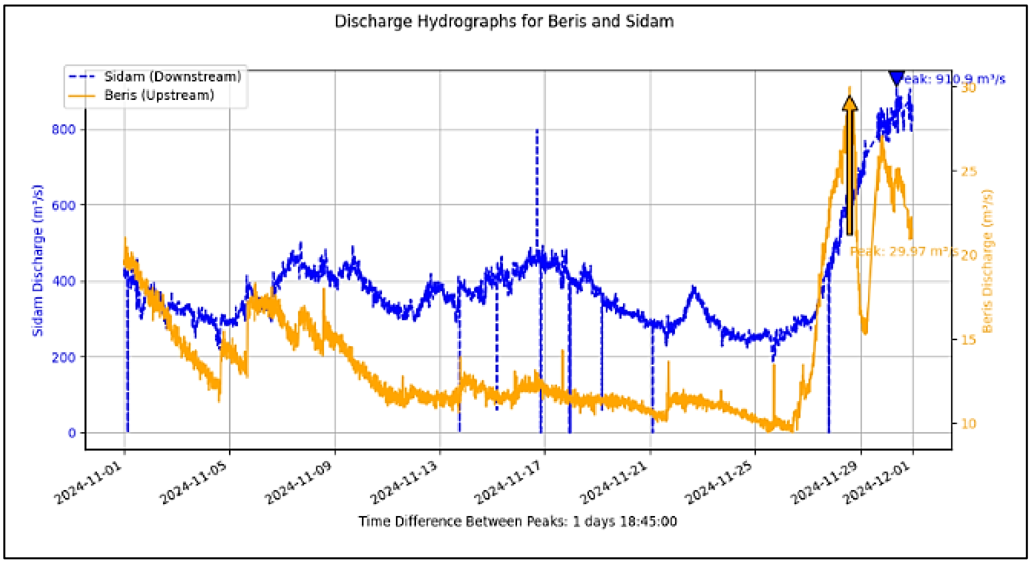

Figure 7. Raw comparison of the actual hydrograph peaks at SIDAM and Titi Beris

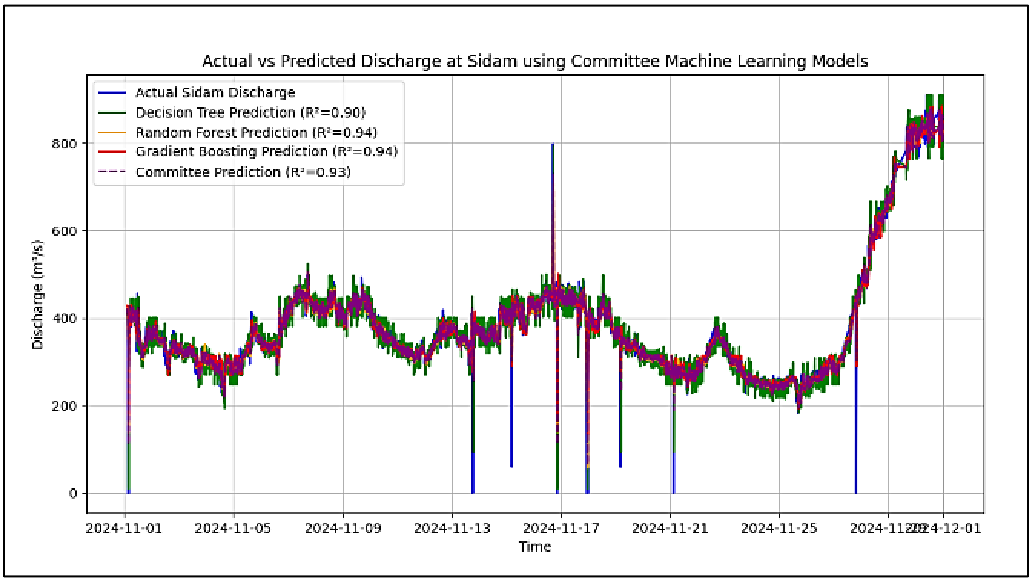

Figure 8. Predicted discharge at SIDAM using Committee Machine Learning Models

3.2 Network Design for Communication

The hybrid communication network design, incorporating Point-to-Point (PtP) and Point-to-Multipoint (PtMP) technologies, ensures reliable data transmission across the large and remote areas of the Sg Muda Basin. This setup allows for efficient communication between key flood management components, ensuring that real-time data on water levels and flow rates can be transmitted without delay [21]. The integration of a self-healing mechanism within the network guarantees uninterrupted communication, even in the event of a network failure. This feature is critical for flood management systems where continuous monitoring and rapid decision-making are required, particularly during extreme weather events. As highlighted by [22], the use of self-healing communication networks in flood monitoring systems enhances system resilience and ensures operational continuity during network disruptions. The ability of the system to autonomously reroute traffic in case of failure significantly reduces the risk of communication breakdowns, a common issue in flood-prone areas with extensive infrastructure.

3.3 Self-Healing Mechanism Illustration

Utilising both PtP and PtMP network topologies, the infrastructure creates a scalable architecture capable of maintaining continuous communication even during network disruptions. As illustrated in Figure 9, the system's dual-network structure, divided into East and West Zones, ensures uninterrupted communication by automatically rerouting traffic in case of a failure. This self-healing capability significantly improves the reliability of flood control system, reduces downtime, and enhances operational efficiency during critical flood events.

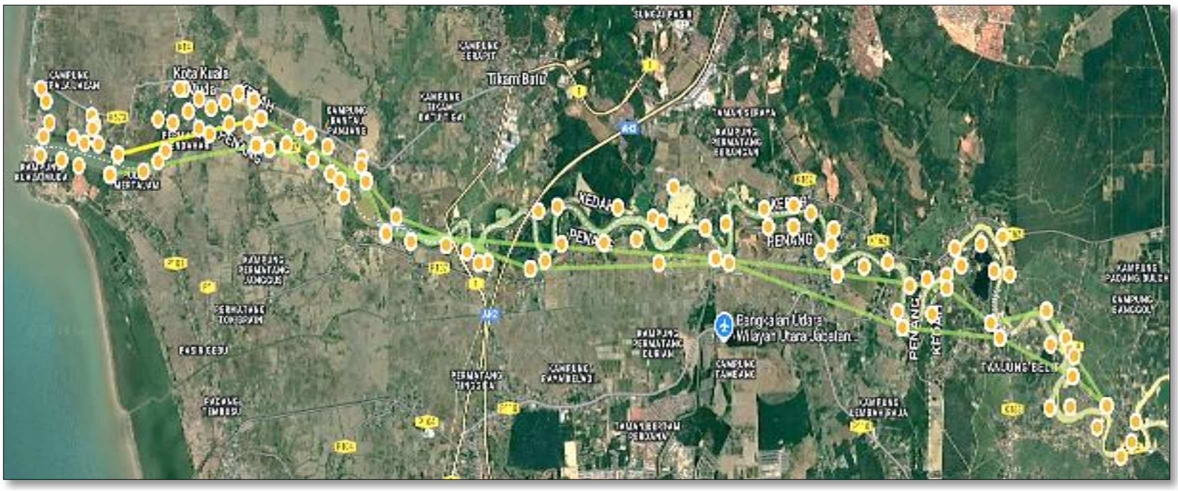

Figure 9. Wireless East and West Zone Ring

The network infrastructure also incorporates a simulated wireless signal coverage analysis to evaluate the feasibility of using 4G/5G networks for flow stations, particularly in upstream areas with fewer devices. This ensures stable communication across remote locations, even when traditional PtP or PtMP links are not feasible [23]. As shown in Figure 10, the feasibility study confirms the potential for reliable communication in these upstream areas, optimising the use of available network resources for flood control operations.

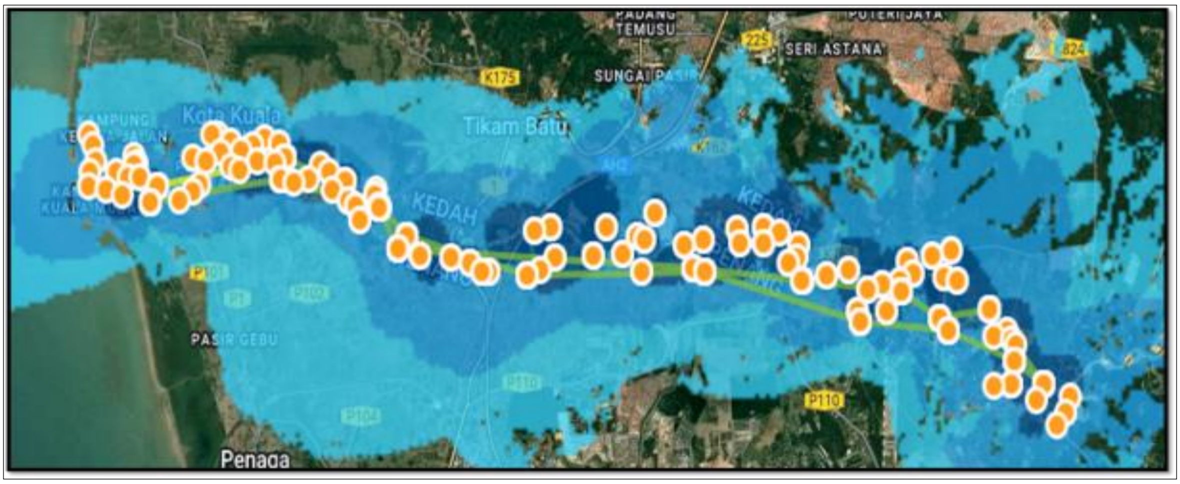

Figure 10. Simulated Wireless Signal Coverage

3.4 Discharge Rate Optimisation and Gate Operation

The implementation of PRIME SCADA system, integrated with real-time data monitoring and advanced algorithms, significantly optimised the operation of the gates in the Sg Muda Basin. Analysis of the Pulau Pinang Barrage and Kedah Barrage demonstrated that the automated gate control system could effectively regulate discharge rates during flood events. Figure 11 provides an aerial view of both barrages, highlighting their geographical placement within the Sg Muda Basin. The gates operate based on real-time water levels, aiming to minimise discharge rates while maintaining the required flow for agricultural and water supply purposes.

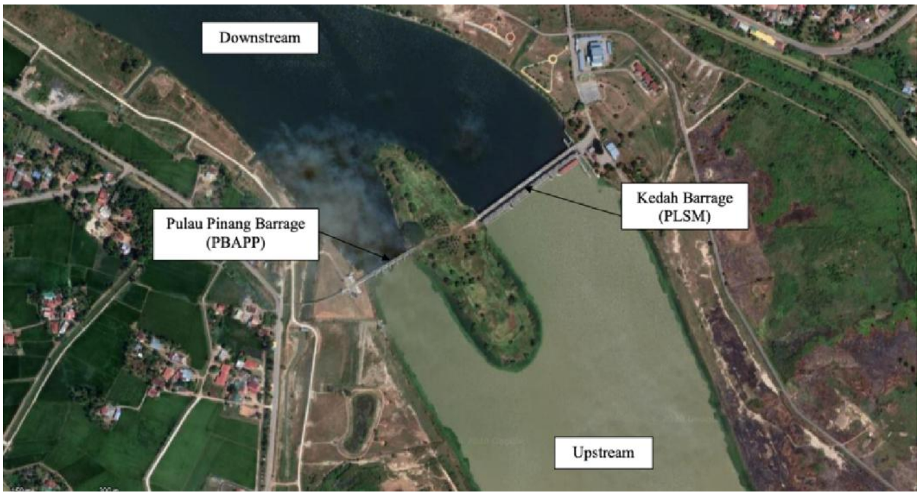

Figure 10. PRIME Sg Muda segments

The results show that by using the PRIME SCADA system, discharge rates were reduced by more than 300 m³/s compared to manual operations, thus enhancing flood control. The system's ability to adjust gate openings dynamically based on predictive data not only reduces discharge but also provides a more responsive system capable of addressing rapid changes in flow dynamics. The flood routing calculation above provides the additional lead time to operate the flood gates, be it the Barrage or the sluice gates.

3.5 Simulation of Flow Rates at the Barrages

Figure 12 presents the Stage-Discharge Curve at Jambatan Merdeka. Typically used to correlate stage measurements to discharge rates, this curve revealed a significant error in the relationship due to the dependency on gate positions at the barrage. This highlights the limitations of traditional methods to accurately predict discharge, particularly during periods of high variability in gate positions. However, by integrating real-time data with computational simulations and predictive algorithms, the proposed system overcame these limitations. The combination of the CFD model and the MOEA allowsed for precise control over the gates, even when the stage-discharge relationship was not entirely reliable. This result underlines the efficacy of the integrated system in optimising discharge control while accounting for uncertainties in the flow dynamics.

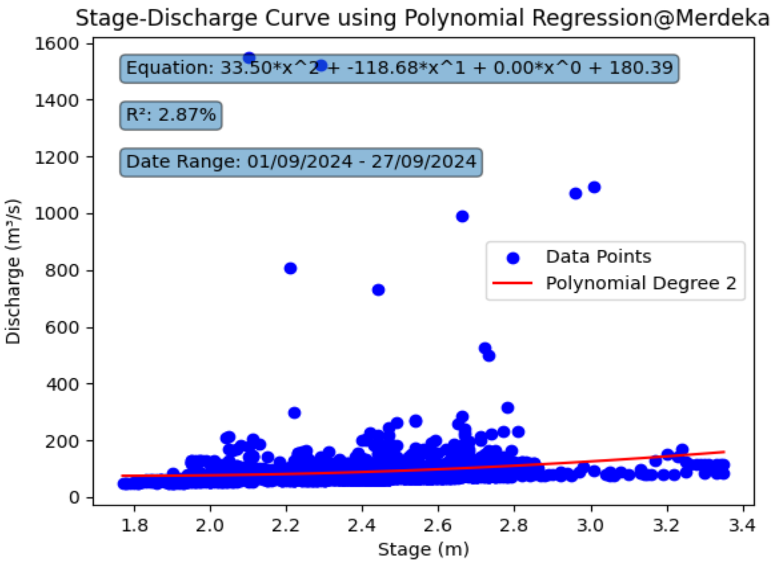

Figure 12. Stage-Discharge Curve at Jambatan Merdeka

For the research in Sg Muda, a Python Software Library called DEAP was used. DEAP (Distributed Evolutionary Algorithms in Python) is an open-source framework for evolutionary computation and genetic algorithms. It provides tools for solving optimisation problems using genetic algorithms, evolutionary strategies, and genetic programming. Figure 13 illustrates the different optimisation strategies applied in the system. The flood-protective strategy keeps peak exceedance close to 0 m³/s (i.e., never above Qsafe = 500 m³/s) but allows higher water level deviation (Obj2 ↑), meaning more storage is used to shave the peak.

The level-conserving strategy holds the pool level closer to target (Obj2 ↓) but results in a higher outflow peak (Obj1 ↑), requiring earlier and larger releases. Figure 14, on the other hand, presents the MOEA Pareto trade-off results, showing how the balanced (knee) strategy limits peak outflow to approximately 500 m³/s at the storm's crest while maintaining the reservoir level within a moderate band. Gate movements in this strategy are modest and fairly even across gate pairs, ensuring both flood protection and operational efficiency.

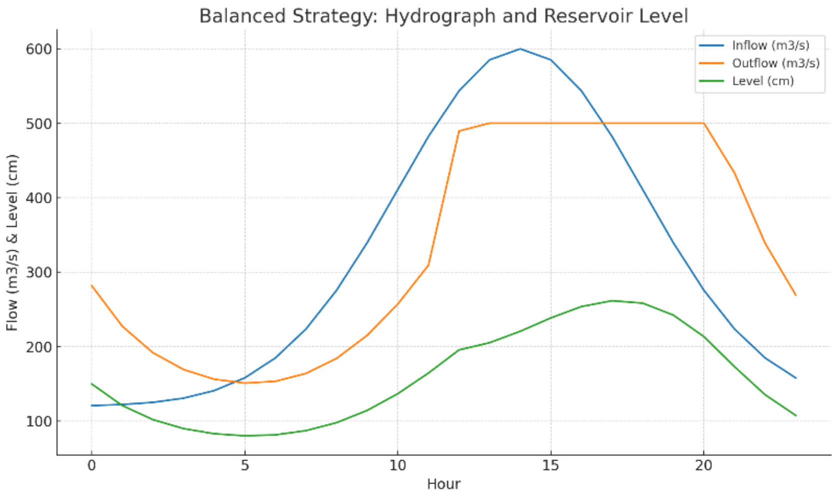

Figure 13. Optimization strategies

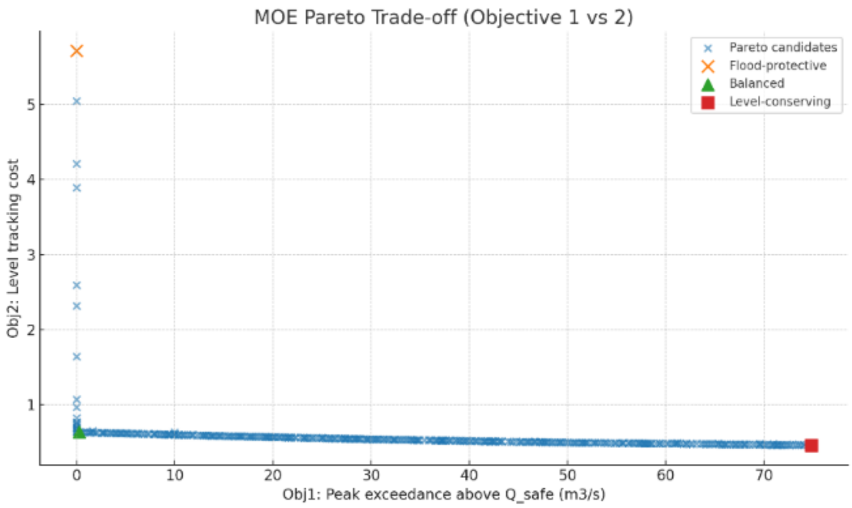

Figure 14. Pareto trade-off

Table 3 summarizes the MOEA performance metrics for the three optimization strategies. The flood-protective strategy achieved zero peak exceedance, ensuring outflows remained below the Qsafe threshold, but resulted in the highest deviation in water level tracking (Obj2) due to increased storage utilisation. In contrast, the level-conserving strategy maintained the most stable pool level, reflected in the lowest Obj2 value, but allowed a significantly higher peak exceedance of 74.86 m³/s. The balanced (knee) strategy provided a compromise, keeping peak exceedance near zero while maintaining moderate water level stability and operational burden.

Table 3: MOE metrics summary

Strategy	**Obj1 Peak exceedance (m^3/s)**	**Obj2 Level tracking (RMS+penalty)**	**Obj3 Ops burden**	**Max Q_out (m^3/s)**	**Mean Q_out (m^3/s)**	**Min Level (m)**	**Max Level (m)**	**Final Level (m)**
Flood-protective	0	5.714	0.413	445	324.1	0.674	3.061	1.64
Balanced (knee)	0.26	0.636	1.409	500.3	333.2	0.804	2.618	1.078
Level-conserving	74.86	0.463	2.369	574.9	338	0.801	2.081	0.801

3.6 Performance of the Proposed System

The performance of the proposed flood management system was validated through simulations and compared against actual measured discharge data at Sidam. Figure 15 compares the actual discharge (blue line) with the controlled discharge (green line) simulated by the system. The simulations showed that the discharge was effectively reduced by adjusting the gates, keeping the discharge under the predefined threshold of 500 m³/s. The method for controlling discharge in this system is akin to the K-Method proposed by [24], which also focuses on real-time adjustments to gate-controlled spillways. Similar to their approach, the flood management system at Sidam uses predictive simulations to adjust gate positions and regulate discharge. These adjustments are designed to prevent overflow by optimizing the flow based on current conditions. The K-Method demonstrated that the optimal gate adjustments could reduce the maximum reservoir levels, improving flood control while also minimizing outflows under high inflow conditions.

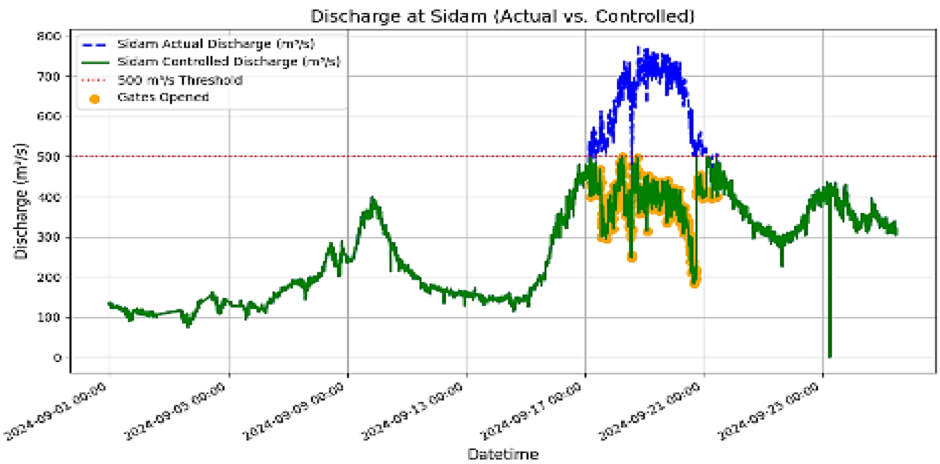

Figure 15. Comparison of Actual vs. Controlled Discharge at Sidam

The simulation results confirm the ability of PRIME SCADA system to predictively adjust hydromechanical gate positions, significantly improving flood management. When compared to the current manual operation, the automated system demonstrated greater efficiency and accuracy in controlling discharge rates, ensuring better preparedness during flood events.

3.7 Implications for Flood Management with Hydromechanical Optimisation

The findings from this research present significant implications for flood management in the Sg Muda Basin and other flood-prone regions. This study provides a new flood control framework by using sophisticated technologies such as CFD simulations, MOEA optimisation, and real-time monitoring via PRIME SCADA, which improve the efficiency and efficacy of hydraulic infrastructure.

a) Automation and Coordination: The transition from manual gate operations to automated systems enables dynamic responses to real-time data, significantly improving the flood management system's ability to react quickly to changing weather patterns and water levels. The integration of predictive algorithms enhances this capability, ensuring optimal gate operations even during extreme flood events.

b) Predictive Flood Forecasting: Long Short-Term Memory (LSTM) networks improve the system's predictive capabilities. These algorithms enhance the accuracy of flood event predictions. These predictions allow for proactive flood management by optimising the operation of gates and sluices to mitigate the risk of flooding.

c) Real-Time Monitoring and Data Integration: The integration of Supervisory Control and Data Acquisition (SCADA) systems with real-time data collection from flow stations, gates, and weather sensors enables a comprehensive flood management approach. Continuous monitoring and analysis allow for informed decision-making, reducing response time and boosting intervention accuracy.

d) Network Design for Communication: The hybrid communication network design, incorporating Point-to-Point (PtP) and Point-to-Multipoint (PtMP) networks, ensures reliable data transmission across the large and remote areas of the Sg Muda Basin. The self-healing mechanism incorporated into the network design guarantees uninterrupted communication, even in the case of a network failure.

3.8 Comparison with Current Systems

The current flood control system relies heavily on manual gate operation, which can be delayed or inefficient during extreme flood events. In contrast, the proposed system offers real-time flood forecasting and automated gate operation, significantly improving response times and operational efficiency. While a direct performance evaluation of the existing system is not feasible, simulation results suggest that the proposed system can optimise gate opening times and reduce discharge rates. The system's dynamic responsiveness to real-time data will improve flood control and allow for more efficient use of available resources. The result of this study will prevent the catastrophe failure to the catchment that occurred on May 14th, 2023.

4.0 CONCLUSION

This study presents an AI-enhanced adaptive flood management system for the hydromechanical infrastructure at the Muda River Basin, combining machine learning models, real-time monitoring, and advanced hydraulic simulations within the PRIME SCADA system. The integration of Long Short-Term Memory (LSTM) networks and Computational Fluid Dynamics (CFD) models within the framework significantly improves flood prediction accuracy and discharge control. The system successfully optimizes gate operations during flood events, reducing discharge rates by more than 300 m^3/s compared to manual operations, demonstrating its ability to mitigate flood risks effectively. The real-time data integration with advanced predictive algorithms, including the use of Multi-Objective Evolutionary Algorithms (MOEA), allows the system to dynamically adjust to changing hydrological conditions, enhancing the overall resilience of flood control infrastructure. The self-healing communication network, combined with Point-to-Point (PtP) and Point-to-Multipoint (PtMP) technologies, ensures uninterrupted data transmission, further strengthening the reliability of the system during critical flood events. Through the validation of the system, it was confirmed that the PRIME SCADA system can proactively manage discharge by predicting flood events and adjusting gate positions accordingly, thus ensuring effective flood mitigation. This approach not only improves decision-making efficiency but also offers a scalable solution for flood-prone regions globally. In conclusion, the AI-powered flood management system proposed in this study offers a robust, adaptable, and scalable framework for mitigating flood risks in the Muda River Basin.

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AUTHORS CONTRIBUTION

The author confirms shared responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

DECLARATION OF COMPETING OF 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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