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Implementation of Industrial IoT Integration Using Node-RED and PLC on Cascade Control Level and Flow Plant

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Abstract: Accurate control of liquid level and flow is essential in industrial processes to ensure efficiency and product quality. Conventional single PID control methods often suffer from steady-state errors and slow response times due to the dynamic interaction between level and flow. This research develops a cascade control system using a PLC integrated with a Node-RED based Industrial Internet of Things (IIoT) platform to overcome these limitations. The cascade control system applies two control loops, the outer loop for level control and the inner loop for flow control, with PID parameters optimized through trial-and-error method. IIoT integration enables real-time monitoring, remote control, and data logging through an interactive dashboard. Experimental results show the system is able to achieve stability with steady-state error reduced to ± 0.5 cm, faster settling time and rise time, and better disturbance resistance. Very low communication delays support real-time operation. The system offers a practical and effective solution for precise liquid level and flow control, aligned with the demands of Industry 4.0 and can be a model for educational and industrial applications.

Keywords: Cascade Control; Industrial Internet of Things (IIoT); Node-RED; PID Tuning; Programmable Logic Controller (PLC).

Introduction

In the modern industrial era, precise process control is a major factor in increasing production efficiency, ensuring operational safety, and maintaining product quality (Jiang, 2021). One parameter that is often the focus is the control of liquid levels and flows in water tank systems, which are vital components in various industrial applications such as water treatment, chemistry, and manufacturing (Suryatini et al., 2024). The complexity of controlling liquid levels and flows is caused by the dynamic interaction between the two, which requires the control system to be able to respond quickly and accurately to changes or disturbances (Dewi et al., 2023). Previous studies have examined various control methods for regulating liquid levels and flows in tanks, such as Proportional-Integral-Derivative (PID), Fuzzy Logic, and Model Predictive Control (MPC) (Ali et al., 2020; Jakowluk & Jaszczak, 2022; Shehu & Wahab, 2016). However, these methods have significant limitations, especially in dealing with system nonlinearity, dynamic parameter changes during operation, and high computational requirements, especially in MPC. For example, a single PID control, although quite commonly used, has been shown to still have a steady-state error of around ±0.7 cm and performance that is hampered by flow fluctuation disturbances, thus affecting the stability and accuracy of control (Suryatini et al., 2024). This shows the need for a more adaptive, responsive control approach that is able to optimize system performance as a whole. Cascade control was chosen in this study as a superior solution to control water levels and flows quickly, accurately, and resistant to external disturbances (Pramanik et al., 2021). By using two control loops, level as the primary loop and flow as the secondary loop, this method is able to

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separate and overcome the effects of disturbances on the flow, thereby increasing stability and accelerating system response significantly (Khan et al., 2020). The cascade control approach is also effective in reducing steady-state errors to below ±0.7 cm, which is the target precision in industrial and educational applications (Pramanik et al., 2021; Suryatini et al., 2024).

However, the application of cascade control in educational plants and industrial scale is still limited. For example, the Festo Labvolt 3531 plant in the Polman Bandung Automation Engineering Department Laboratory, although designed for learning process control, has not adopted this approach (Suryatini et al., 2024). In fact, the integration of cascade control with a Programmable Logic Controller (PLC) is very relevant to represent real industrial conditions and provide an effective training platform (Możaryn et al., 2022). PLC was chosen because of its ability to run multi-loop logic in real-time with high reliability, as well as its compatibility with industrial protocols such as Modbus TCP/IP that support structured data communication (Nițulescu & Korodi, 2020).

In the Industry 4.0 era, the demands of automation systems are not only precise but also connected and intelligent. Therefore, this study integrates the Node-RED-based Industrial Internet of Things (IIoT) with PLC to facilitate remote monitoring, data logging, and real-time predictive analysis (Thuluva et al., 2020). Node-RED was chosen as the main platform because of its ability to connect heterogeneous devices (sensors, PLCs, databases) through an intuitive visual interface and support low-latency communication with industrial protocols such as Modbus TCP/IP and MQTT (Embong et al., 2024; Subekti et al., 2024). Node-RED's flexibility in interactive visualization, data management, and integration with analysis tools such as Python and MATLAB, thus increasing the optimization of control system performance and more effective predictive maintenance (Omidi et al., 2023; Subekti et al., 2024).

In addition to playing a role in monitoring and analysis, Node-RED also functions as a data logger that records critical parameters such as water level, flow rate, and percentage of control valve opening in CSV format (Nugraha et al., 2023). This data storage allows historical evaluation of system performance and supports the development of predictive models or digital twins in the future (Guerra-Zubiaga et al., 2021). The implementation of a data prioritization strategy in Node-RED, where flow data is processed with a higher priority than level data, together with buffering techniques in Modbus TCP/IP communication, overcomes the challenges of latency and data synchronization in PLC-IIoT-based cascade control systems (Hijazi et al., 2024; Uzougbo et al., 2024).

Along with the development of technology, the integration of control systems with machine learning and big data analysis has begun to receive significant attention. The use of artificial intelligence algorithms for PID parameter optimization and system condition prediction so that there is an increase in adaptive and real-time control performance, thus answering the challenges of increasingly complex and dynamic industrial systems (Lv & Li, 2021; Rai et al., 2021; Zhou et al., 2022). Therefore, the integration of cascade control with IIoT and intelligent analytical technology is a strategic step to create a faster, more accurate, and more reliable control system in an industrial environment (Bahri et al., 2024; Levin et al., 2021; Stojkic et al., 2021). Based on these challenges, this study aims to design a PLC-based cascade control level-flow system with a smaller steady-state error (±0.5 cm) compared to the previous single PID approach (±0.7 cm) (Suryatini et al., 2024). The main novelty of this study is the integration of the cascade control system with the Node-RED-based IIoT platform, which enables real-time monitoring, predictive data analysis, and fast data communication. Thus, the results of this study provide a more precise and adaptive control solution, and can be a reference model in implementing Industry 4.0 technology, both for educational and industrial applications.

Method

This study uses an experimental method with a scientific approach that controls relevant variables to produce objective and valid data. The stages include literature studies, electrical, mechanical, informatics, and control system design, and trial-error to observe and improve system performance directly. This method allows for accurate evaluation of the impact of changes and produces optimal solutions through continuous improvement, with control of interfering factors (Fadilla & Ardiawan, 2022).

The research begins with a literature study, which is the process of searching for information and references from previous studies that are relevant to the topic to be studied. These references come from various sources such as scientific journals, books, articles on the internet, conference reports, and so on. At this stage, the author also conducts a reference analysis to understand the methods, results, and weaknesses of previous research. From the results of this analysis, a journal review table is compiled containing a summary of the main findings, methodology, and research gaps or novelties that are opportunities for research contributions. At the design stage, the author develops a comprehensive design covering the following aspects.

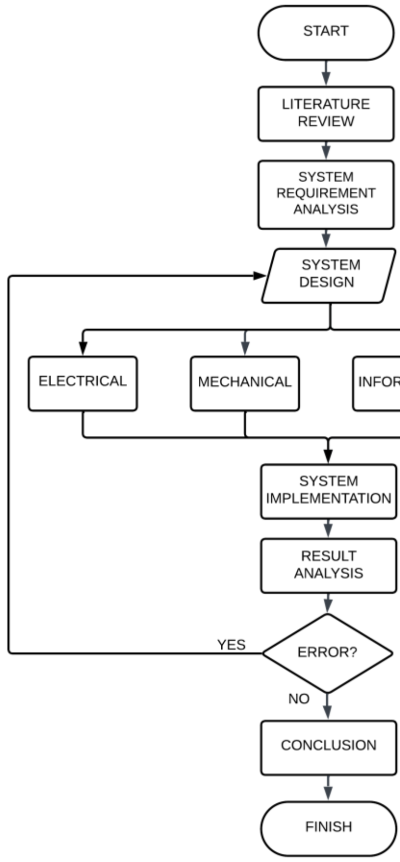


Figure 1. Research flow

(a) (b) (c) (d)

Figure 2. Design stage of research: (a) PLC Digital Input Design; (b) PLC Digital Output Design; (c) PLC Analog Input Design; and (d) PLC Digital Output Design

Electrical System Design

At this stage, the electrical system design is carried out, including the selection and arrangement of electrical components such as level and flow sensors, control valve actuators, and interface devices with the PLC. The electrical circuit is arranged to ensure that signals from the sensors can be received accurately by the PLC, while ensuring a stable and safe power supply to all devices. Electrical wiring and protection are also designed to minimize electromagnetic interference and improve system reliability during operation.

Mechanical System Design

Mechanical design includes the physical design of tanks, pipes, and control valve installations that are in accordance with the needs of controlling the level and flow of liquids. The dimensions and materials of the components are selected to be resistant to pressure and corrosion, while also facilitating maintenance. The mechanical system is also designed to support accurate measurements from level and flow sensors, and to facilitate responsive control to changes in process parameters. As shown in Figure 3.

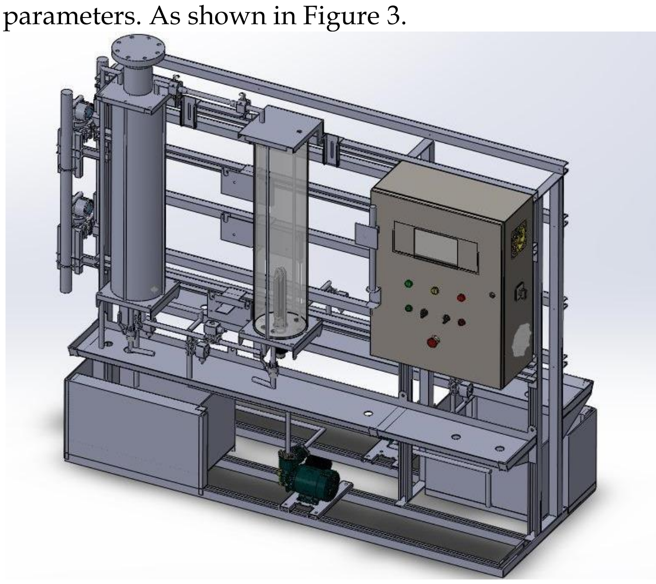


Figure 3. Mechanical Design

Information Systems Design

In this section, an informatics system is developed that includes PLC programming for cascade control and integration with the Node-RED-based IIoT platform. The design includes creating control algorithms, setting up data communication using the Modbus TCP/IP protocol, and developing a visual interface for real-time monitoring and data logging. This informatics system is designed to be flexible, easy to develop, and able to support predictive data analysis.

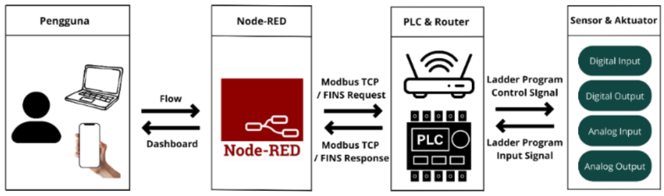


Figure 4. Information System Design

Control System Design

The design of the cascade control system is carried out by building two integrated control loops, namely the primary loop that controls the liquid level and the secondary loop that regulates the liquid flow. The primary loop is responsible for maintaining the liquid level according to the setpoint by sending a reference signal to the secondary loop as a control variable for flow manipulation. The PID control parameters in both loops are optimized through a tuning process to obtain a fast, stable, and accurate system response with a very small steady-state error. In addition, this design also considers handling external disturbances, such as pump pressure fluctuations, so that the system is able to maintain optimal control performance.

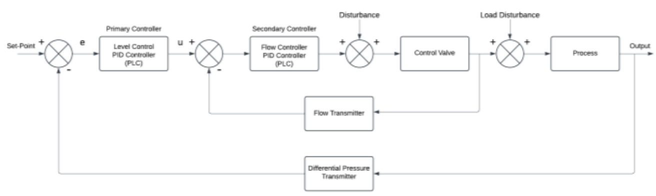


Figure 5. Cascade Control Level Flow Block Diagram

System Implementation

The system design used consists of three main parts, namely Plant, Process, and Monitoring. As shown in Figure 6.

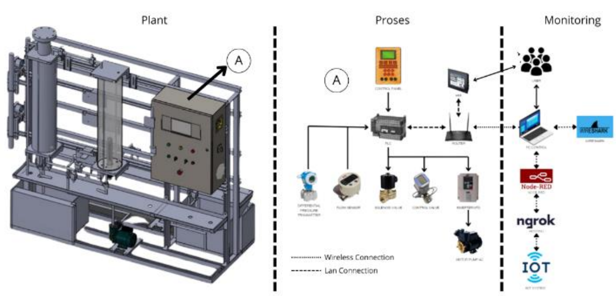


Figure 6. Overall System Diagram

Figure 6 shows the overall system diagram consisting of three main parts. In the Plant section, there are hardware such as tanks, flow and pressure sensors, control valves, and pump motors that function to regulate and control the flow and level of liquids mechanically and electrically. The Process section involves control using a Programmable Logic Controller (PLC) that receives data from differential pressure sensors and flow sensors, and sends control signals to actuators such as solenoid valves, control valves, and AC pump motor inverters. Communication between devices uses a LAN connection, while communication between the PLC and the monitoring system is done wirelessly. The Monitoring section functions as a visual interface and real-time data management that allows remote monitoring and control. The monitoring system uses a PC connected to a wireless network and Node-RED software, and is integrated with the ngrok service and supported by a network analysis tool, namely Wireshark.

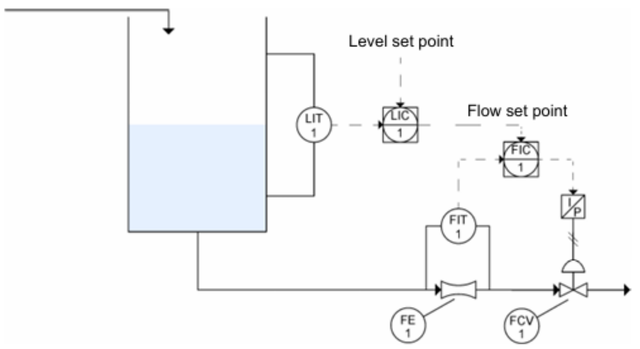


Figure 7. P&ID Cascade Level-Flow

Result and Discussion

Implementation of Electrical and Mechanical Systems

Figure 8 shows the implementation of the mechanical system of the water tank plant, including the main tank, connecting pipes, pumps, control valves, and level and flow sensors. This mechanical structure is designed to ensure stable fluid flow and accurate measurement of process parameters. The installation of mechanical components is carried out with attention to ease of maintenance and resistance to laboratory operational conditions.

Sensor & Actuator Testing

Differential Pressure Transmitter PMD 75

This test was conducted to ensure the performance and reliability of the height sensor to be used. In this study, measurements were made at a height range between 0 and 90 cm.

As shown in Table 1, the error value (%) is calculated using equation 1. The average error between the actual value and the sensor reading is 1.044%, while the average error in the use of scaling in the PLC program when compared to the actual value is relatively larger, reaching 1.222%.

Figure 8. Implementation of Electrical and Mechanical Systems

To reduce this error in centimeters (cm), the author uses a linear regression method to maximize the calibration process (Ardhi et al., 2023). This approach is carried out by analyzing the relationship between the digital value read by the PLC as a predictor variable, and the actual value measured on the acrylic tube as a response variable.

Table 1. Endress Hauser PMD75 DPT Sensor Reading

Parameters	Standard					Actual Plant (Scalling PLC)	
	%	mmH2O	Input cm	mmH2O	Error (%)	Input cm	Error (%)
1	0	0	0	0	0.000	1	1.111
2	11.1	100	10	92	0.889	9	1.111
3	22.2	200	20	193	0.778	19	1.111
4	33.3	300	30	293	0.778	28	2.222
5	44.4	400	40	392	0.889	41	1.111
6	55.5	500	50	490	1.111	52	2.222
7	66.6	600	60	589	1.222	61	1.111
8	77.7	700	70	687	1.444	70	0.000
9	88.8	800	80	787	1.444	79	1.111
10	100	900	90	883	1.889	89	1.111
Average Error (%)					1.044		1.222

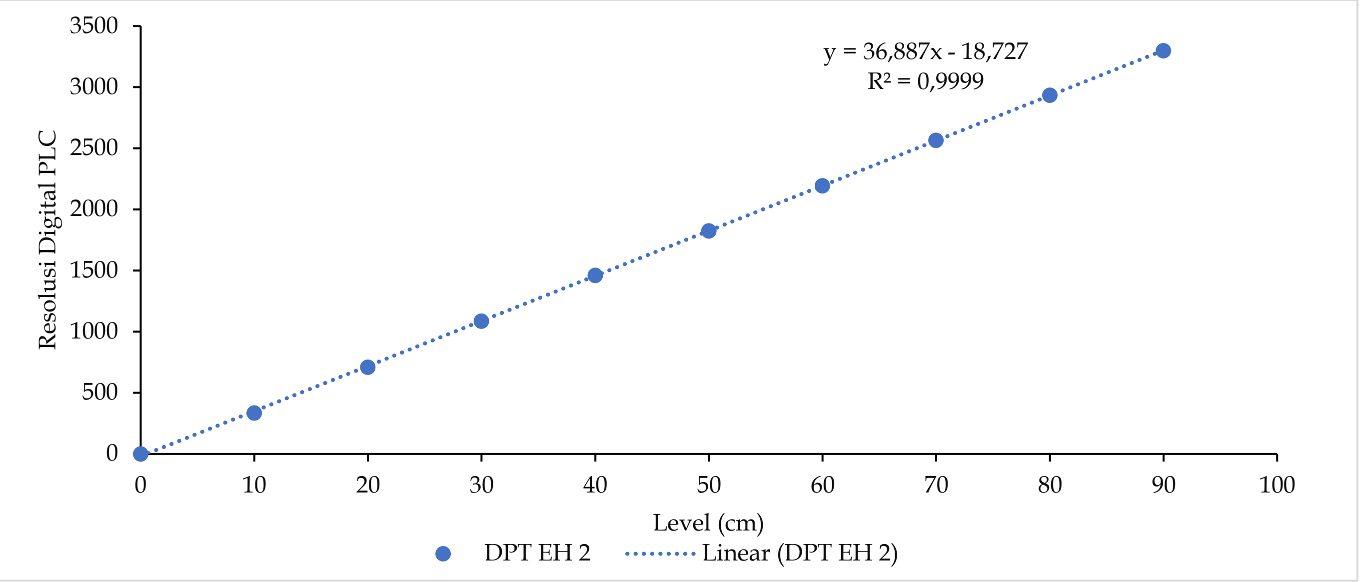


Figure 9. Linear Regression Graph of Endress Hauser PMD75 DPT Sensor

Table 2. Linear Regression Data of Endress Hauser PMD75 DPT Sensor

Digital Value	Actual Level Value (cm)
0	0
335	10
710	20
1087	30
1460	40
1825	50
2195	60
2565	70
2935	80
3300	90

The data from Table 2 is processed into a graph so that the linear regression value is known as in Figure 9. It can be seen in Figure 9 that there is a linear regression equation, namely y = 36.887x-18.727, the equation is then entered into the PLC program so that the level of sensor accuracy with the actual value is higher. The following are the test results after linear regression are carried out.

Table 3. Linear Regression Test Results of Endress Hauser PMD75 DPT Sensor

Actual Level (Standard)	PLC Linear Regression (cm)	Error (%)
0	1	1.111
10	9	1.111
20	19	1.111
30	30	0.000
40	40	0.000
50	50	0.000
60	60	0.000
70	70	0.000
80	80	0.000
90	90	0.000
Average Error (%)		0.333

After the application of linear regression, the average value of accuracy between the actual reading and the results obtained from the PLC experienced a significant increase, namely decreasing to 0.333% with the calculation of the error value (%) using equation 1. This shows that the linear regression method is effective in improving and minimizing sensor reading errors. Complete data related to this improvement can be seen in detail in Table 3.

Turbine Flow Sensor

Table 4 contains linear regression data between the actual flow value in Liters per Minute (LPM) and the digital value read by the PLC. The PLC digital value here acts as a predictor variable to model a linear relationship with the actual flow value. This data is the basis for creating a linear regression equation that can be used to improve the accuracy of flow readings from the sensor.

Table 4. Turbine Flow Meter Linear Regression Data

Actual Flow Value (LPM)	PLC Digital Values
0	-12
1	-12
2	-12
3	-12
4	-12
5	-12
6	-12
7	-12
8	-12
9	5
10	125
11	320
12	520
13	805
14	1050
15	1250

Actual Flow Value (LPM)	PLC Digital Values
16	1590
17	1906
18	2200
19	2530
20	2825
21	3180
22	3520
23	3870
24	4190
25	4360

Figure 10 shows a graph of the linear regression results between the PLC digital value and the actual flow value (LPM) on the Turbine Flow Meter. The regression curve with the equation y = 0.0039x + 8.5458 and the coefficient of determination (R^2) value of 0.8705 shows a fairly strong linear relationship between the PLC digital variable and the actual flow value, indicating the effectiveness of the regression model in estimating the flow value.

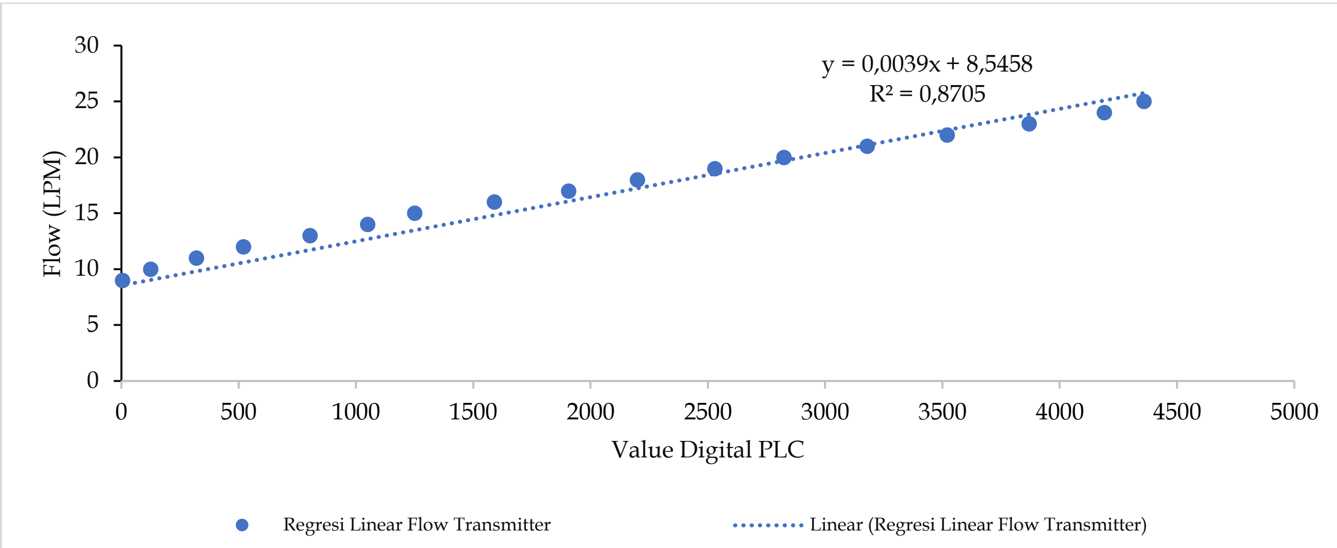


Figure 10. Linear Flow Transmitter Regression

Table 5. Linear Regression Test Results of Turbine Flow Meter

Actual Flow Value (LPM)	PLC Linear Regression Value (LPM)	Error (%)
0	0	0
1	9	32
2	9	28
3	9	24
4	9	20
5	9	16
6	9	12
7	9	8
8	9	4
9	9	0
10	10	0
11	11	0
12	12	0
13	13	0
14	14	0
15	15	0
16	16	0
17	17	0
18	18	0
19	19	0
20	20	0
21	21	0
22	22	0
23	23	0
24	24	0
25	25	0
Average Error (%)		5.538462

Table 5 shows the results of the actual flow reading (LPM) test compared to the linear regression value calculated on the PLC, along with the percentage error. It can be seen that after linear regression was applied, the error value decreased significantly, especially at higher flow ranges, with an overall average error of 5.54%. This shows that the application of linear regression has succeeded in increasing the accuracy of the Turbine Flow Meter reading.

Control Valve

Table 6 shows the relationship between the PLC digital value and the percentage of Control Valve (CV) opening in the form of discrete data. This data is used to create a linear regression model that describes the linear relationship between the PLC digital input and the valve opening as the output variable. The range of PLC digital values is from 0 to 5915, which represents the control valve opening from 0% to 100%.

Table 6. Control Valve Digital Value Reading Data

Nilai Digital PLC	Nilai Bukaan CV (%)
0	0
1420	25
2940	50
4400	75
5915	100

Data from Table 6 is processed into a graph to determine the linear regression value in Figure 11. This graph shows the results of linear regression between PLC digital resolution and control valve opening percentage. The regression equation y=0.0169x+0.4614 and the coefficient of determination (R^2) of 0.9999 indicate that the linear regression model is very accurate and approaches a perfect relationship between PLC digital values and control valve openings.

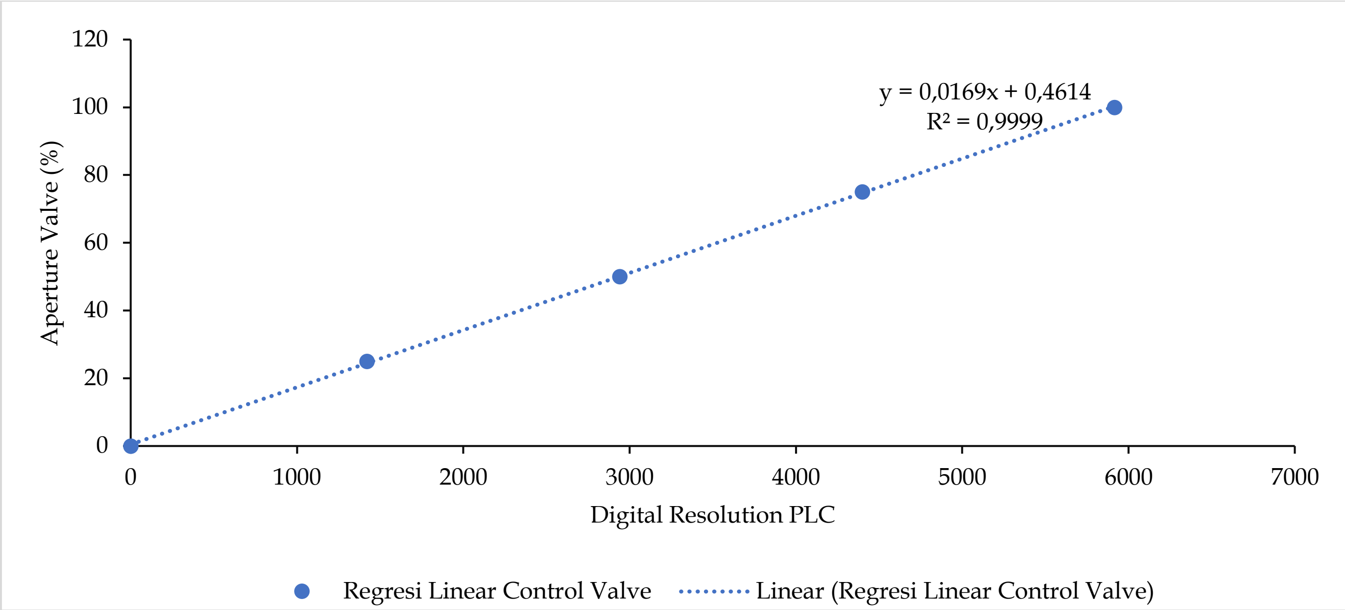


Figure 11. Linear Regression Graph of Control Valve

Table 7 shows the results of the standard valve opening reading test compared to the linear regression results, along with the percentage of error. It can be seen that most of the errors are at 0%, with only a small error of 1% at the opening values of 100% and 101%. The overall average error is very low, which is only 0.2%, indicating that the use of linear regression is very effective in increasing the accuracy of control valve opening readings.

Table 7. Linear Regression Control Valve Test Results

Standard Valve Opening (%)	Linear Regression Valve Opening (%)	*Error* (%)
0	0	0.000
25	25	0.000
50	50	0.000
75	75	0.000
100	101	1.000
100	101	1.000
75	75	0.000
50	50	0.000
25	25	0.000
0	0	0.000
Average Error (%)		0.200

Informatics Implementation

PLC IP Configuration

In the first stage of informatics implementation, namely IP configuration on the PLC ladder program, the selection of the PLC type is selected according to the PLC in the plant, namely CP1H, then the selection of the Network Type by selecting Ethernet FINS/TCP is continued with the registration of the static IP registered on the router that has a subnet of 192.168.250.1 to 192.168.250.254, namely by registering the IP 192.168.250.15 for the PLC.

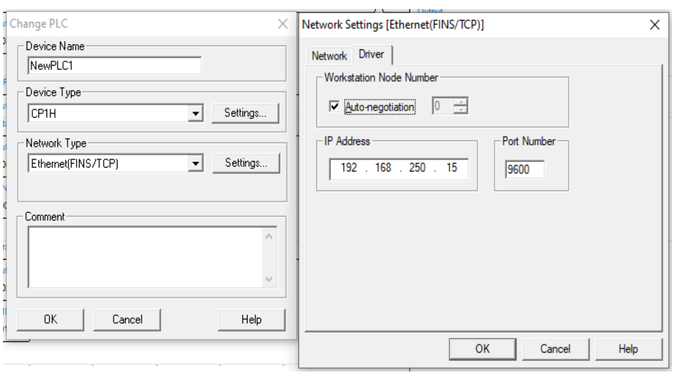
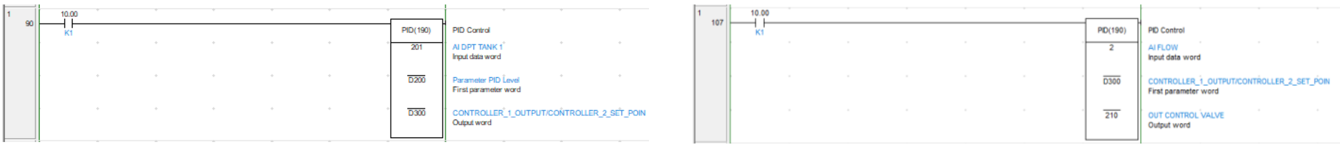


Figure 12. PLC IP Configuration

PLC Program Implementation

The creation of a PLC ladder diagram includes sequential programs, digital input, digital output, analog input, and analog output. After this stage, a sensor reading program is created and the sensor value scale is made into centimeters (cm) for the level sensor and Liters Per Minute (LPM) for the flow sensor, which is then continued with the creation of the main program for the implementation of PID cascade control on the Omron CP1H PLC.



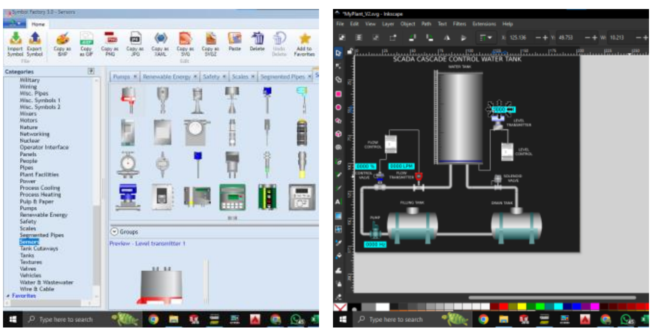
(a) (b)

Figure 12. Program: (a) Outer Loop Control; (b) Program Inner Loop Control

Figure 12(a) shows the Outer Loop Control program that is tasked with regulating the PID parameter level based on input data from the tank level sensor, while Figure 12(b) shows the Inner Loop Control program that regulates the output flow and control valve as an actuator in the system. With this division of control, the system is able to respond to changes more precisely and efficiently.

Node-RED Custom Flow Implementation

The implementation of custom flow in Node-RED is carried out to visually regulate the communication flow and control logic. Node-RED allows the integration of sensor data and PLC devices through industrial protocols such as Modbus TCP and FINS, thus facilitating the development of flexible control systems.



(a) (b)

Figure 13. custom flow in Node-RED: (a) Software Symbol Factory 3; and (b) Software Inkscape

Figure 13(a) shows the implementation of custom flow in Node-RED which begins with the selection of instrument symbols using Symbol Factory 3 software. The selected symbols are then exported into SVG file format to simplify the next process. Next, in Figure 13(b), the interface layout is created using Inkscape software by importing the exported SVG file. At this stage, adjustments are made to the component layout and the creation of IDs for each component part that functions to display changes in level, flow, control valve, inverter, and tank values. This adjustment also supports animation of changes in water level, resulting in an interface display that meets the needs of the system visually and interactively.

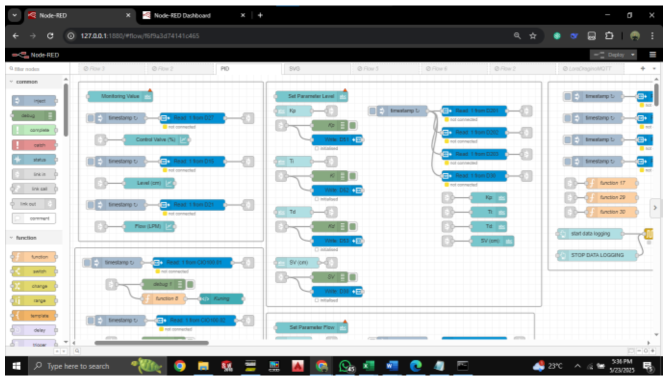


Figure 14. Node-RED Cascade Control Flow

Figure 14 shows the Node-RED interface display containing the complete program flow. At this stage, various FINS nodes that have been configured with the PLC IP address are combined with other nodes such as input, function, and output to form a complex control logic. This flow represents the process of reading data from the PLC, processing data, and sending it back to the PLC and dashboard display.

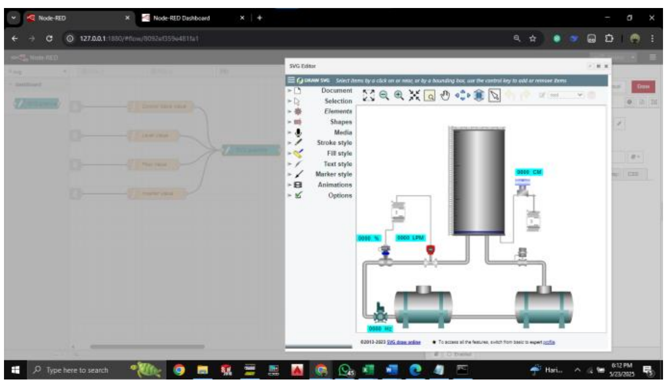


Figure 15. Node-RED SVG Editor

Figure 15 shows the creation of an interface in Node-RED starting by importing an SVG file that has been designed using graphic design software into the Node-RED SVG Editor. At this stage, graphic elements are adjusted by assigning special IDs to text objects and other visual components. Determining this ID is very important because it functions as a reference for connecting sensor data and variables from the PLC so that they can be displayed in real-time on the dashboard. In addition to displaying sensor values such as liquid level and flow rate in text form, graphic elements such as tanks are also set to be animated, so that changes in system conditions can be visualized dynamically.

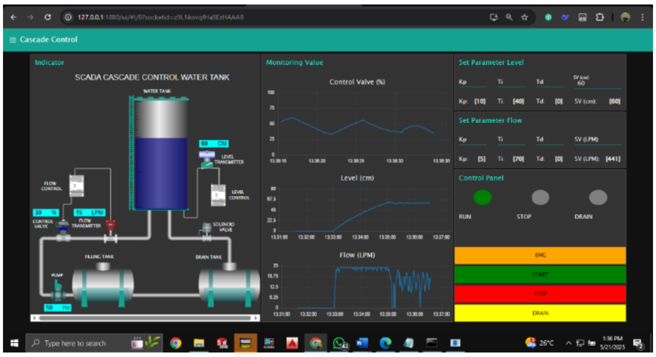


Figure 16. Node-RED IIoT Control & Monitor Interface

In Figure 16, the interface created in the SVG Editor is imported into the Node-RED IIoT dashboard, which displays continuous parameter monitoring graphs and a control panel for PID setpoint settings and RUN, STOP, and DRAIN buttons. Tank animations depicting fluid level changes provide immediate visual feedback to the operator, making it easy to monitor the overall system. This combination of dynamic data and interactive dashboards results in an effective and user-friendly control and monitoring system.

Testing System

Figure 17 shows the hosting configuration using Ngrok, which functions as a tunneling service to connect the Node-RED server running locally to the public internet network. With this configuration, the IIoT dashboard can be accessed from outside the local network using the URL address provided by Ngrok. Thus, remote monitoring and control of the system through any device connected to the internet.

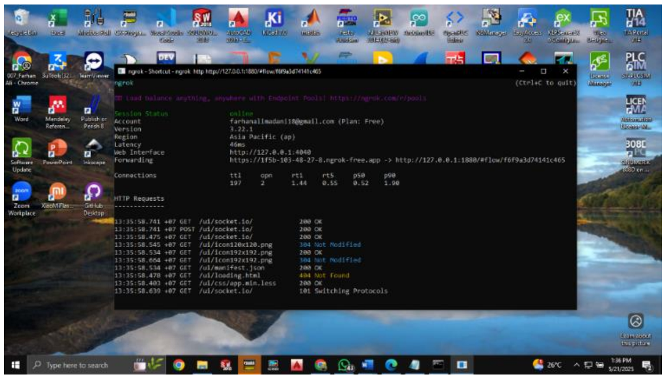


Figure 17. Ngrok Hosting Configuration

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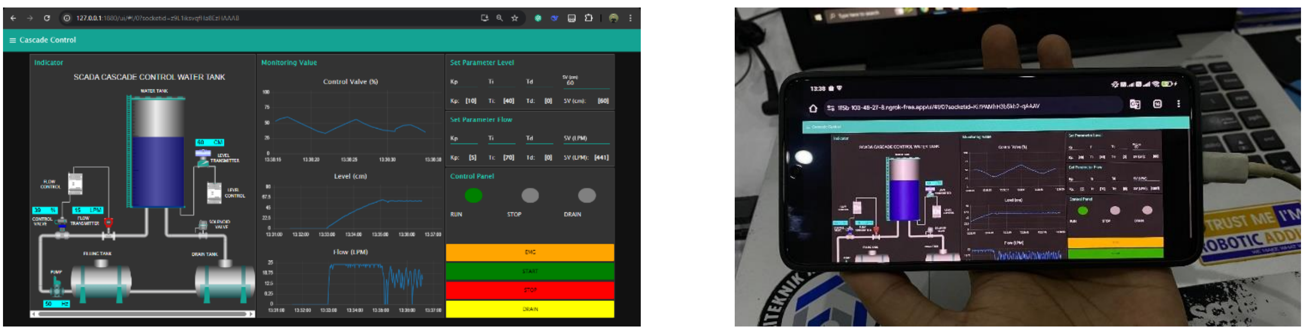
Figure 18(a) 18(b) show the display of the control and monitoring dashboard that is accessed via PC and mobile phone devices responsively. This dashboard displays various important parameters such as liquid level, flow rate, real-time monitoring graphs, and a control panel with RUN, STOP, and DRAIN buttons.



(a) (b)

Figure 18. Display of IIoT: (a) Dashboard on PC; and (b) Dashboard on Mobile Phone

Table 8. Results of Control & Monitoring Function Testing

Parameters	Features	Input/Output	Address	Working/Not Working
Indicators	Green Light (RUN)	Output	CIO 100.00	√
	Yellow Light (DRAIN)		CIO 100.01	√
	Red Light (STOP)		CIO 100.02	√
Monitoring Value	Control Valve (%)	Output	D27	√
	Level (cm)		D15	√
	Flow (LPM)		D21	√
	Inverter (Hz)		D101	√
	Parameter Level (SP, Kp, Ki, Kd)		D30, D201, D202, D203	√

Parameters	Features	Input/Output	Address	Working/Not Working
	Parameter Flow (SP, Kp, Ki, Kd)		D300, D301, D302, D303	√
Setting Parameter	Set Point (Level)	Input	D30	√
	Kp (Level)		D51	√
	Ki (Level)		D52	√
	Kd (Level)		D53	√
	Kp (Flow)		D41	√
	Ki (Flow)		D42	√
	Kd (Flow)		D43	√
Control Panel	Start Button	Input	W0.00	√
	Stop Button		W0.01	√
	Drain Button		W0.02	√
	Emergency Button		W0.03	√

Then the system function test is carried out in Table 8 by checking the function of various features listed in the test table. Based on the specified PLC address, all indicators (RUN, DRAIN, STOP) function properly as output. Monitoring parameters such as control valve, level, flow, and inverter are also successfully monitored in real-time via the dashboard. In the parameter setting section, the input for setpoint and PID parameters (Kp, Ki, Kd) show functions that mostly work well. With the help of Wireshark software, the average delay or delay time required to send and receive data packets in this IIoT system is obtained, as can be seen in Table 9.

As can be seen in Table 9, the data communication speed can be said to be fast and has a very small delay. The data reception process has an average delay of 0.0941ms on the indicator feature, 0.0303ms on the monitoring value feature, 0.0566ms on the parameter setting, and 0.0586ms on the control panel. While the sending (write data) and receiving (read data) processes have an average delay of 0.0599ms.

PID Testing

The Cascade Control system testing was conducted using the Trial and Error tuning method for both control loops, namely the inner loop (flow control) and the outer loop (water level control). The setpoint value was determined to be fixed at 40 cm in the first and second tests, with the aim of evaluating the control performance in two scenarios, namely without disturbance and with disturbance.

Table 9. PLC Data Transmission and Reception Latency Test Results

Fitur	Input/Output	Address	Delay (ms)
Indicator	Output	CIO 100.00	0.0187
			0.2022
			0.0000
			0.0019
			0.1108
			0.0001
			0.0156
			0.1670
			0.0455
			0.3787
Delay Average (ms)			0.0941
Monitoring Value	Output	Level Value (D15)	0.0631
			0.0230
			0.0642
			0.0454
			0.0292
			0.0132
			0.0160
			0.0328
			0.0024
			0.0137
Delay Average (ms)			0.0303
Setting Parameter	Input	Set Point (D30)	0.0019
			0.0270
			0.0522
			0.0242

Fitur	Input/Output	Address	Delay (ms)
			0.0019
			0.0443
			0.0546
			0.0243
			0.3185
			0.0173
Delay Average (ms)			0.0566
Control Panel	Input	Start Button (W0.00)	0.0137
			0.0184
			0.0359
			0.0492
			0.0065
			0.1578
			0.0683
			0.0291
			0.1950
			0.0116
Delay Average (ms)			0.0586

The PID parameters resulting from tuning are shown in Table 10 and Table 11.

Table 10. Inner Loop Control (Level) Tuning Results

Controller Type (*Inner Loop*)	Kp	Ti	Td
PI	5	70	0

Table 11. Outer Loop Control (Flow) Tuning Results

Controller Type (*Outer Loop*)	Kp	Ti	Td
PI	10	40	0

In the first test, the system is not given any external disturbance so that the natural response characteristics can be analyzed. It is shown in Figure 19.

The test results are shown in Figure 20. It can be seen that the system is able to reach a setpoint of 40 cm with a Settling Time (Ts) of 84 seconds, a Rise Time (Tr) of 58 seconds, with an overshoot of 7.5% which is immediately damped. After that, the water level remains at around 40 cm with very small fluctuations, indicating that the Steady State Error (SSE) is 0.5 cm. This indicates that the tuning parameters obtained through trial and error in Cascade Control have produced effective control, both in terms of stability and accuracy.

The second test was conducted by providing external disturbance to the system, namely the sudden opening of the drain valve with a valve opening of 50%. The setpoint value was set at 40 cm. The response characteristics of the Cascade Control system using the Trial and Error tuning method are shown in Table 12.

Table 12. System Response Characteristics

Method	Settling Time (s)	Rise Time (s)	Overshoot (%)	Error Steady State (cm)
No Disturbance	84	58	7.5	0.5
Disturbance	91	60	7.5	0.5

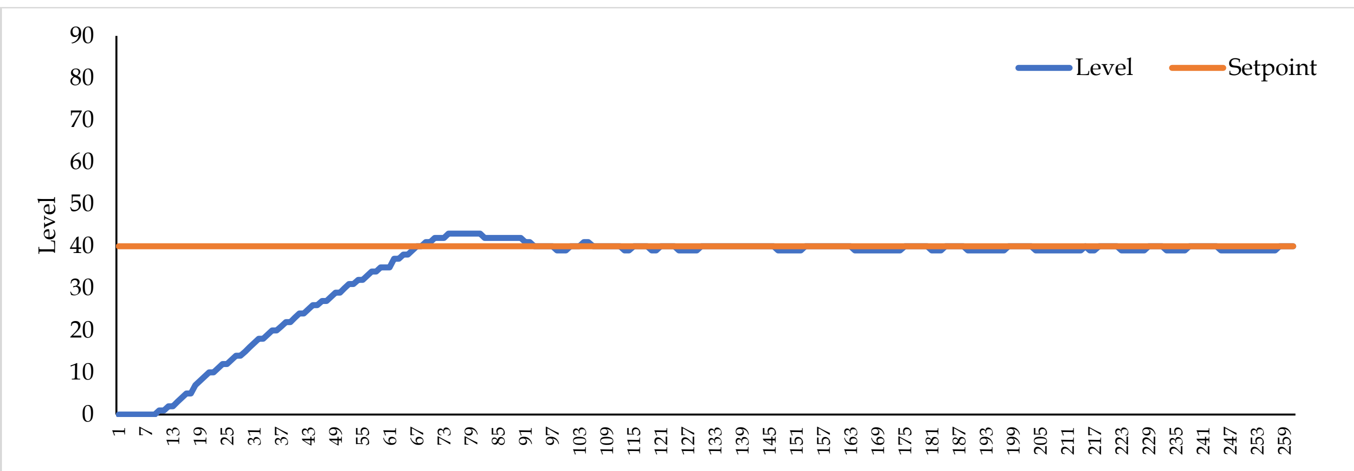


Figure 19. Uninterrupted Cascade Control Testing

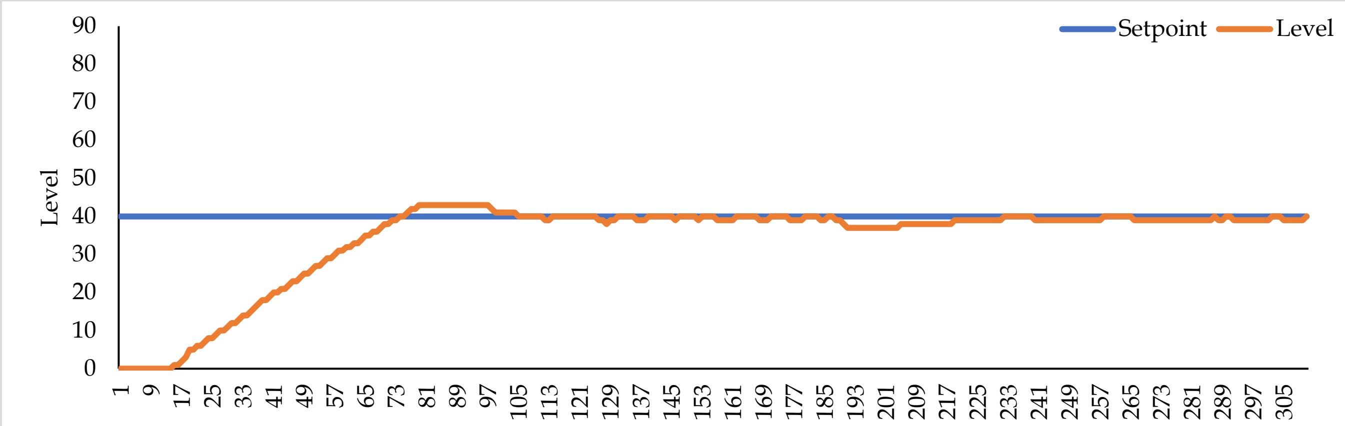


Figure 20. Cascade Control Testing With 50% Valve Fault

The test results shown in Figure 20 can be observed that the system is still able to reach setpoint 40 quite well with Settling Time (Ts) 91 seconds, Rise Time (Tr) 60 seconds, with an overshoot of 7.5% which is immediately damped, even though there is a decrease in the water level when 50% of the disturbance is given. However, thanks to the cascade control configuration, the inner loop that regulates the flow responds quickly to changes, and the outer loop successfully returns the level to the setpoint within 43 seconds. Fluctuations due to disturbances are successfully dampened, and the Steady State Error (ESS) is ±0.5cm.

Discussion

Previous research has shown that the use of a single PID control in a liquid level control system still has limitations, especially in terms of a relatively large steady-state error, which is around ±0.7 cm, and a slow response to flow disturbances (Suryatini et al., 2024). This is due to the dynamic interaction between level and flow variables that cannot be effectively overcome with just one control loop. In this context, the cascade control method used in this study offers a better solution by dividing the control into two loops, namely the primary loop for level and the secondary loop for flow. This approach successfully reduces the steady-state error to ±0.5 cm and increases the system response speed. In addition, integration with the Node-RED-based IIoT platform provides convenience in real-time monitoring, remote control, and better data management. Although the trial and error method used for PID tuning requires sufficient testing time, the results obtained show better control stability and accuracy compared to conventional single PID. Thus, the cascade control approach integrated with PLC and IIoT provides significant added value in industrial process control and automation engineering learning.

Conclusion

This study successfully developed a PLC-based Cascade Control level-flow system integrated with the Industrial Internet of Things (IIoT) platform using the Node-RED platform in a water tank plant. By applying the trial and error tuning method to two control loops, namely the outer loop for level and the inner loop for flow, the system was able to achieve level control with a steady-state error of ±0.5 cm which is better than the results of previous studies using a single PID with a steady-state error of around ±0.7 cm. The system also showed good response time with optimal settling time (Ts) and rise time (Tr), and was able to withstand external disturbances effectively. IIoT integration provides added value in the form of real-time monitoring, remote control, and data logging that supports continuous and predictive evaluation of system performance. By combining the robustness of PLC for real-time multi-loop control and the flexibility of Node-RED in data management and visualization, this solution not only improves control precision and stability but is also in line with the demands of Industry 4.0. This research also opens up opportunities for the development of more adaptive and efficient control systems for industrial and educational applications. It is recommended for further testing on an industrial scale and the application of adaptive tuning methods so that system performance can be further optimized.

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Conceptualization, methodology, formal analysis, investigation, resources, data curation, and original draftwriting: A.S.R; validation, review and editing, and visualization: I.H., A.S., and D. R. All authors have read and approved the published version of themanuscript

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Conflicts of Interest
The author declares that there is no conflict of interest, either between the authors or with the research objects discussed in this paper.

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