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# Sistem Monitoring dan *Datalogger Suspended Sedimentation Concentration* Berbasis *Internet of Things* dan *Fuzzy Logic* di Flume Trapesium

# Monitoring and Datalogging System for Suspended Sediment Concentration in a Trapezoidal Flume Using IoT and Fuzzy Logic

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**Abstrak**

**Penelitian ini bertujuan mengembangkan sistem monitoring dan prediksi konsentrasi sedimen layang (*Suspended Sediment Concentration*) berbasis Internet of Things (IoT) dan *fuzzy logic* menggunakan LabVIEW pada prototipe flume trapesium skala laboratorium. Sistem terintegrasi dengan sensor *flow rate* (YF-S201), sensor *turbidity* kekeruhan air (SEN0189), dan sensor fotodioda untuk mengukur konsentrasi sedimentasi layang. Sampel sedimen yang digunakan berupa tanah lanau berasal dari Kanal Banjir Barat (KBB). Data diakuisisi oleh mikrokontroller ESP32 setiap 10 detik, dikirim melalui komunikasi TCP/IP ke LabVIEW, disimpan dalam file Excel, dan dikirim secara realtime ke Google Sheets sebagai cloud database. Fitur monitoring juga ditampilkan melalui LCD menampilkan data secara realtime dari Google Sheets menggunakan fungsi API, sehingga sinkron sebagai data logger terintegrasi. Implementasi *Fuzzy Logic Designer* LabVIEW menggunakan tipe Sugeno dengan input *flow rate* dan *turbidity* sedangkan SSC sebagai output prediksi dalam satuan mg/L. Hasil pengujian pada 2050 data pengukuran dengan rata-rata interval pencatatan waktu 8-10 detik secara konsisten tanpa *lag*, *error* waktu pencatatan hanya 0.2%. Model ANFIS digunakan untuk evaluasi performa menunjukkan akurasi prediksi tinggi $R^2$ =0.995. Integrasi monitoring, data logger, potensi *fuzzy logic* berbasis IoT untuk analisis konsentrasi sedimen layang akurat secara *realtime* pada flume trapesium skala laboratorium.**

**Kata kunci:** konsentrasi sedimen melayang, IoT, Fuzzy Logic, Monitoring

**Abstract**

**This research aims to develop a real-time IoT-based monitoring and prediction system for suspended sediment concentration (SSC) via the Internet of Things (IoT) and fuzzy logic, implemented through LabVIEW on a laboratory-scale trapezoidal flume prototype. The system incorporates a flowmeter sensor (YF-S201), a water turbidity sensor (SEN0189), and a photodiode sensor for the measurement of SSC. The sediment samples utilized were silty clay soil from the West Flood Canal (KBB). The ESP32 microcontroller acquires data every 10 seconds, transmits it over TCP/IP communication to LabVIEW, stores it in an Excel file, and simultaneously uploads it to Google Sheets as a cloud database. The monitoring functionality is presented via an LCD, displaying real-time data from Google Sheets through API capabilities, thereby functioning as a synchronized integrated data logger. Execution of fuzzy logic: The LabVIEW Fuzzy Logic Designer employs the Sugeno model, utilizing flow rate and turbidity as input variables, with SSC predicted as the output. The testing results on 2050 measurement data indicate a steady average time**

**recording period of 8-10 seconds without latency, with a time recording error of merely 0.2%. ANFIS model was employed for performance with prediction accuracy $R^2$ =0.995. Integration of monitoring and datalogging of IoT-based fuzzy logic real-time assessment of SSC in a trapezoidal flume.**

**Keywords:** Suspended Sediment Concentration, IoT, Fuzzy Logic, Monitoring

# I. INTRODUCTION

An elevated concentration of suspended sediment (Suspended Concentration System) in the downstream region of the river channel is the result of the relatively sluggish water flow velocity and the flat riverbed contour. This phenomenon is known as siltation. The downstream area of Jakarta is dominated by organic clay soil, which has a high tendency to be transported as suspended sediment and easily settles when flow velocity decreases during heavy rainfall, causing river siltation and flood risk [1]. An investigation through laboratory simulation is necessary to comprehend the correlation between suspended sediment concentration, turbidity level, and flow rate. A trapezoidal flume prototype is employed in the civil engineering laboratory to replicate the flow of water in a river estuary. Water conditions with a comparatively flat bottom contour and slow water flow velocity are simulated by the flow characteristics of the flume, which facilitate the processes of sediment transport and deposition of suspended sediment. Nevertheless, the laboratory's manual measurement of sediment concentration (SSC) continues to this day. Measurements were obtained by reading the values immediately from the measuring instrument and subsequently recording them one by one at each observation time interval. This procedure is time- consuming and poses a risk of data recording errors. Consequently, a method of approach is required that can automatically and accurately conduct surveillance and measurement.

Numerous prior studies have established sensor systems and monitoring techniques to quantify suspended silt concentration with greater efficiency and accuracy. Between 2020 and 2024, diverse sensors and computer algorithms were employed to identify alterations in the properties of suspended sediment. Acoustic method such as YOLOv5 have been employed to monitor aquatic sediments [1], LISST-ABS [2], and signal processing and visual imaging algorithms like OCEAN code [2]. The technique for quantifying integrated surface reflectance from satellite data entails assessing the intensity of light reflected by sediment distribution on the sea surface to determine suspended sediment concentration [3]. Optical instrument measurements are significantly influenced by aspects like particle size, content, shape, and ambient conditions [4]. The sensor design aims to quantify water velocity, suspended sediment content, and depth, integrating these three variables to evaluate and assess sediment movement [5]. Turbidity sensors provide real-time assessments of SSC and transport dynamics as sediment fluctuates within the water flow [5].

The utilization of optical instrument sensors in prior studies has been notably costly and intricate, requiring a more precise and economical sensor design alternative. A light detection sensor with an LED source and a detector can be positioned within a control volume in a river [7]. This measuring technique is comparatively more economical and straightforward, employing near-infrared as the transmitter, a photodiode as the receiver, and a microcontroller as the Human Machine Interface (HMI) connecting the sensor to the PC [7]. The creation of a suspended sediment measurement system for the Cikapundung River in Bandung employs the infrared spectroscopy approach, utilizing LEDs and photodiodes as the transmitter and receiver, alongside wireless monitoring for real-time data transmission that allows for remote observation. Previous studies concerning the efficacy of fuzzy logic implemented in LabVIEW have established monitoring and control systems for textile industry wastewater utilizing fuzzy Mamdani in LabVIEW [10], real-time monitoring of pond water quality through a fuzzy rule-based methodology [11], and the design of a fish farming water quality control system employing fuzzy logic for turbidity and temperature parameters grounded in IoT [12]. Real-time viewing of shrimp pond water quality, incorporating turbidity and salinity metrics, is achieved with LabView and rules-based Fuzzy Mamdani in the LabView GUI [13].

This study presents an automated system for measuring and predicting suspended sediment concentration utilizing flow rate, turbidity, and SSC sensors, connected with a microcontroller and data logger, facilitating real-time data recording on a laboratory scale. Integration of measurement with an ESP32-based wireless sensor network (WSN) for the assessment of flow rate and turbidity, transmitting data in real-time to LabVIEW as a Human Machine Interface (HMI) and a Sugeno-type fuzzy logic control center [15]. The SSC prediction results are visually presented and automatically stored in Google Sheets as a cloud database, and are displayed on an LCD panel that retrieves data from Google Sheets. SSC predictions are effective, precise, and derived from IoT fuzzy logic processing on the LabVIEW platform. This study provides a novelty contribution by integratted a real-time IoT based sensing framework withSugeno-type fuzzy logic in LabVIEW for SSC prediction in a trapezoidal flume. Unlike ANFIS-based, ANN-based, or PID controlled sediment monitoring system that rely on pre-trained models or fixed- parameter cobtrol, the proposed system combines direct sensor acquisition, fuzzy inference, and cloud based datalogging to generate SSC predictions on realtime wtihout requiring prior datasets. This integration echances praticality, reduces computational overhead, and enables continous monitoring of sediment dynamics under laboratory hydraulic conditions. The approach strengthens the scientific contribution by offering a stable, interpretable, and operationally efficient monitoring and prediction platform for suspended sediment concentration.

## II. RESEARCH METHOD

This study employs an experimental quantitative approach executed in the Civil Engineering laboratory, focusing on the creation of a monitoring system for suspended sediment concentration based on fuzzy logic and the Internet of Things (IoT). The design for real-time monitoring and prediction of suspended sediment concentration (SSC) values in mg/L utilizes two input parameters: flow rate and turbidity sensor variables, with the output being the projected SSC value. Specifications for prototype hardware design and trapezoidal flume. Figure 1 illustrates a flume with a length of 4.81 meters, a height of 15 cm, a point length of 20 cm, and a slope angle of 0.50. The soil sample utilized is silt soil [16] sourced from the West Flood Canal (KBB).

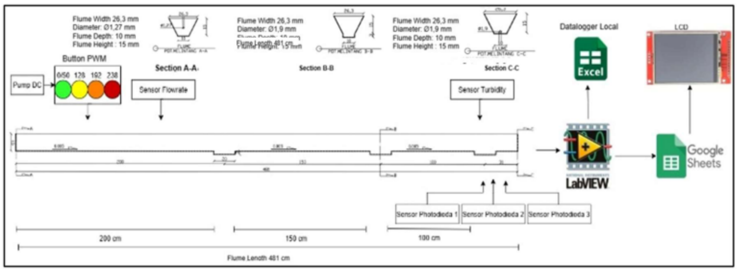



Figure 1 Design System Architecture

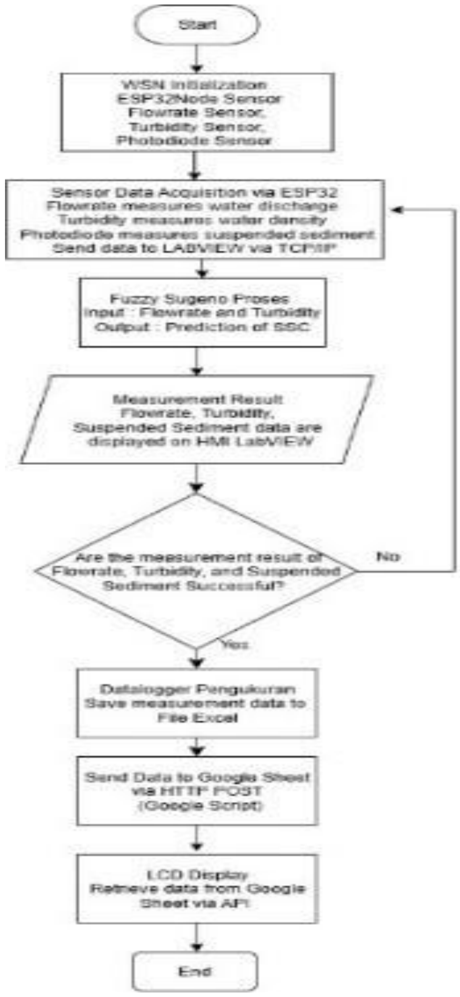



Figure 2 Flowchart system

The flowchart presented in Figure 2 illustrates the integration of monitoring and prediction of suspended sediment concentration (SSC) utilizing ESP32 and LabVIEW. The procedure begins with the setup of the ESP32 sensor node, which interfaces with flow rate, turbidity, and photodiode sensors. Data from sensors is transmitted to LabVIEW through a TCP/IP connection and analyzed using Sugeno-type fuzzy logic, utilizing flow rate and turbidity as inputs to produce SSC predictions. The measurement results are presented in the LabVIEW HMI and recorded in an Excel file serving as a local data logger. Data is transmitted to Google Sheets using HTTP POST and is displayed on the LCD in real-time, retrieving information from the Google Sheets data through an API. This outlines the complete procedure for integrating a real- time IoT monitoring system. The design of the IoT system incorporates five ESP32 microcontroller boards, with each board linked to a distinct sensor to enhance the performance of a laboratory-scale trapezoidal flume prototype [19]. The initial ESP32 board equipped with a YFS201 type flow rate sensor quantifies the water flow rate in liters per minute (L/min). The flow rate calculation in LabVIEW from the YFS201 pulse flow sensor is transmitted through the ESP32.

The second ESP32 board equipped with a SEN0189 turbidity sensor quantifies water turbidity in NTU units by detecting variations in light intensity caused by suspended particles in the water [20]. The third ESP32 board equipped with a photodiode module sensor quantifies the concentration of suspended sediment [21], [22]. The optical properties of suspended particle concentration in water, specifically sedimentation, are measured through light detection techniques. The photodiode module sensor is positioned vertically beneath a transparent flume, accompanied by an LED light source. As the water sediments move through the transmitter and receiver, the output voltage of the photodiode [23], [24] varies and is transformed according to equation (1).

$$SSC = 0.01925 \exp\left(\frac{V_{out}}{3.8925}\right) + 0.00097 \quad (1)$$

Determining suspended sediment concentration through the analysis of LabVIEW voltage data obtained from the photodiode sensor transmitted by the ESP32. The output voltage is transformed into SSC values utilizing the exponential model outlined in the equation [25]. Board ESP32 interfaces with a 2.4- inch ILI9341 TFT LCD, enabling the local monitoring panel to present data in real-time. Every ESP32 unit is linked to the local Wi-Fi network and systematically transmits TCP/IP data to Google Sheets at regular intervals. The configuration of the wiring is illustrated in Figure 3. The ESP32 is utilized to manage the DC pump through the BTS7960 motor driver, incorporating buttons that function as on/off switches, along with three additional buttons designed to regulate the Pulse Width Modulation (PWM) signals, enabling adjustments to the speed variation of the DC pump [26].

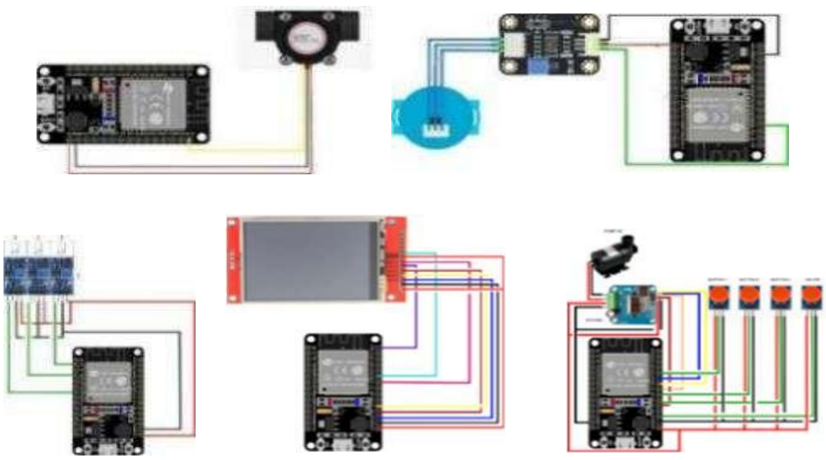


Figure 3 System Integration Wiring Diagram

The transmission of data occurs wirelessly via Wi-Fi TCP/IP to the LabVIEW application, which functions as both a data collector and a data logger [25]. The data underwent processing through a Sugeno-type fuzzy inference system utilizing the Fuzzy Logic Designer toolbox, aimed at establishing the parameter range and fuzzy rules necessary for predicting the output of suspended sediment concentration. The prediction results are systematically stored in an Excel file and subsequently transmitted to Google Sheets for cloud-based data logging. The prediction values are presented on an LCD by retrieving the data directly from Google Sheets through an internet connection [22]. Data was collected through direct measurements in the laboratory utilizing flow rate sensors, turbidity sensors, and photodiode sensors over a three-hour period to model the prediction of suspended sediment concentration (TSS) employing the fuzzy logic method [27], [28]. The interval for data measurement is set at every 10 seconds. The exchange of data between the ESP32 and LabVIEW via the TCP/IP protocol is conducted through a character-based command and response method (a, b, c). The ESP32 functions as a server, interpreting character commands from LabVIEW through the WifiClient.read method and transmitting sensor data in response to the client's character requests. The TCP/IP connection is established using the IP address and port 8000, and it is terminated after data is received at the TCP/IP Write and TCP/IP Read blocks [22], as shown Figure 4.

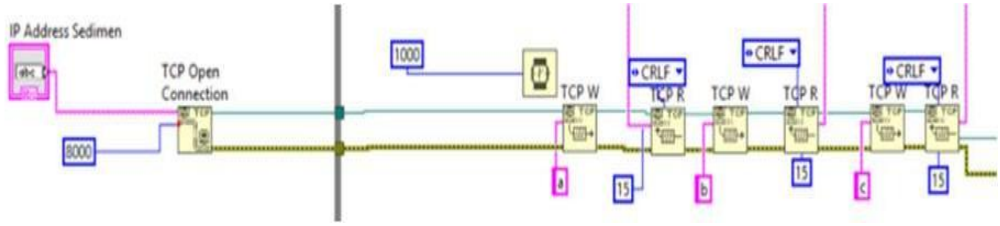



Figure 4 ESP32- LabVIEW Data Communication

The sensor readings and TSS predictions are transmitted to Google Sheets automatically through an internet connection (HTTP POST) for cloud data logging [29]. Build text integrates the parameter data results as strings and utilizes URLs as the endpoint for data reception and input into Google Sheets [30]. Figure 5 illustrates the HTTP POST function utilized for transmitting string data to an Apps Script endpoint.


Figure 5 Data Transmission to Google Sheets

The sensor readings and Fuzzy logic predictions generated by LabVIEW are recorded in a local Excel file, serving as a data logger. Data from sensors is gathered through the function label Set Dynamic Data Attributes. This information is then consolidated into a signal array and transmitted to the LabVIEW write to measurement file function for documentation in the log file (Excel) [31], as illustrated in Figure 6.

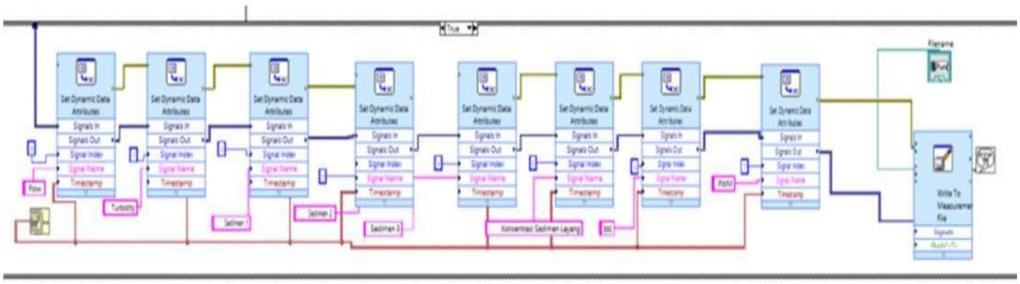


Figure 6 Local data logging into excel file

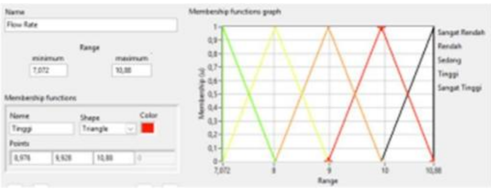
The integration of Google Sheets within this system functions as a medium for real-time data capture and visualization from the ESP32, utilizing the Apps Script feature and its deployment capabilities. The Sugeno fuzzy inference method was utilized for data processing to forecast the concentration of suspended sediment (mg/L) in real-time. Conducted experimental research utilizing a prediction model based on Fuzzy Logic Designer in LabVIEW, incorporating two primary inputs: flow rate and turbidity, while the output represents the concentration of suspended sediment in a trapezoidal open channel flume [24], [32].

Table 1. Variable Parameter Fuzzy

| Function | Variable | Very Low | Low | Medium | High | Very High |
|---|---|---|---|---|---|---|
| Input | Flow rate (L/min) | 7.027, 7.027, 8.024 | 7.027, 8.024, 8.976 | Flow rate 8.024, 8.976,9.928 | 8.976,9.928,10.88 | 8.976,9.928,10.88 |
| | Turbidity (NTU) | 0, 0 ,6.25 | 0, 6.25, 12.5 | Turbidity 6.25, 12.5, 18.75 | 12.5, 18.75, 25 | 18.75, 25, 25 |
| Output | SSC (mg/L) | 0 ,25,75 | 25, 75, 125 Suspended | Sediment Concentrat 75, 125, 175 | ion (SSC) 125, 175, 225 | 175, 225, 250 |

The range for the flow rate, turbidity, and SSC parameters in this study was established through a synthesis of laboratory-scale observations and established scientific references and technical standards,as shown a Table 1 [9]. The flow rate parameter is established from laboratory observations of the actual flow velocity in the prototype flume, alongside references for real discharge variations, indicating a range of 0.13 - 0.2 m/s [33]. The flow rate range has been converted to a range of 7.072 to 10.88 L/min. The turbidity parameter is established within a range of 0 to 25 NTU, aligning with the maximum limit derived from laboratory observation outcomes and environmental health quality standards for hygienic purposes, as outlined in the Minister of Health Regulation Number 32 of 2017 concerning turbidity quality standards for hygienic applications [34].

The parameter for suspended sediment concentration was established within the range of 0 to 250 mg/L [35], taking into account laboratory observation results and the sensor's maximum capacity of 252 mg/L. While various studies indicate that SSC quality scale category values can vary from 0 to 500 mg/L in artificial waters depending on factors such as location, season, and hydrological conditions [36], this range was constrained to align with the sensor's upper limit to ensure the accuracy and validity of the predictions [14]. The three subset division parameters are represented through fuzzy modeling with five symmetrically arranged membership functions utilizing equilateral triangles (triangular membership function - trimf) [37], which proportionally indicates the SSC level, as illustrated in Figure 7.



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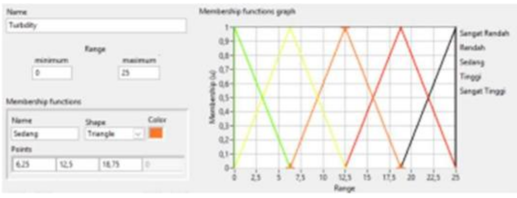

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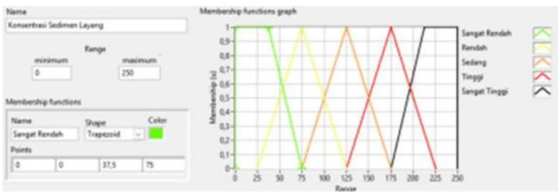


(c)

Figure 7. Fuzzy Input Output Membership Function. (a) Flow Rate; (b) Turbidity; (c) SSC

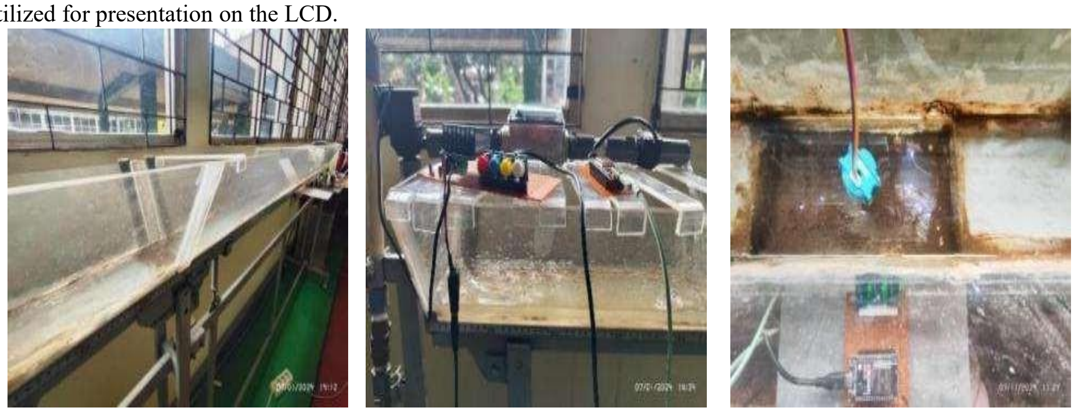
The ANFIS method was selected because it provides a complete and systematics fuzzy rule generation framework, enabling the model to represent all possible interactions between input variables. The ANFIS approach constructs a full rule base derived from predefined membership function, ensuring that the nonlinear interaction between flowrate and turbidity as two variables controlling suspended sediment concentration are fully captured by the model. In addition, ANFIS offers higher transparency in rule interpretation, making it suitable for require clear representation of the relationship between hydrodynamic and optical parameters. Overall, the ANFIS model demonstrates strong reliability for SSC prediction under flume experimental conditions.

# III. RESULTS AND DISCUSSION

## A. System Implementation

The SSC monitoring and data logging system was deployed on a laboratory-scale trapezoidal flume prototype outfitted with flow rate, turbidity, and photodiode sensors. Figure 8 illustrates the laboratory- scale trapezoidal flume prototype, which serves as the primary testing medium for modeling water flow conditions under a gradual sediment addition scenario to evaluate factors for predicting suspended sediment concentration. The SSC monitoring system implemented in the flume features a PWM-controlled pump that manages the flow rate. Figure 9 illustrates the installation of the flow rate sensor for monitoring water flow at the input. Figure 10 illustrates the placement of sensors within the flume, specifically the photodiode for quantifying suspended sediment concentration (mg/L) and the turbidity sensor for assessing water turbidity.

Integration of sensor data acquisition with the ESP32 processor hub, transmitting measurement results to LabVIEW via TCP/IP communication. In LabVIEW, the acquired data is processed, parsed, and transformed into flow rate, turbidity, and suspended sediment concentration characteristics utilizing the fuzzy logic modeling toolbox, and presented as numerical indicators and graphs on the front panel. The block diagram in LabVIEW autonomously archives data to an Excel file and uploads it to Google Sheets as a cloud-based data logger. Figure 11 illustrates the system that embodies the processes of data transmission, processing, and recording. The Google Sheets API data is utilized for presentation on the LCD.



(a) (b) (c)

Figure 8. (a) Prototype Flume (b) Flow Rate System (c) Turbidity and Photodiode Sensor System

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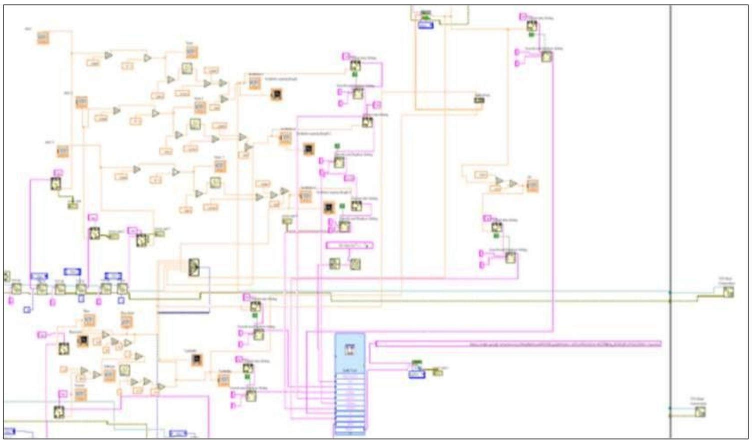


Figure 9. Diagram Block LabVIEW

The experimental phase lasted for 5 hours and 30 minutes, by measurements taken at 10-second intervals, leading to a total of 2,000 data points. The dataset was split into three subsets: 60% for training, 20% for testing, and 20% for validation. Statistical analysis was conducted to ascertain the range and mean values of the key parameters—flowrate (L/min), turbidity (NTU), and SSC (mg/L). Data visualization was demonstrated through time series plots and scatterplots to analysis the correlation among input and output variables. The training structure for all three ANFIS methods is outlined in Table 3, reveals high level of accuracy and robust correlation in SSC model by ANFIS.

## B. Sensor Calibration and Validation

A water faucet was used to control the flow velocity, directing water through both the YF-S201 flow sensor and the K24 digital flowmeter. The water then entered a trapezoidal flume before being collected in a container measuring 32 cm x 17 cm. The flow measurements were conducted by allowing the water to fill the container up to a height of 5 cm, while the elapsed time was recorded using a stopwatch. The cross- sectional area of the flow was then calculated as follows:

$$A = Length \times Width = 32 \times 17 = 544cm^2 \quad (2)$$

$$v = \frac{5cm}{39s} = 0{,}1282cm/s \quad (3)$$

$$Q = V \times A = 0{,}1282 \times 544 = 69{,}7435cm^3/s = 4{,}18L/minutes \quad (4)$$

The flow velocity was calculated by measuring the time it took for the water level in the container to reach 5 cm, that was 39 seconds. The K24 digital flowmeter recorded a flowrate of 4.2 L/min, while the YF-S201 sensor produced an average reading of 4.2526 L/min, by a measurement range between by 4.055 to 4.469 L/min. The difference between the sensor reading and the actual flow rate was 0.0686 L/min, that corresponds to a percentage error of 1.64%, meaning the sensor achieved an accuracy of 98.36%. These results that the YF-S201 flow sensor provides sufficiently precise and reliable for monitoring flow rate in laboratory-scale experiments.

A calibration test was performed to assess the accuracy and precision of three photodiode sensor modules—Sensor 1, Sensor 2, and Sensor 3—in measuring suspended sediment concentration (SSC) expressed in milligrams per liter (mg/L). The sensor readings were compared against a reference value obtained by a TDS meter, that recorded 124 ppm, as shown in Fig.12. Each sensor's output is represented in a separate data column in Table.2. Since parts per million (ppm) is equivalent to milligrams per liter (mg/L) in this context, the calibration outcomes were interpreted as SSC values in mg/L to evaluate the measurement performance of each sensor. All three sensors demonstrated accuracy within ±3%, confirming that the photodiode modules are sufficiently process and reliable for SSC measurements in laboratory-scale experiments, as shown Table 2.

Table 2. Summary of Sensor Calibration and Accuracy

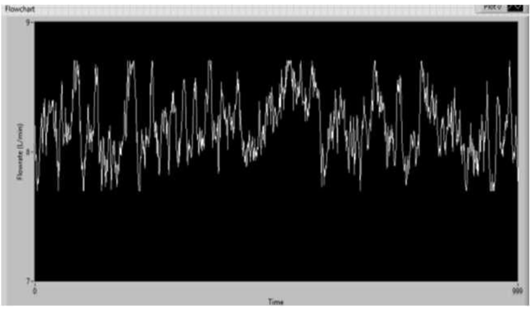
| Sensor | Average Measurement | Reference | Error (mg/L) | % Errror | Accuracy |
|---|---|---|---|---|---|
| Flow | 4.2526 L/min | 4.18 L/min | 0.0686 | 1.64% | 98.36% |
| Photodiode 1 | 122.24 | 124 | -1.76 | 1.42% | 98.58% |
| Photodiode 2 | 121.17 | 124 | -2.83 | 2.28% | 97.72% |
| Photodiode 3 | 127.43 | 124 | 3.43 | 2.77% | 97.23% |

## C. Experimental Result

ESP32 acquisition monitoring system utilizing TCP/IP data connection, where each node possesses a distinct IP address serving as its communication identifier. Figure 13 illustrates the flow rate at 192.168.8.116, turbidity at 192.168.8.105, sediment photodiode at 192.168.8.112, and control PWM at 192.168.8.115. All data is transmitted across the local network (LAN/WiFi) to the LabVIEW HMI panel. Reliable data transfer conveys real-time information and the HMI panel display. The data logger indicator in LabVIEW is operational, and data is automatically recorded in an Excel file.

The flow rate measurement findings indicate a fluctuation range of 7 to 10 L/min. Figure 14 illustrates the test results graph, demonstrating a progressive rising pattern indicative of the DC pump's response. The pump speed is affected by PWM modulation. The alteration in discharge conditions is a significant factor as it directly influences sediment particles within the flume. An increase in discharge results in an augmented shear stress at the channel bed, facilitating the suspension of silt into the water column. The flow rate variable functions as an input for the suspended sediment concentration (SSC) prediction model.

The turbidity measurements indicate levels ranging from 8 to 14 NTU, with the test results illustrated in Figure 15, which depicts a progressive rise in silt added to the flume. Elevated turbidity signifies a rise in the quantity of suspended particles inside the water. The NTU value is an optical measure for sediment dynamics, forecasting the concentration of suspended sediment. At elevated flow rates, the transport of suspended sediment induces light scattering, hence elevating the NTU reading for the sensor; conversely, at diminished flow rates, particles are prone to sedimentation, resulting in a comparatively lower turbidity measurement. The turbidity parameter denotes the non-linear correlation between light intensity and sediment particle concentration, illustrating sediment transit within the flume.



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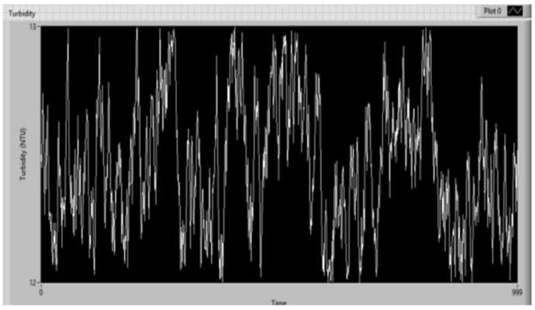

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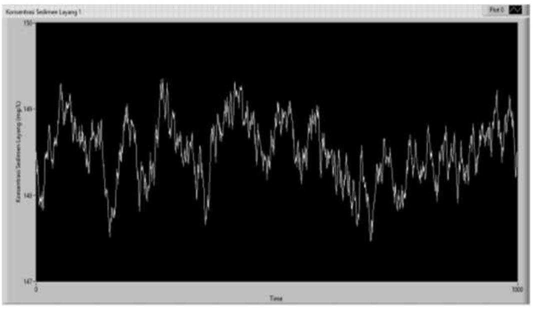

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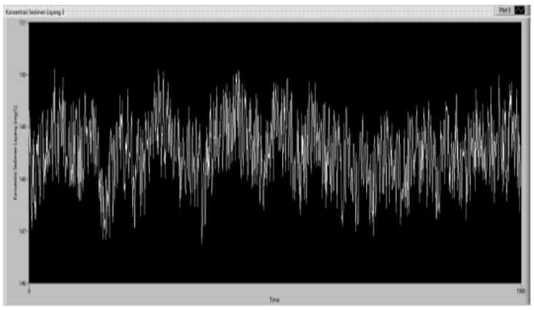

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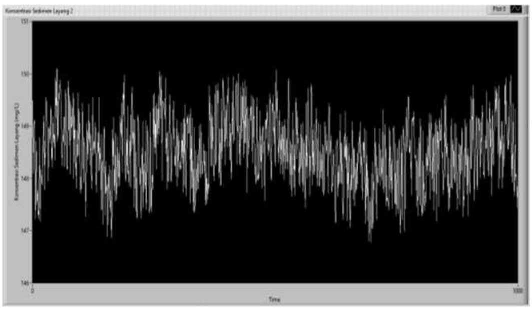


(e)

Figure 11. (a) Flow Rate Measurement (b) Turbidity Measurement (c) SSC Measurement Photodiode 1 (d) SSC Measurement Photodiode 2 (e) SSC Measurement Photodiode 3

The SSC readings obtained with the photodiode sensor indicate a value range of 125 to 172 mg/L. Figure 16 illustrates the test results for the three sensors, demonstrating a progressive increase in response to the addition of silt to the flume. At elevated flow rates, the shear stress at the flume's base intensifies, resulting in the suspension of sediment particles. The ESP32 node quantifies the photodiode sensor, with variations in particle concentration reflecting the physical phenomena associated with sediment transport analysis. The experimental setup for the sediment transport investigation was devised to replicate the process of particle suspension in open channels. The analysis of elevated flow rates (7-10 L/min) indicates that augmenting the basal shear stress of sediment particles elevates them into the water column, hence immediately enhancing turbidity (8-14 NTU), which signifies the concentration of suspended sediment. The elevation in turbidity value is directly related to the rise in SSC, flow rate, and turbidity parameters affecting the concentration of suspended material.

This relationship is depicted as the primary impact, with turbidity serving as a supplementary indicator; collectively, they ascertain the observed SSC value as the input variable and SSC as the output variable. SSC

(125-172 mg/L) signifies that the interplay between flow rate and turbidity parameters adequately accounts for the variability in suspended sediment concentration; nevertheless, the connection is non-linear and affected by the dynamics of particle suspension. Augmenting the flow rate enhances the transfer of additional suspended sediment particles, hence elevating NTU and SSC. The validation of the SSC measurement data was conducted utilizing a TDS meter, revealing a 1% discrepancy between the system's projected values and the TDS meter's reference.

The deployment of the monitoring and data recording system facilitates real-time acquisition of flow rate, turbidity, and suspended sediment concentration parameters through an ESP32 module linked via TCP/IP protocol to the LabVIEW HMI platform. Each sensor node possesses a distinct IP address to ensure consistent communication devoid of data conflicts, with a transmission period of 10 seconds. The test findings indicate that the monitoring system presents real-time trends of parameter variations. Figure 17 illustrates the LabVIEW HMI.

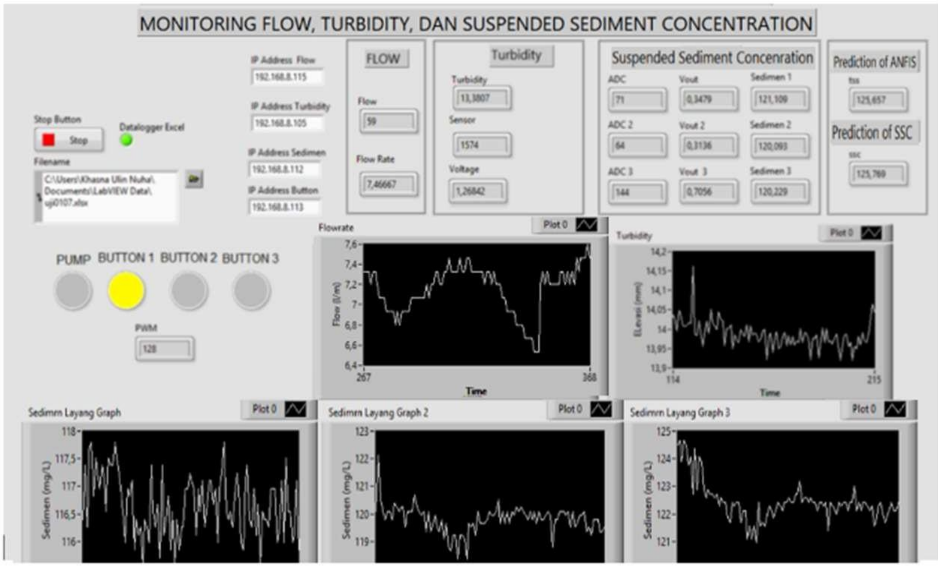


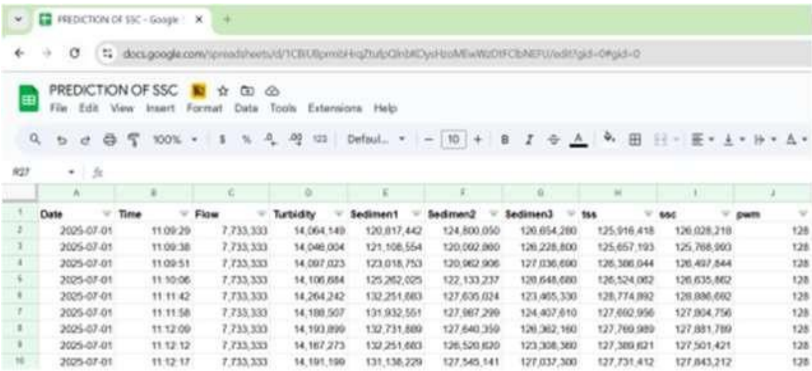

Figure 12. LabVIEW Based HMI Interface During Experimental Testing

The IoT methodology provides adaptability in the positioning of sensor nodes without physical cabling and facilitates the amalgamation of numerous sensors into a singular local network. This expedites the automatic collection of real-time experimental data recorded in local Excel format and cloud-based Google Sheets. The retained data encompasses the subsequent parameters: date, time, flow, turbidity, photodiode 1, photodiode 2, photodiode 3, calculated SSC, forecasted SSC, and pump PWM value: 2025-07-01 11:09:38

1.733333, 14.046004 121.108554, 120.09286, 120.2288 125.657193, 125.768993, 128. The sensor measurement data

exhibited on the LabVIEW HMI is transmitted to Google Sheets as a data logger, recording the time, sensor readings, and SSC prediction results in a cloud-based data repository, as illustrated in Figure 18. The local data storage presentation is instantly accessible in Excel file format, as illustrated in Figure 19.

Figure 13. Data in Table Format



| Date | Time | Flow | Turbidity | Sedimen1 | Sedimen2 | Sedimen3 | tss | ssc | pwm |
|---|---|---|---|---|---|---|---|---|---|
| 2025-07-01 | 11:09:29 | 7,733,333 | 14,064,149 | 120,817,442 | 124,800,050 | 120,654,280 | 125,916,418 | 126,028,218 | 128 |
| 2025-07-01 | 11:09:38 | 7,733,333 | 14,048,004 | 121,108,554 | 120,092,860 | 126,228,800 | 125,657,193 | 125,768,993 | 128 |
| 2025-07-01 | 11:09:51 | 7,733,333 | 14,097,023 | 123,018,753 | 120,962,906 | 127,036,690 | 126,386,044 | 126,497,844 | 128 |
| 2025-07-01 | 11:10:06 | 7,733,333 | 14,106,684 | 125,262,025 | 122,133,237 | 128,648,680 | 126,524,062 | 126,635,862 | 128 |
| 2025-07-01 | 11:11:42 | 7,733,333 | 14,264,242 | 132,251,683 | 127,635,024 | 123,465,330 | 128,774,892 | 128,886,692 | 128 |
| 2025-07-01 | 11:11:58 | 7,733,333 | 14,188,507 | 131,932,551 | 127,987,299 | 124,407,610 | 127,692,956 | 127,804,756 | 128 |
| 2025-07-01 | 11:12:09 | 7,733,333 | 14,193,899 | 132,731,889 | 127,640,359 | 128,382,160 | 127,769,989 | 127,881,789 | 128 |
| 2025-07-01 | 11:12:12 | 7,733,333 | 14,167,273 | 132,251,683 | 126,520,620 | 123,308,380 | 127,389,621 | 127,501,421 | 128 |
| 2025-07-01 | 11:12:17 | 7,733,333 | 14,191,199 | 131,138,229 | 127,545,141 | 127,037,300 | 127,731,412 | 127,843,212 | 128 |

The data logger testing findings indicate that, from 2050 data points, the meantime interval between records is 8 seconds. The time interval error is 0.2%, signifying that the data logger system captures data more rapidly than intended.

Consequently, the timer period must be modified to provide a more uniform recording procedure. Execution of a PWM-controlled DC pump system featuring an on/off switch and three speed settings: PWM 50.22% for low flow, PWM 75.3% for medium flow, and PWM 93.3% for high flow. The pump ON button initiates PWM 19.6% in standby mode, but the OFF button deactivates the pump at PWM 0%.


Figure 14. LCD Display Showing Realtime SSC Monitoring

Besides recording and storage, data from Google Sheets is also accessed through an API and presented locally on the LCD, as illustrated in Figure 20. The LCD panel showcases the real-time monitoring interface. Date and time, flow rate, turbidity and pump PWM value. Three photodiode sensor measurements (S1, S2, S3). Exhibition of TSS (LabVIEW fuzzy prediction output) and SSC (suspended sediment concentration prediction) for real-time surveillance of flume conditions for incorporation with an IoT system monitoring log.

## D. ANFIS Manual Calculation for SSC Prediction

Data Input: Flow = 1.944828 L/min; Turbidity = 14.016817 NTU;
Measure SSC = 125.24024 mg/L; Prediction SSC = 125,704249 mg/L
Membership Function Parameter based on the fuzzy sets as shown Table 1,
Flow: category Very Low = VL < 7 L/min ; $\mu$VL (flow) = 1 , $\mu$others (2)
Turbidity: Category Medium (6.25, 12.5, 18.75) $\mu_{medium} = \frac{18{,}75-14{,}016}{18{,}75-12{,}5} = 0{,}757$
Category High (12.5, 18.75, 25) $\mu_{high} = \frac{14{,}016-12{,}5}{18{,}75-12{,}5} = 0{,}243$
Firing Strengths (Rule Weights)
$\omega 1 = \mu_{\text{VL (flow)}} . \mu_{\text{medium (Turbidity)}} = 1.\ 0.7575 = 0.757$; $\omega 2 = \mu_{\text{VL (flow)}} . \mu_{\text{High (Turbidity)}} = 1.\ 0.243 = 0.243$
Normalized Weight $\overline{\omega_1}\ \frac{0{,}757}{0{,}757+0{,}243} = 0.757$; $\overline{\omega_2}\ \frac{0{,}243}{0{,}757+0{,}243} = 0.243$

Rule Output (Linear Function) VL &Medium p=0, q=0.8, r=115; VL &High p=0.2, q=0.7, r=114
Output f1 = 0.1 $x$ 1.944828 + 0.8 $x$ 14.016817 + 115 = 126.213
f2 = 0.2 x 1.944828 + 0.7 x 14.016817 + 114 = 124.201
$SSC_{predict} = \overline{\omega_1}$ . f1 + $\overline{\omega_2}$ . f2 = 0.757 x 126.213 + 0.243x 124.201 = 125.79 mg/L, pred 125.704249 mg/L

## E. SSC Prediction Performance Analysis

The performance of the ANFIS model in predicting suspended sediment concentration (SSC) was evaluated by comparing the measure SSC values with SSC prediction, as shown Figure 21. The predicted SSC values closely follow the trend of measured data, with slightly higher amplitudes, indicating the model's high sensitivity to sediment concentration variation.

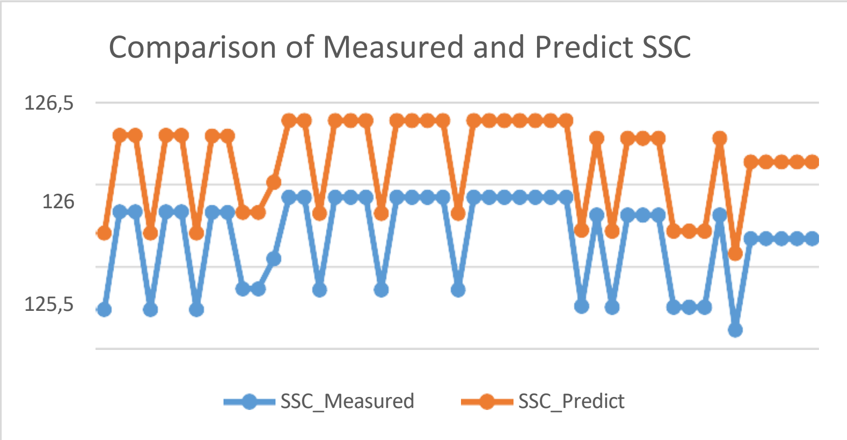



Figure 15. Comparison of Measurement and Predict SSC

The graphical comparison is supported by quantitative performance indicators summarized in Table 3. The model achieved a Root Mean Square Error (RMSE) of 0.466 mg/L and a Mean Absolute Percentage Error (MAPE) of 0.37%, confirming that the prediction errors remain extremely small. In addition, the Coefficient of Determination ($R^2$ =0.995) indicate that predicted SSC values demonstrate a near-perfect linear relationship with measured data. The residual error of approximately ±0.46 mg/L further confirms the stability and unbiased nature of the model.

Table 3. Comparison of Measurement and Prodict SSC

| Parameter | Value |
|---|---|
| RMSE | 0,466 |
| MAPE (%) | 0,37% |
| $R^2$ | 0.995 |
| Residual (Measurement and Predict) | ±0,46 |

The Correlation analysis of flowrate, turbidity, and SSC was conducted to understand the physical relationships among 3 parameters, with the results shown in Tabel 4. Fow Rate & SSC (r=0.6001) a strong positive meaning higher flow rate tends to re-suspend more particles into the water column. Turbidity & SSC a very strong positive correlation (r=0.7963) confirming turbidity as a highly sensitive optical indicator of suspended sediment, Meanwhile, the correlation between Flow Rate & Turbidity (r=-0.0191) a very weak negative, suggesting between hydrodynamic factor and optical factor not directly during tested laboratory conditions.

Table 4. Analysis Correlation of Flow Rate, Turbidity, and SSC

| Parameter Relationship | Correlation Coefficient | Interpretation |
|---|---|---|
| Flow Rate & SSC | 0,6001 | Strong Possitive Correlation |
| Turbidity & SSC | 0,7963 | Very Strong Positive Correlation |
| Flow Rate & Turbidity | -0.0191 | Very Low Negative Correlation |

Overall, the combination graphical comparison and statistical metrics demonstrates that the ANFIS model provides highly accurate and reliable SSC predictions. The close alignment between measured and predicted values, supported by strong physical correlations among key parameter, confirm that the model effectively sediment concentration dynamics within the laboratory flume system.

## IV. CONCLUSION

This study explores a system for monitoring and predicting suspended sediment concentration in real-time, utilizing IoT and fuzzy logic through the LabVIEW platform. The system combines flow rate, turbidity, and photodiode sensors with ESP32, presenting the data on the LabVIEW HMI, while employing Sugeno fuzzy logic to predict SSC values and display them on an LCD. Data is transmitted to Google Sheets functioning as a cloud data logger and is also stored locally in an Excel file. The system exhibits optimal performance, as evidenced by SSC prediction results that fall between 125-172 mg/L, aligning with the SSC quality standard threshold, and a TDS meter validation error of just 1%. The system provides real-time monitoring with a measurement time interval of 10 seconds and a time recording error of 0.2% faster than the target time, making it appropriate for implementation as a laboratory-scale SSC monitoring prototype. The ANFIS model achieved excellent predictive reliability $R^2 > 0.995$ with minimal error RMSE 0.466 mg/L, supported by strong correlation between flow rate, turbidity, and SSC. Residual and scatter plot evaluations confirmed that the model is unbiased and robust. These findings strengthen the analytical contribution of the study by demonstrating that the proposed model effectively captures the nonlinear sediment transport dynamics within the flume. Moreover, the results open several opportunities for further development, including enhancing the ANFIS approach prediction framework, integrating additional sensor parameter, validating the system in real operational environment, applying it in practical settings, and improving the HMI and dashboard display for broader decision support applications.Summarize sentences the primary outcomes of the study in a paragraph. Explain if the results support the claims in this section and if they seem reasonable. Also, describe whether the result support or contradicts previous theories and explain how the research has moved the body of scientific knowledge forward.

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## AUTHOR CONTRIBUTION

KUN, PO, and DY constructed the study design and and analyzed the data. KUN prepared the manuscript and revised the final version of the paper. PO and DY have read the final manuscript and approved the submission. KUN, PO, and DY are the abbreviation of First, Second, and Third Author respectively.

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