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Greywater treatment system based on fuzzy logic control

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ABSTRACT

Greywater from households and public facilities represents a major source of untreated wastewater, carrying high microbial loads and variable chemical composition that threaten environmental and public health. Conventional treatment systems often lack adaptive control mechanisms capable of handling the dynamic fluctuations of greywater quality. This study presents the design and validation of an intelligent greywater treatment system that integrates real–time sensing with a Sugeno fuzzy logic controller to regulate pump and solenoid valve operation. The system continuously monitors pH, total dissolved solids (TDS), dissolved oxygen (DO), and ammonia (NH_3), and dynamically adjusts treatment cycles based on sensor feedback. Experimental deployment demonstrated significant improvements in effluent quality, with pH reduced from 9.04 to 8.08, TDS from 611.04 ppm to 393.96 ppm, and NH_3 from 0.52 ppm to 0.19 ppm, while DO increase from 2.52 mg/L to 6.07 mg/L. These results confirm that fuzzy logic–based control enhances system responsiveness and ensures effluent compliance under variable influent conditions. The proposed framework provides a scalable, cost-effective solution for decentralized wastewater management, advancing the development of intelligent treatment technologies for sustainable urban water systems.

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1. INTRODUCTION

Water has a percentage of around 71% on earth, with a division of around 96.5% being water in the ocean, 1.7% being water in the ground, and 1.7% being water in nature in the form of snow and glaciers [1]. Water consists of hydrogen (H) and oxygen (O) compounds with the formula H_2O, which are very important for living creatures on earth for survival and daily needs. Water quality must be maintained by respective standards to create a healthy and hygienic environment. Wastewater is residual water from activities or a business, which is divided into two, namely domestic and non-domestic wastewater. Domestic wastewater is wastewater that comes from household activities, offices, and public facilities [2], [3]. Domestic wastewater is one of the largest contributors to water pollution, accounting for around 50-80% of the total effluent discharged into the environment [1], [4], [5]. It is generally categorized into blackwater and greywater [6]. Greywater, which originates from household activities such as washing clothes and dishes, represents one to seven times the volume of blackwater and contains relatively low organic content compared to toilet wastewater [6], [7]. According to the Regulation of the Minister of Environment and Forestry of the Republic of Indonesia Number P.68/Menlhk-Setjen/2016, which establishes domestic wastewater quality standards to minimize environmental and health risks (Minister of Environment and Forestry, 2016), greywater is rich in soaps, detergents, suspended solids, and microbial populations that can deteriorate soil and vegetation quality, while also serving as a breeding ground for disease-causing microorganisms [8], [9]. If untreated, household wastewater must be managed within 24 hours due to its high organic load otherwise, it poses significant risks to both the environment and public health [8]–[11].

A wastewater treatment plant (WWTP) is an engineered system designed to remove contaminants from wastewater, enabling its safe reintroduction into the natural water cycle [8]. Treatment targets a wide spectrum of pollutants, including organic matter, suspended solids, pathogenic microorganisms, heavy metals, and hazardous chemicals, all of which pose environmental and public health risks if discharged untreated [10]. Through the integration of physical, chemical, and biological processes, WWTPs convert wastewater into effluent that meets regulatory standards, thereby protecting aquatic ecosystems and ensuring water quality for downstream users. This comprehensive treatment approach is central to sustainable water resource management and environmental protection.

The WWTP process typically involves two main stages. Primary treatment focuses on physical separation of solids through sedimentation and filtration [12]–[14]. Secondary treatment removes residual organic matter, dissolved solids, and biodegradable colloids primarily through aerobic biological processes, during which nitrogen, phosphorus, and pathogenic microorganisms are reduced [15], [16]. While effective, these conventional approaches face challenges in maintaining consistent treatment efficiency when wastewater characteristics fluctuate, as is often the case with greywater.

To strengthen compliance with regulatory requirements such as the Minister of Environment Regulation No. 68/Menlhk/Setjen/Kum.1/8/2016 [17], intelligent control strategies are increasingly being explored. This regulation specifies standards for key parameters including biochemical oxygen demand (BOD), total suspended solids (TSS), pH, and fat, oil, and grease (FOG), which must be reduced to acceptable limits before discharge [18]. Conventional static control methods are often inadequate in meeting these dynamic requirements, underscoring the need for adaptive, real-time control solutions.

Fuzzy logic offers an effective approach to managing such complexity. As a branch of artificial intelligence, fuzzy logic emulates human reasoning through algorithms capable of handling uncertainty and partial truths, assigning values within a continuum from 0 to 1 rather than rigid binary classifications [19]–[22]. This capability allows it to interpret and process imprecise or fluctuating data, making it well suited for wastewater management where parameter variability is high [20]. When applied through the Sugeno inference method, fuzzy logic enables precise decision-making by dynamically weighting multiple input parameters. This makes it particularly effective for real-time control of pumps and solenoid valves, ensuring that water is either recirculated for additional treatment or safely discharged when quality standards are achieved [23]. Building on these foundations, this study develops and validates a fuzzy logic-based intelligent control system for greywater treatment. The system integrates real-time monitoring of pH, total dissolved solids (TDS), dissolved oxygen (DO), and ammonia (NH_3), coupled with actuator control to maintain treated effluent within regulatory limits. Sensor calibration, actuator response testing, and full system evaluation are performed to demonstrate robustness, accuracy, and practical feasibility for decentralized domestic wastewater management.

2. METHOD

2.1. Development of greywater treatment plant prototype

The experimental setup consists of a compact two-tank greywater treatment system designed for both pretreatment and storage of treated effluent, as presented in Figure 1. Tank 1 functions as a pretreatment basin, while tank 2 stores the treated water prior to discharge. A recirculation mechanism is incorporated, allowing water from tank 2 to be redirected to tank 1 when quality standards are not met.

The treatment pathway includes a multi-layer filtration chamber with five media layers: i) silica sand for coarse filtration, ii) manganese for oxidation of dissolved metals, iii) active sand for fine particle removal, iv) activated carbon for adsorption of organics, and v) zeolite for ion exchange and polishing. This combination provides a progressive reduction of suspended solids, dissolved organics, and other contaminants prior to sensor-based evaluation. Both tanks are equipped with four calibrated sensors to monitor critical water quality parameters: pH, TDS, DO, and NH_3 gas. These sensors provide real-time data streams for intelligent control of the treatment process.

2.2. Intelligent control architecture

The system is governed by an adaptive control strategy that determines whether water in tank 2 should be discharged or recirculated. Conventional on–off control is used as the baseline, where actuators (pump and solenoid valve) operate between discrete states depending on whether individual parameters meet predefined setpoints. While straightforward, such binary logic can lead to oscillations, delayed responses, and inefficient pump operation under fluctuating greywater quality.

To enhance reliability and adaptability, a fuzzy logic controller based on the Sugeno inference method was developed. The controller simultaneously evaluates the four input parameters (pH, TDS, DO, and NH_3), assigning weighted priorities according to their relative environmental importance. Sensor measurements are continuously compared against predefined thresholds, and instead of relying solely on a simple error–setpoint calculation, the fuzzy controller applies rule-based reasoning to interpret deviations. The resulting decision outputs are converted into digital control signals for actuator operation.

If the effluent meets regulatory standards, the solenoid valve is triggered to release treated water into the environment. If not, the pump is activated to recirculate water from tank 2 back to tank 1 through the multi-layer filtration chamber, thereby subjecting it to further treatment. This closed-loop configuration enables iterative quality improvement until compliance is achieved. The overall system block diagram is illustrated in Figure 2, showing the interaction between sensors, controller, actuators, and the treatment unit.

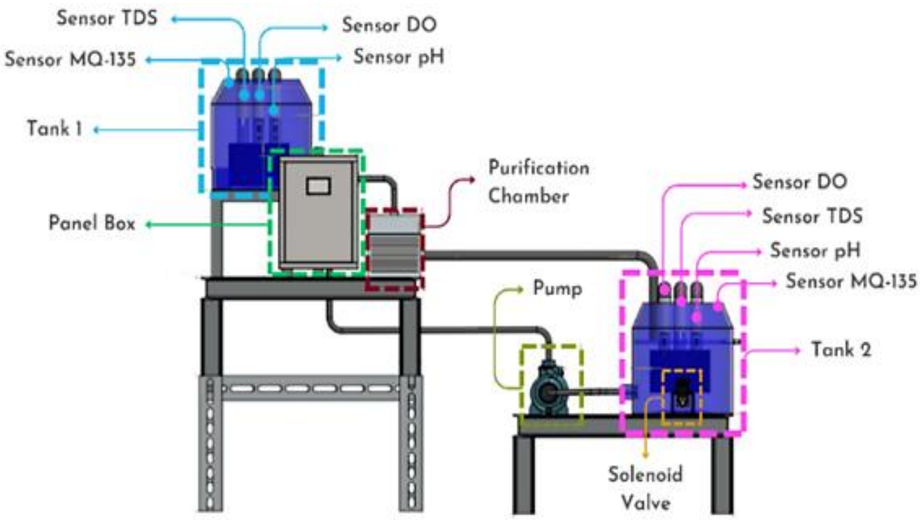


Figure 1. The prototype of the greywater treatment plant

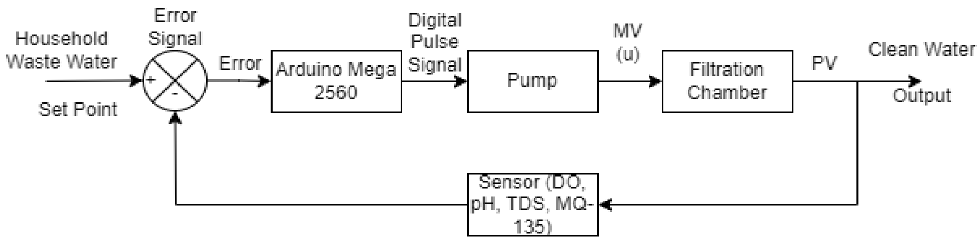


Figure 2. Block diagram of the intelligent control system for the greywater treatment prototype

2.3. Fuzzy logic controller design

This study employs a fuzzy logic controller based on the Sugeno inference method to regulate the greywater treatment process. The controller integrates four input variables (pH, TDS, DO, and NH_3 gas) and produces two binary outputs, namely the recirculation pump and the solenoid valve. The membership functions for each input variable were defined in three fuzzy sets of low, good, and high). According to regulatory guidelines and the typical characteristics of greywater. In the control scheme, the operational decisions for the pump and solenoid valve are determined by the fuzzy inference rules. When all input variables fall within the good range, the system assumes that the treated water meets the required standards; under these conditions, the pump remains inactive while the solenoid valve opens to allow discharge. Conversely, when one or more inputs deviate from the good range, the system interprets this as an indication of insufficient treatment, resulting in pump activation for recirculation while the solenoid valve remains closed. This decision-making structure ensures that the effluent complies with quality standards while minimizing unnecessary recirculation, thereby improving both treatment efficiency and energy utilization.

The membership functions for the four input variables were defined as follows. For pH, values under 6.5 were categorized as low, values between 6.5 and 8.5 as good, and values above 8.5 as high. For TDS, values under 200 ppm were low, 200-400 ppm were good, and above 400 ppm were high. For DO, concentrations under 4 mg/L were low, 4-8 mg/L were good, and above 8 mg/L were high. For NH_3, values under 1 ppm were low, 1-3 ppm were good, and above 3 ppm were high. The fuzzy logic controller uses these membership functions to govern two output variables: the recirculation pump and the solenoid valve. When all inputs fall within the good category, the pump is deactivated (OFF) and the solenoid valve is activated (ON), allowing discharge of treated water. If any input deviates from the good range, the pump is activated (ON) to recirculate the water, while the solenoid valve remains closed (OFF). This output structure ensures that only water meeting quality standards is released into the environment.

3. RESULTS AND DISCUSSION

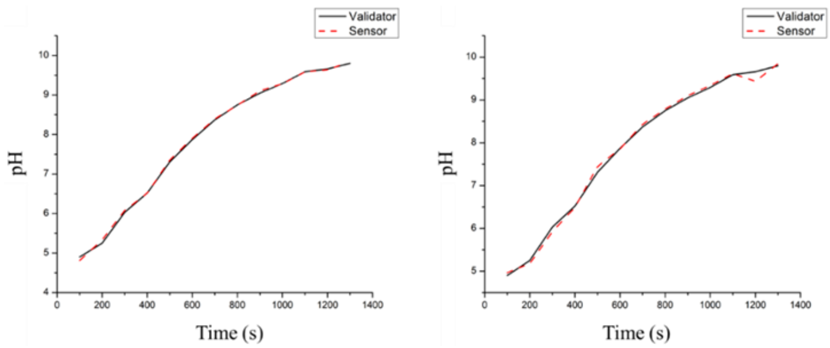
3.1. Sensor performance evaluation

Prior to deployment, all sensors were calibrated against certified standards to quantify measurement error and ensure accuracy, as these factors directly determine the reliability of the control system. Since each parameter involves distinct measurement principles, tailored calibration protocols were applied. The validation confirmed that all sensors achieved acceptable accuracy for real-time monitoring of greywater quality, although performance varied by sensor type.

The pH sensors in tank 1 and tank 2 were tested across a range of pH 5 to 10 over a 1,400-second period using representative greywater samples (Figure 3). Their readings were compared with those of a laboratory-grade pH meter. Both sensors showed excellent precision. The sensor in tank 1 (Figure 3(a)) recorded an average error of 0.94%, corresponding to 99.06% accuracy, while the sensor in tank 2 (Figure 3(b)) performed slightly better with an error of 0.55%, equivalent to 99.45% accuracy. These results confirm the sensors' suitability for detecting pH fluctuations, which are critical for both treatment efficiency and compliance with discharge regulations.

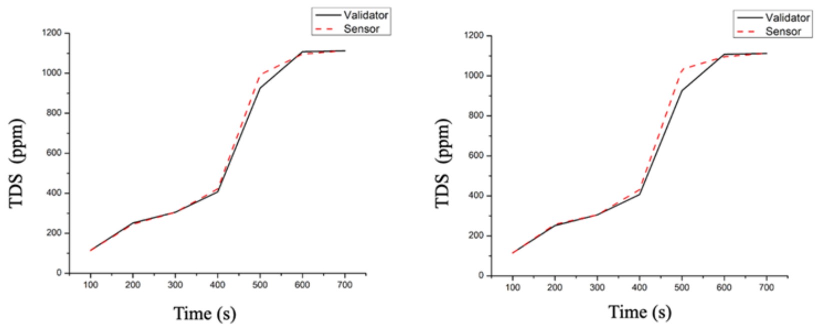
The TDS sensors were evaluated within the range of 0 to 1,000 parts per million (Figure 4). The sensor in tank 1 (Figure 4(a)) recorded an average error of 3.19% with 96.81% accuracy, whereas the sensor in Tank 2 (Figure 4(b)) demonstrated higher precision with 2.16% error and 97.83% accuracy. Although less accurate than the pH sensors, both TDS sensors maintained acceptable operational thresholds. Variations can be attributed to the heterogeneous nature of greywater, particularly the influence of soap residues and detergent salts on conductivity measurements.

The pH sensor test results for tank 1 (Figure 3(a)) and tank 2 (Figure 3(b)) demonstrate strong performance, with tank 1 exhibiting an average error of 0.94% (99.06% accuracy) and tank 2 showing even better precision with a 0.55% average error (99.45% accuracy). These measurements were validated against a standard pH reference over a 1,400-second (≈40-minute) testing period. Meanwhile, the TDS sensor tests conducted across a 0-1,000 ppm range using various greywater samples were evaluated for tank 1 (Figure 4(a)) and tank 2 (Figure 4(b)). Sensor readings were compared against a standard TDS validator to determine error margins and accuracy, ensuring reliability under different water conditions. The TDS sensor on tank 1 had an average error of 3.19% with an average accuracy of 96.81% and the TDS sensor on tank 2 had an average error of 2.16% with an average accuracy of 97.83%.



(a) (b)

Figure 3. pH sensor testing in (a) tank 1 and (b) tank 2

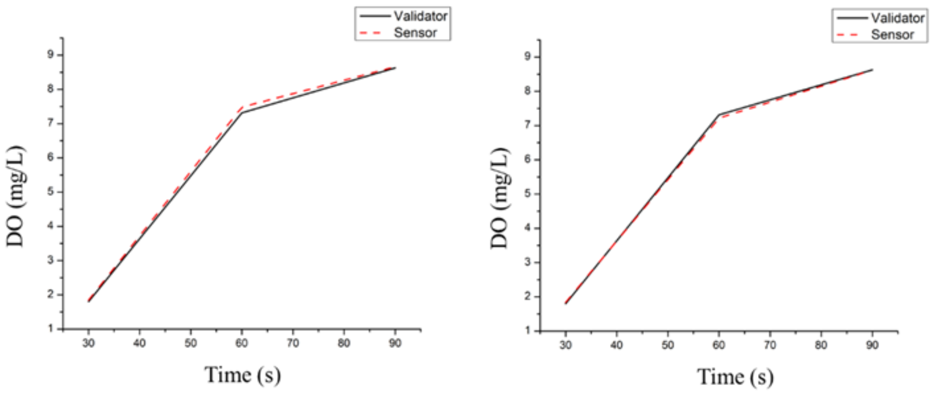


(a) (b)

Figure 4. TDS sensor testing in (a) tank 1 and (b) tank 2

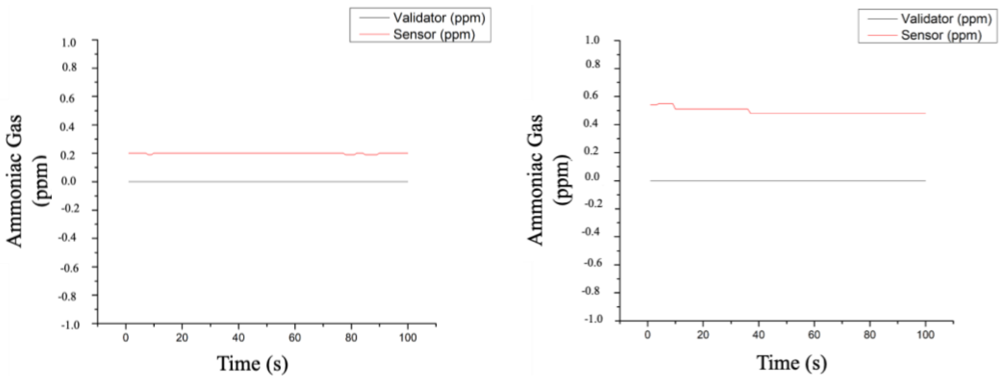
The DO sensors were tested across a range of 2 to 9 milligrams per liter (Figure 5). The sensor in tank 1 (Figure 5(a)) achieved an average error of 1.55% with 98.45% accuracy, while the sensor in tank 2 (Figure 5(b)) recorded 1.8% error with 98.2% accuracy. Both sensors provided stable and reliable performance within the operational range, confirming their robustness for continuous monitoring of biological treatment conditions.

In contrast, the ammonia gas sensors (MQ-135) displayed noticeable baseline drift at low concentration ranges (Figure 6). Despite the standard reference indicating zero ammonia, tank 1 (Figure 6(a)) consistently registered 0.2 ppm and tank 2 (Figure 6(b)) 0.5 ppm. This discrepancy suggests cross-sensitivity to other volatile compounds in greywater, a known limitation of MQ-135 technology. While the sensors are still effective in detecting relative changes in NH_3 concentrations, calibration offsets or signal correction algorithms will be required to enhance absolute accuracy in future iterations of the system.



(a) (b)

Figure 5. DO sensor testing in (a) tank 1 and (b) tank 2



(a) (b)

Figure 6. Ammoniac gas sensor testing in (a) tank 1 and (b) tank 2

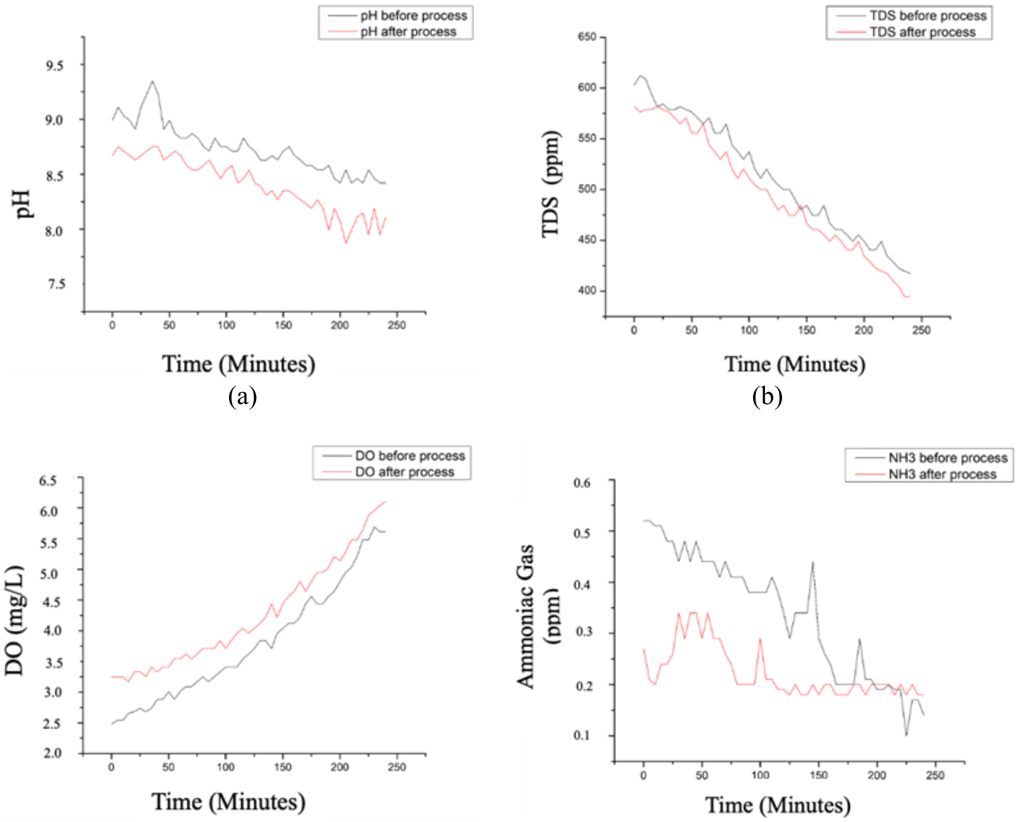
Collectively, the validation results demonstrate that the sensor array provides sufficient accuracy to support fuzzy logic control of the greywater treatment process. The pH and DO sensors exhibited the highest stability, the TDS sensors performed reliably despite greywater variability, and the ammonia sensors identified opportunities for refinement. These outcomes confirm that the intelligent greywater treatment system is grounded in dependable monitoring data, thereby ensuring robust and reliable operation.

3.2. Greywater treatment plant testing

Greywater treatment plant testing was performed by supplying household wastewater to tank 1, where sensors measured pH, TDS, DO, and NH_3 gas. The greywater then entered the purification chamber for filtration, after which the treated effluent was transferred to tank 2 for storage. At this stage, the same parameters were monitored. If the sensor readings did not meet the standard limits, the pump was activated to return the greywater to tank 1 for re-filtration. Once the measured values complied with the standards, the solenoid valve was activated to discharge the treated water into the environment.

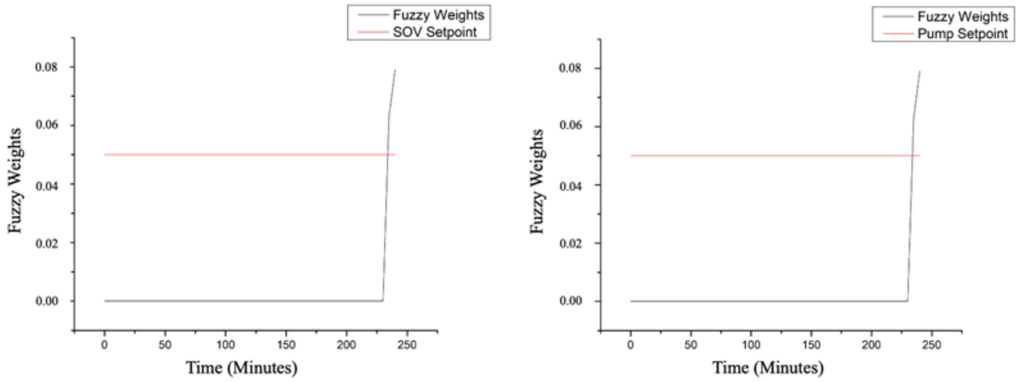
The entire process lasted approximately four hours under the fuzzy logic–based control system. As shown in Figure 7, the filtration process significantly improved water quality. The pH decreased from an initial value of 9.04 to 8.08 (Figure 7(a)) [24]. The TDS concentration decreased from 611.04-to 393.96 ppm (Figure 7(b)) [24]. The DO content increased from 2.52-6.07 mg/L (Figure 7(c)) [24]. The NH_3 concentration decreased from 0.52-0.19 ppm (Figure 7(d)) [25]. These results demonstrate the effectiveness of the fuzzy logic control system in enhancing water quality through automated monitoring and feedback-driven re-filtration.

The fuzzy control strategy also produced a dynamic response for the actuators during the four-hour operation. Figure 8 presents the response profiles of the solenoid valve and the pump. The solenoid valve was activated once the fuzzy weight value reached or exceeded 0.05, signifying that the water was suitable for discharge into the environment (Figure 8(a)). Conversely, the pump was deactivated when the fuzzy weight value reached or exceeded 0.05 (Figure 8(b)), preventing unnecessary re-filtration. This coordinated response highlights the reliability of the system in maintaining optimal treatment efficiency while minimizing energy consumption.



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

Figure 7. Testing result of the parameters before and after filtration (a) pH, (b) TDS, (c) DO, and (d) NH_3



(a) (b)

Figure 8. Dynamic response of (a) solenoid valve (SOV) and (b) pump

Together, these results demonstrate the robustness of the intelligent greywater treatment system. The synergy between sensor accuracy, actuator responsiveness, and fuzzy logic decision-making enabled consistent attainment of effluent quality standards while minimizing unnecessary reprocessing. This highlights the potential of fuzzy logic-based control to support decentralized, automated wastewater treatment systems that can adapt to variable influent conditions while ensuring compliance with environmental regulations.

4. CONCLUSION

This study demonstrated the successful development and validation of an intelligent greywater treatment system that integrates real–time monitoring with a fuzzy logic–based control framework. Sensor calibration confirmed reliable performance for pH, TDS, and DO, while identifying the need for further refinement of NH_3 detection, thereby ensuring dependable input data for decision-making. Actuator testing verified consistent responses of the solenoid valve and pump to dynamic sensor values, confirming the robustness of the control rules. When deployed in a prototype plant, the system achieved significant improvements in greywater quality, reducing pH from 9.04 to 8.08, lowering TDS from 611.04 ppm to 393.96 ppm, and decreasing NH_3 concentration from 0.52 ppm to 0.19 ppm, while DO increase from 2.52 mg/L to 6.07 mg/L. The findings highlight the potential of fuzzy logic control to enhance household wastewater treatment under fluctuating influent conditions. The system improved effluent parameters to meet discharge standards and demonstrated adaptive decision-making without reliance on complex mathematical models. This approach offers a scalable and cost-effective pathway toward smart, decentralized wastewater management, with future work focusing on long-term stability, advanced sensing integration, and field-scale deployment.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
I Putu Eka Widya Pratama	✓	✓							✓			✓	✓	✓
Muhammad Rasyid Ridha		✓		✓				✓	✓					
Anis Mahmuda Chafsah			✓		✓	✓			✓					
Akhmad Ibnu Hija		✓	✓			✓				✓	✓	✓		
Siti Nur Azella Zaine					✓	✓				✓		✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

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.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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