Gunung Djati Conference Series, Volume 61 (2025)
International Conference of the 17th OISAA's International Symposium Türkiye
ISSN: 2774-6585
Website: https://conferences.uinsgd.ac.id/

Data Quality in an IoT Sensor System for Water Quality: Demonstrated on Time-Dependent Water Temperature Fluctuations

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Abstract

The increasing demand for reliable and efficient Internet of Things (IoT) applications underscores the importance of ensuring high-quality sensor data for accurate monitoring and decision-making. This study focuses on data quality in an IoT sensor system for water quality monitoring, specifically demonstrated on time-dependent water temperature fluctuations. The system integrates fuzzy logic–based analysis and IoT connectivity using the Adafruit MQTT platform to enable real-time data acquisition, monitoring, and anomaly detection through smartphones, tablets, or computers. To ensure systematic development, the research employs the ADDIE methodology (Analysis, Design, Development, Implementation, Evaluation), enabling iterative refinement of both hardware and software components. Experimental results show that the system effectively captures temperature variations over time while identifying anomalies that may indicate sensor drift, environmental irregularities, or potential system faults. By addressing both measurement reliability and anomaly detection, this research contributes to improving data quality in IoT-based water monitoring systems, providing a scalable solution for sustainable water resource management and industrial applications.

Keywords: *Fuzzy Logic, ESP32, Internet of Things, PZEM004T, Power Factor, Water Temperature*

1. INTRODUCTION

Fuzzy logic represents a mathematical methodology designed to address uncertainty and ambiguity within complex systems by permitting truth values to exist within a continuum between absolute truth (1) and absolute falsehood (0)(Chen, 2013). This approach is grounded in modeling principles and decision-making processes that emulate human reasoning, particularly in situations where knowledge cannot be precisely articulated through conventional mathematical expressions. One of the notable applications of fuzzy logic in the field of electrical engineering is in power factor correction systems(Melin, 2014). Low power factors are associated with increased energy losses, elevated operational costs, and reduced efficiency of electrical equipment. Consequently, power factor correction systems employ control mechanisms based on fuzzy logic to enhance the power factor of the system, thereby achieving optimal performance and energy efficiency(Ma, 2019).

The application of fuzzy logic in power factor correction systems facilitates adaptive modeling and control in response to variations and uncertainties inherent in power grid loads and operational conditions(Benali et al., 2020). The implementation of fuzzy logic in such systems generally follows a structured sequence of steps. 1). Fuzzification: In this stage, input variables such as voltage, current, or the current power factor are transformed into membership values within predefined fuzzy sets by means of appropriate membership functions(Qiu, 2019), (Zhou, 2017). These functions determine the degree to which each input value corresponds to linguistic categories such as low, medium, or high. 2). Rule Base: A set of fuzzy inference rules, developed from expert knowledge or empirical research, is employed to relate input membership values to corresponding output values(Mendel, 2014). A typical fuzzy rule might take the form: "IF [input_1 is A] AND [input_2 is B], THEN [output is C]". 3). Fuzzy Inference System: This component is responsible for processing the fuzzy rules and combining them to infer output membership values. It aggregates the degrees of membership derived from the rules to determine the overall system response. 4). Defuzzification: In the final step, the resulting output membership values are converted into crisp, actionable signals. These signals are then used to control capacitors or other compensatory devices, thereby regulating the power factor of the system to align with desired performance levels(Benali et al., 2020).

One of the primary advantages of employing fuzzy logic in power factor correction systems is its inherent capability to manage uncertainty and non-linearity within complex electrical networks. Through the implementation of adaptive fuzzy control(Surya & Kustija, 2022), these systems are able to maintain efficient operation even under dynamic and fluctuating network conditions. However, similar to other applications of fuzzy logic, a notable limitation lies in the complexity associated with the interpretation and tuning of fuzzy rules. This process typically necessitates substantial domain expertise and experience to ensure optimal system performance(Kustija & Purnawan, 2022). Nevertheless, with ongoing advancements in computational technology and the development of increasingly sophisticated algorithms, the integration of fuzzy logic into power factor correction systems offers considerable potential for enhancing the efficiency and overall performance of power grids(Kustija et al., 2022).

This research aims to develop an electrical load monitoring and power factor correction system based on IoT and fuzzy logic, utilizing the Adafruit MQTT platform as its user interface dashboard(Nuratch, 2019). The system is designed to provide real-time monitoring and control of electrical load usage and power factor improvement through fuzzy logic, leveraging the capabilities of the NodeMCU ESP32 microcontroller and the Adafruit MQTT server(Kustija et al., 2022). The development process follows the Analysis, Design, Development, Implementation, Evaluation (ADDIE)(Anggala et al., 2022). The stages are as follows: 1). Analysis: A comprehensive literature review is conducted to examine the research background, identify challenges, and analyze existing systems. 2). Design: Based on the results of the analysis, a system architecture is formulated to support the integration of fuzzy logic control with IoT-based monitoring. The design includes hardware components such as the NodeMCU ESP32 microcontroller, sensors for measuring electrical parameters, and network configurations for connecting to the Adafruit MQTT server. Additionally, fuzzy logic control structures including membership functions and rule bases are designed to regulate the power factor based on real-time input data. 3). Development: Following the design phase, a functional prototype is developed. This involves assembling the hardware, coding the embedded system to process sensor data and execute fuzzy logic algorithms, and configuring the MQTT communication protocol for data transmission to the Adafruit dashboard(Kustija, Afifah, et al., 2024). The prototype is tested to ensure proper integration of all components, with a focus on achieving accurate monitoring and responsive control in real time(Surya & Kustija, 2023). 4). Implementation: The prototype is deployed on the research object, enabling real-time data acquisition and control over the monitored electrical loads(Kustija, Fahrizal, et al., 2024). The system's performance is validated in a real-world environment. 5). Evaluation: Feedback and performance data are gathered to evaluate the system's functionality, usability, and effectiveness. Insights from this evaluation are used to improve the system further(Hsieh et al., 2024). Internet of things is a concept in which objects or objects are implanted with technologies such as sensors and software with the aim of communicating, controlling, connecting and exchanging data through other devices while still connected to the internet(Kustija, Purnama, et al., 2023). The Internet of Things is a concept whereby an object has the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction(Cornetta et al., 2019).

The rapid development of the Internet of Things (IoT) has been driven by the convergence of several key technologies(Shi et al., 2024), including wireless communication, microelectromechanical systems (MEMS), internet connectivity, and Quick Response (QR) code technologies. In its early stages, IoT was frequently associated with Radio Frequency Identification (RFID) as a primary method of communication between devices(Akbar et al., 2024). Over time, IoT has evolved significantly, leading to the modernization of numerous electronic devices, transforming conventional systems into embedded systems that can be programmed with specific algorithms to enable remote monitoring and control capabilities.

In the context of industrial applications, this technological evolution has given rise to the Industrial Internet of Things (IIoT), which focuses on the integration of IoT technologies within industrial environments to enhance automation, monitoring, and data analysis. IIoT enables more efficient operations, predictive maintenance, and real-time control of industrial equipment, including power systems and energy management devices.

One of the platforms supporting this development is NodeMCU, an open-source IoT platform. NodeMCU hardware is based on the ESP32 system-on-chip (SoC) developed by Espressif Systems(Pravalika, 2019). It can be considered analogous to an Arduino board, but with integrated wireless communication features, including both Wi-Fi and Bluetooth(Somantri et al., 2025). The ESP32 microcontroller offers several advantages, including low cost, low power consumption, integrated Wi-Fi modules, dual-mode

Bluetooth, and advanced power-saving features, making it highly suitable for flexible and scalable IoT applications(Surya et al., 2023).

To facilitate communication between the IoT devices and users, this system employs the Adafruit MQTT service, a cloud-based MQTT broker tailored for IoT applications(Kustija, Surya, et al., 2023). Using Adafruit, the NodeMCU ESP32 can transmit and receive data remotely via the publish-subscribe communication model(Faro, 2020)(Kustija, Surya, et al., 2024). One of the key benefits of Adafruit MQTT is its user-friendly interface, which allows users to access real-time data and control functionalities directly through a web-based dashboard without requiring additional software installation(Kustija, Afifah, et al., 2023). Moreover, Adafruit offers a free tier for account creation and usage, making it an accessible and cost-effective solution for IoT system integration with the NodeMCU ESP32(Kustia et al., 2024).

2. RESEARCH METHOD

The research method employed in this study is the ADDIE approach, which stands for Analysis, Design, Development, Implementation, and Evaluation. This method is widely adopted in research and industrial contexts for the systematic development of products, tools, or equipment. Given that the output of this research is a functional prototype in the form of an IoT-based monitoring and power factor correction device, the ADDIE framework is deemed highly suitable for guiding the research process (see Figure 1). Each phase of the ADDIE model ensures structured progress, from identifying needs and designing solutions, to developing, implementing, and evaluating the final system to ensure it meets its intended objectives effectively.

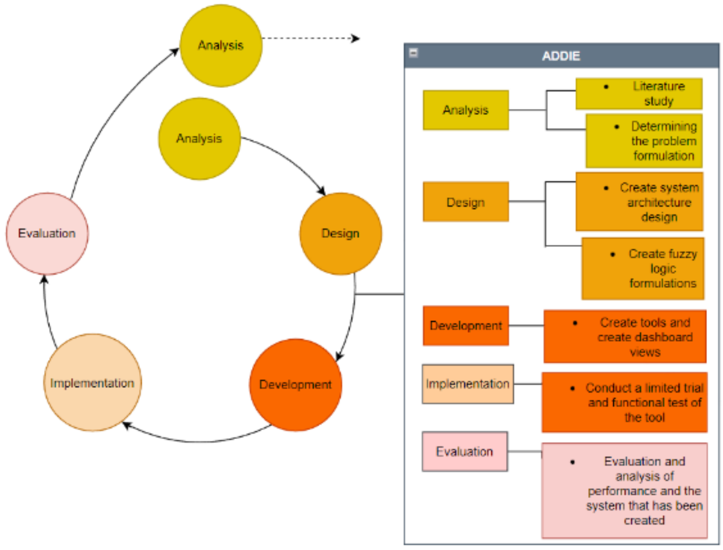

Figure 1. Research Method

2.1 Analysis Stage

The analysis stage serves as the initial step of this research, focusing on an in-depth literature study by observing, comparing, and reviewing previous studies published in both national and international journals. To strengthen the analysis process, VOSviewer software is utilized to visualize bibliometric data and identify relevant research clusters and trends. The outcomes from VOSviewer assist in pinpointing research gaps and formulating novelty. Based on the analysis results, it was found that previous studies had not explored the use of Adafruit MQTT as a user interface for monitoring electrical loads and improving power factor. This observation forms the basis for this study's novelty. Moreover, the analysis stage concludes with the formulation of the research problem, which serves as a reference for subsequent stages.

2.2 Design Stage

The design stage follows the analysis, translating insights from the literature review and problem formulation into a tangible system design. In this phase, a system architecture is developed, interconnecting the essential components required for tool realization. The architecture comprises three core components: (1) the user interface component, (2) the cloud and MQTT communication component, and (3) the load-side component. Additionally, material selection is conducted, identifying key hardware such as the PZEM-004T module, NodeMCU ESP32, relays, and power factor correction capacitors as critical elements for system operation. A fuzzy logic model is then designed, incorporating rule sets that will be implemented within the system to determine the appropriate capacitor activation based on the measured power factor. This model forms the core control mechanism, as illustrated in Figure 2.

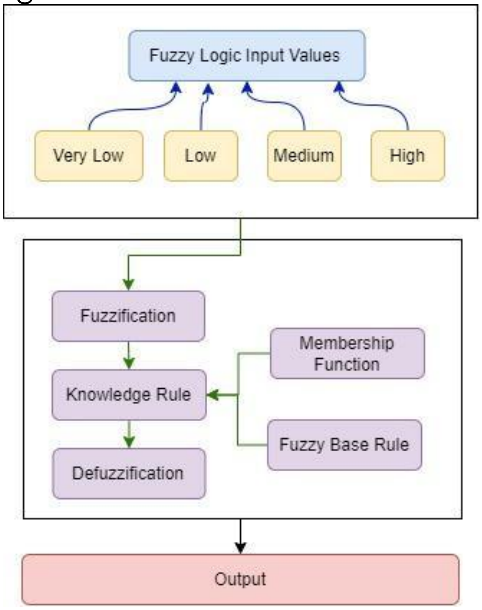

Figure 2. Fuzzy Inference System

2.3 Development Stage

The development stage constitutes the execution phase of the previously designed system. At this stage, the conceptual design is translated into a functional prototype by assembling the necessary hardware components and integrating them with the fuzzy logic control system. The initial development involved experimental testing using a single relay module connected to one power factor correction capacitor to validate the logic and control accuracy. Upon successful testing and validation of this initial setup, the system was expanded by integrating four relays, each connected to a separate capacitor, to accommodate multiple capacitor configurations for more dynamic and accurate power factor correction. This iterative development ensured that the system could be scaled up while maintaining stability and performance in real-time control and monitoring.

2.4 Implementation Stage

The implementation stage follows the completion of system development, during which the fully assembled prototype is tested and deployed under real electrical load conditions within a factory environment. This phase aims to evaluate the system's functionality in accordance with the established design specifications and to confirm its capability in improving power factor as well as enabling remote monitoring and control. The fuzzy logic controller is assessed for its responsiveness in real-time by determining the appropriate capacitor activation based on the input power factor values. Concurrently, the IoT-based interface, powered by the Adafruit MQTT dashboard, is evaluated for its effectiveness in transmitting data and control signals between the hardware and the user interface. Particular attention is given to the accuracy and consistency of the system's output as displayed on the Adafruit dashboard, ensuring intuitive and seamless interaction via web-based platforms accessible through smartphones, laptops, or tablets(Li, 2017). In addition to performance verification, a simulation of anomaly detection is conducted to test the system's ability to detect irregularities in electrical parameters, such as voltage, current, or power factor deviations, based on sensor data from the PZEM-004T module. These simulations are designed to emulate potential faults or inconsistencies in electrical machines. The system utilizes predefined thresholds and fuzzy logic-based evaluation to identify anomalies, triggering alerts or preventive actions accordingly(Nie et al., 2021). This implementation within an industrial setting demonstrates not only the system's ability to optimize power factor but also its capacity to enhance operational reliability through real-time anomaly detection and intelligent monitoring.

2.5 Evaluation Stage

The evaluation stage serves as the final phase in this research methodology, aimed at assessing the overall performance, accuracy, and usability of the developed system. This evaluation includes both technical testing and user-oriented assessments to ensure that the system meets predefined objectives and operates effectively in real-world applications. The system is evaluated based on several parameters, including the accuracy of fuzzy logic decisions, response time of the relay control, real-time data transmission reliability via the Adafruit MQTT platform, and the usability of the IoT-based user interface. In addition, an anomaly detection feature integrated into the system is evaluated for its ability to identify deviations in electrical parameters (voltage, current, and power factor) that may indicate malfunctions or inefficiencies in electrical machines. The system alerts users through the dashboard when values fall outside of predefined thresholds, enabling preventive maintenance and enhanced operational reliability.

3. RESULTS AND DISCUSSION

3.1 User Interface and Architecture Components

The user interface component represents the part of the system that allows end-users or technicians to interact with the system for monitoring and controlling purposes. Through this component, users can remotely monitor electrical parameters and perform power factor correction using a computer, laptop, smartphone, or tablet with internet connectivity (see Figure 3). The use of an IoT-based dashboard enables remote access, eliminating the need for technicians to be physically present at the control or monitoring panel. This capability significantly enhances operational efficiency, allowing for real-time control and monitoring of power factor conditions from virtually any location, thereby reducing downtime and increasing responsiveness.

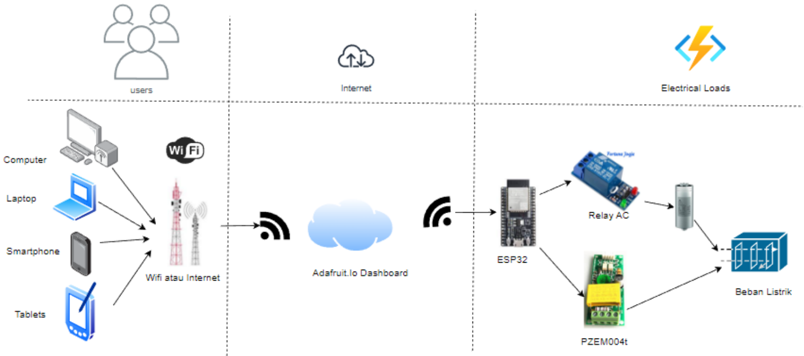

Figure 3. System Architecture

3.2 Internet System Components

The internet system component acts as the central communication bridge between the user interface and the electrical load components(Laksmi et al., 2022). Utilizing the Adafruit MQTT platform, this component facilitates the transmission of data between the hardware and the user dashboard(Zhou, 2018). Users can monitor key electrical parameters such as voltage, current, real power, apparent power, reactive power, and power factor through a web-based dashboard. Additionally, users can perform power factor correction by activating relays connected to power factor correction capacitors remotely via the dashboard's virtual push buttons. This seamless communication is essential for ensuring real-time interaction and control within the system.

3.3 Electrical Load Components

The electrical load component comprises the core hardware of the system, including the NodeMCU ESP32, which serves as the main microcontroller and communication interface. The NodeMCU ESP32 collects real-time data from the PZEM-004T module, a multifunction sensor capable of measuring voltage, current, real power, apparent power, reactive power, and power factor, and transmits this data to the Adafruit MQTT dashboard. In addition, AC 220V relays are utilized to control the operation of power factor correction capacitors by switching them on or off based on fuzzy logic decisions.

These components collectively ensure accurate measurement, control, and communication within the system.

3.4 Implementation System

Figure 4 illustrates the architecture of a cloud-based data monitoring and analytics system designed to support efficient and secure data access, processing, and visualization. The system consists of multiple integrated components, beginning from data generation at the office, which is connected to the internet via Base Transceiver Stations (BTS). These BTS towers provide wireless communication, facilitating real-time data transmission from on-site systems to the cloud infrastructure. The transmitted data is securely sent to the Cloud Web Portal, where it undergoes processing via the Analytics and Visualization Service. This service enables real-time analytics, graphical data representation, and user interaction. Data is stored in Cloud Storage, allowing scalable and reliable access, while ensuring data integrity and availability. Within the Cloud Computing Infrastructure, several backend processes run to support resource management and task execution.

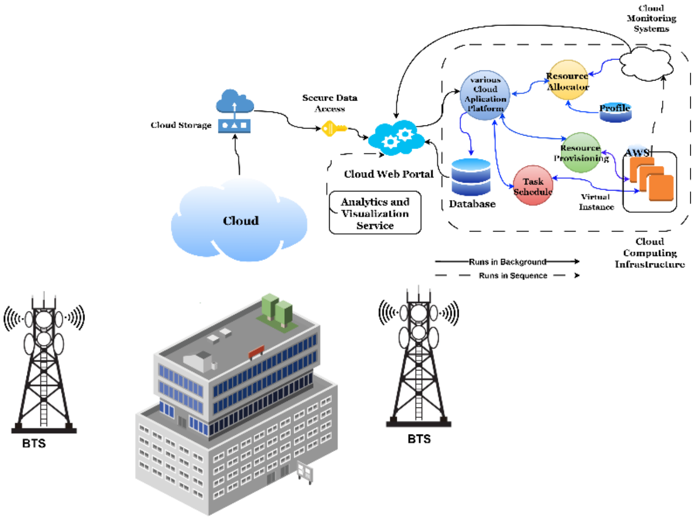

Figure 4. System Architecture Cloud for Seamless Data Flow and Smart Integration

The Cloud Monitoring System ensures that all cloud resources are operating efficiently. The Resource Allocator dynamically assigns computing resources based on system demands, while the Task Scheduler manages the sequence of operations and task executions. These services interact with various cloud application platforms, and provisioning of resources is handled via virtual instances through AWS (Amazon Web Services) or similar providers.

The database plays a central role in storing and retrieving data for application use, ensuring a seamless integration between the front-end user interface and the back-end cloud services. This entire architecture supports secure, scalable, and efficient data-driven decision-making, and is ideal for real-time monitoring, analytics, and system management from remote locations.

Figure 5 illustrates a two-phase anomaly detection framework designed for an IoT smart environment, focusing on monitoring and detecting anomalous network activities through machine learning techniques. The process begins within the IoT Smart

Environment, where network packets are captured using a packet sniffer. These packets are saved in PCAP format, which contains raw network traffic data. The next step involves a flow extractor that processes the PCAP files to derive meaningful flow features, which are then stored in a structured CSV file for further analysis (Wang, 2015).

In this phase, the system filters out benign (normal) activities and trains a Novelty Detection model to recognize standard behaviors. Simultaneously, the CSV data is used to sample both benign and anomalous activities to train an Outlier Detection model. These models are built to learn normal operational patterns and differentiate them from potentially harmful or unexpected behaviors. Once trained, both Novelty Detection and Outlier Detection models are deployed for real-time evaluation of new network data. Incoming traffic is processed similarly, and features are extracted and fed into the models. The Novelty Detection model continues to filter and detect new, previously unseen patterns, while the Outlier Detection model identifies deviations from established normal behaviors, indicating potential anomalies or cyber threats. This architecture enables proactive security monitoring and anomaly detection in IoT environments, improving system resilience against emerging threats without requiring constant human intervention.

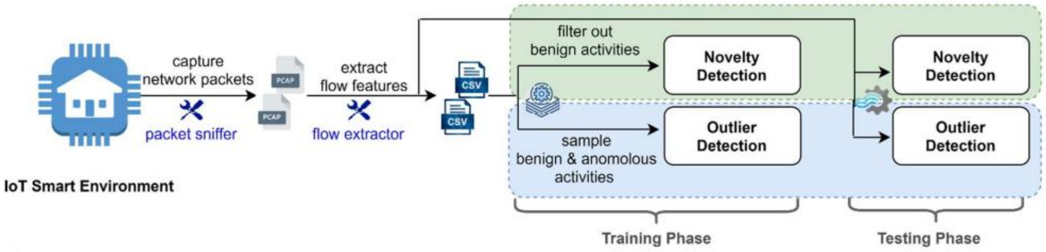

Figure 5. Two-Phase Anomaly Detection Framework

Figure 6 illustrates the results of anomaly detection applied to temperature sensor data in the context of an IoT-based industrial monitoring system. The blue line represents the temperature readings over time (indexed along the x-axis), while the red dots indicate the points identified as anomalies based on deviations from the expected pattern. The detection algorithm successfully highlights abnormal temperature values, which could signify potential faults or irregularities in machine operation or environmental conditions within the monitored system(Zhao et al., 2015). The anomaly detection process utilizes a trained model that distinguishes between normal and anomalous patterns, allowing for real-time identification of sensor data that falls outside the acceptable threshold. This capability is particularly critical in Industrial Internet of Things (IIoT) environments, where maintaining optimal machine temperature is essential for performance and safety. The identification of such anomalies enables preventive maintenance and reduces the risk of equipment failure, ultimately enhancing system reliability and operational efficiency. The visualization confirms that the anomaly detection system is effective in capturing outliers across the entire range of temperature readings, providing actionable insights for technicians and operators via the IoT dashboard interface.

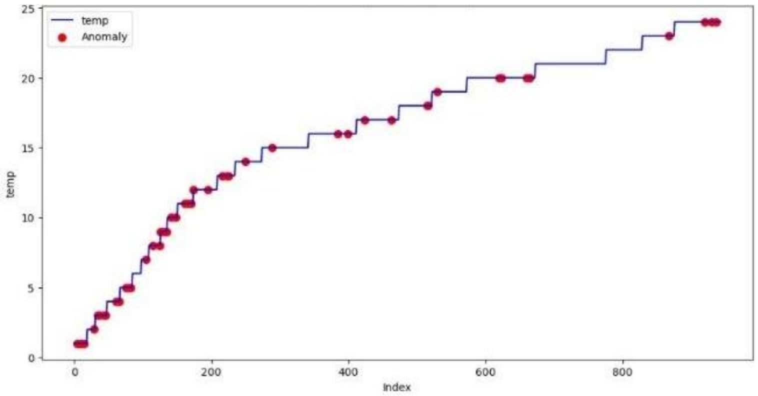

Figure 6. Anomaly Detection Results for Temperature

Figure 7 presents the anomaly detection results for out pressure data in an industrial IoT environment. The blue lines represent real-time pressure readings (labeled out pressure) across a range of data points indexed along the x-axis, while the red dots mark the detected anomalies instances where the pressure values deviate significantly from the established normal pattern. This visualization demonstrates the system's capability to handle high-frequency, fluctuating sensor data by effectively identifying pressure readings that are outside the expected operational range. These anomalies could indicate issues such as valve malfunctions, leaks, over-pressurization, or sensor errors, which require immediate attention to avoid system failures or safety hazards. The anomaly detection algorithm applied here utilizes advanced techniques to distinguish benign variations from critical deviations in pressure, ensuring that only meaningful anomalies are flagged for operator intervention. This capability is critical in automated monitoring scenarios, where rapid identification and response to pressure irregularities can prevent equipment damage and production downtime. Overall, the figure validates the effectiveness of the anomaly detection system in monitoring dynamic and complex sensor environments, enhancing predictive maintenance efforts and ensuring process stability in industrial applications.

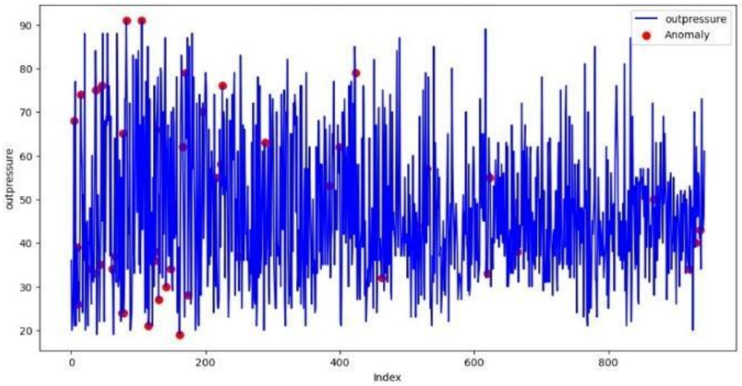

Figure 7. Anomaly Detection Results for Out Pressure

Figure 8 illustrates the Loss Curve (Anomaly Scores), which shows the relationship between the number of estimators and the resulting simulated loss during the anomaly detection process(Liu et al., 2021). The x-axis represents the number of estimators used in the detection model, while the y-axis indicates the corresponding simulated loss values. The blue curve represents the loss scores across different estimator counts, with the goal of minimizing loss while accurately detecting anomalies(Villegas et al., 2014). As observed, the loss initially fluctuates and increases slightly as the number of estimators increases, but it eventually converges to a stable value around -0.08, indicating optimal model performance beyond approximately 50 estimators. The red dashed line at y = 0 marks the threshold boundary. All loss values fall below this threshold, indicating that the anomaly scores remain within an acceptable and efficient detection range throughout the evaluated estimator counts. This figure is critical for model evaluation and tuning, helping to determine the optimal number of estimators for stable performance without overfitting or underfitting. By identifying the point at which additional estimators yield diminishing returns in reducing loss, the model can be optimized for efficient and accurate anomaly detection in IoT-based industrial environments.

4. CONCLUSION

This research successfully developed an IoT-based monitoring and power factor correction system using the ADDIE model, which provided a structured framework from analysis to evaluation. The novelty of this study lies in the integration of Adafruit MQTT as a user interface, enabling real-time monitoring and control of electrical loads through web-based platforms accessible on multiple devices. The prototype, built with NodeMCU ESP32, PZEM-004T sensors, and fuzzy logic control, demonstrated effective performance in optimizing power factor, dynamically activating capacitors, and ensuring reliable communication via MQTT. Implementation in a factory environment confirmed the system's ability to improve power factor, enhance operational efficiency, and support anomaly detection for preventive maintenance. Furthermore, evaluation results validated the system's accuracy, responsiveness, usability, and scalability, making it suitable for industrial applications in the context of smart energy management and Industrial IoT (IIoT). Overall, this research contributes a practical, intelligent, and innovative solution for improving power efficiency and reliability in modern industrial environments.

REFERENCE

Akbar, M. A. H., Fahrizal, D., Kustija, J., & Surya, I. (2024). Digital Technology Integration in TVET for Tourism: A Case Study for an Android-Based Application Development and Implementation. *9th International STEM Education Conference, ISTEM-Ed 2024 - Proceedings*, 1–6. https://doi.org/10.1109/iSTEM-Ed62750.2024.10663108

Anggala, A., Teresa, Cipta, Y. H., Maulana, F. I., & Wijaya, I. B. A. (2022). Augmented Reality Design Using the ADDIE Model as An Introduction to Kindergarten Interior Interactive Elements. *2022 4th International Conference on Cybernetics and Intelligent System, ICORIS 2022*. https://doi.org/10.1109/ICORIS56080.2022.10031339

Benali, A., Khiat, M., & Denai, M. (2020). Voltage profile and power quality improvement in photovoltaic farms integrated medium voltage grid using dynamic voltage restorer. *International Journal of Power Electronics and Drive Systems*, *11*(3), 1481–1490. https://doi.org/10.11591/ijpeds.v11.i3.pp1481-1490

Chen, S. (2013). Solar radiation forecast based on fuzzy logic and neural networks. *Renewable Energy*, *60*, 195–201. https://doi.org/10.1016/j.renene.2013.05.011

Cornetta, G., Touhafi, A., Togou, M. A., & ... (2019). Fabrication-as-a-service: A web-based solution for STEM education using internet of things. *IEEE Internet of Things* …. https://ieeexplore.ieee.org/abstract/document/8915690/

Faro, A. (2020). ESP32 based edge devices to bridge smart devices to MQTT broker for healthcare purposes in the COVID scenario. In *PECCS 2020 - Proceedings of the 10th International Conference on Pervasive and Parallel Computing, Communication and Sensors* (pp. 30–41). https://api.elsevier.com/content/abstract/scopus_id/85107931349

Hsieh, Y. K., Hsieh, J. W., Hu, W. C., & Tseng, Y. C. (2024). AIoT-Based Shrimp Larvae Counting System Using Scaled Multilayer Feature Fusion Network. *IEEE Internet of Things Journal*, *11*(22), 36438–36451. https://doi.org/10.1109/JIOT.2024.3410539

Kustia, J., Fahrizal, D., & Surya, I. (2024). *Mecha-Learn: Innovative Learning Media for Mechatronics to Improve Technological in the SDGs Era* (Issue Veic 2023). Atlantis Press SARL. https://doi.org/10.2991/978-2-38476-198-2_69

Kustija, J., Afifah, A. U., Fahrizal, D., & Surya, I. (2024). Solutions to Improve Performance of IoT-Based Air Quality Monitoring System to Achieve The Sustainable Development Goals in Indonesian. *E3S Web of Conferences*, *484*. https://doi.org/10.1051/e3sconf/202448403006

Kustija, J., Afifah, A. U., Hasbullllah, & Surya, I. (2023). Solutions to Preventing Mistake in Building Electrical Installation and Maintenance In Urban Area Based on Skills Training. *Community Service Journal*, *4*(2), 100–107.

Kustija, J., Fahrizal, D., Nasir, M., Setiawan, D., & Surya, I. (2024). Design and development of coastal marine water quality monitoring based on IoT in achieving implementation of SDGs. *Indonesian Journal of Electrical Engineering and Computer Science*, *36*(3), 1470–1484. https://doi.org/10.11591/ijeecs.v36.i3.pp1470-1484

Kustija, J., Purnama, I., Surya, I., & Fahrizal, D. (2023). Wireharness continuity test equipment design microcontroller-based aircraft module and atmega328p NRF24l01 + Wireless. *International Journal of Science and Technology Research Archive*, *04*(2), 1–11. https://doi.org/https://doi.org/10.53771/ijstra.2023.4.2.0056

Kustija, J., & Purnawan. (2022). Solutions To Overcome Inequality in Laboratory Facilities and Laboratory Sharing in Similar Institutions Remote Laboratory Based. *Journal of Engineering Science and Technology*, *17*(3), 1792–1809.

Kustija, J., Surya, I., Akbar, M. A. H., & Fahrizal, D. (2024). Utilization of Remote Laboratory as STEM Implementation (Case Study of Mechatronics Competency). *9th International STEM Education Conference, ISTEM-Ed 2024 - Proceedings*, 1–6. https://doi.org/10.1109/iSTEM-Ed62750.2024.10663163

Kustija, J., Surya, I., & Fahrizal, D. (2022). Design of automated power factor monitoring and repair tool for industry in real time based on Internet of Things. *International Journal of Science and Technology Research Archive*, *02*(03), 0–7. https://doi.org/https://doi.org/10.53771/ijstra.2022.3.2.0106

Kustija, J., Surya, I., & Fahrizal, D. (2023). ELECTRICAL ENERGY SAVINGS BY UTILIZING INTERNET-BASED AUTOMATIC. *International Journal of Engineering Applied Sciences and Technology*, *7*(10), 144–150. https://www.ijeast.com/papers/144-150, Tesma0710,IJEAST.pdf

Laksmi, I. C., Hatta, P., & Wihidayat, E. S. (2022). A Systematic Review of IoT Platforms in Educational Processes. In *Proceedings of the International* …. ieomsociety.org. https://ieomsociety.org/proceedings/2022istanbul/1063.pdf

Li, H. (2017). Adaptive Fuzzy Control of Stochastic Nonstrict-Feedback Nonlinear Systems with Input Saturation. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *47*(8), 2185–2197. https://doi.org/10.1109/TSMC.2016.2635678

Liu, Z., Nie, Y., Long, C., Zhang, Q., & ... (2021). A hybrid video anomaly detection framework via memory-augmented flow reconstruction and flow-guided frame prediction. *Proceedings of the IEEE …*. https://openaccess.thecvf.com/content/ICCV2021/html/Liu_A_Hybrid_Video_Anomaly_Detection_Framework_via_Memory-Augmented_Flow_Reconstruction_ICCV_2021_paper

Ma, H. (2019). Adaptive Fuzzy Event-Triggered Control for Stochastic Nonlinear Systems with Full State Constraints and Actuator Faults. *IEEE Transactions on Fuzzy Systems*, *27*(11), 2242–2254. https://doi.org/10.1109/TFUZZ.2019.2896843

Melin, P. (2014). Edge-Detection Method for Image Processing Based on Generalized Type-2 Fuzzy Logic. *IEEE Transactions on Fuzzy Systems*, *22*(6), 1515–1525. https://doi.org/10.1109/TFUZZ.2013.2297159

Mendel, J. (2014). General type-2 fuzzy logic systems made simple: A tutorial. *IEEE Transactions on Fuzzy Systems*, *22*(5), 1162–1182. https://doi.org/10.1109/TFUZZ.2013.2286414

Nie, L., Lin, C., Liao, K., Liu, S., & ... (2021). Unsupervised deep image stitching: Reconstructing stitched features to images. *IEEE Transactions on …*. https://ieeexplore.ieee.org/abstract/document/9472883/

Nuratch, S. (2019). Applying the MQTT protocol on embedded system for smart sensors/actuators and IoT applications. In *ECTI-CON 2018 - 15th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology* (pp. 628–631). https://doi.org/10.1109/ECTICon.2018.08619981

Pravalika, V. (2019). Internet of things based home monitoring and device control using Esp32. *International Journal of Recent Technology and Engineering*, *8*(1), 58–62. https://api.elsevier.com/content/abstract/scopus_id/85069903437

Qiu, J. (2019). Observer-Based Fuzzy Adaptive Event-Triggered Control for Pure-Feedback Nonlinear Systems with Prescribed Performance. *IEEE Transactions on Fuzzy Systems*, *27*(11), 2152–2162. https://doi.org/10.1109/TFUZZ.2019.2895560

Shi, J., Chen, X., Zhang, Y., Chen, X., & Pan, C. (2024). Joint Optimization of Task Offloading and Resource Allocation in Satellite-Assisted IoT Networks. *IEEE Internet of Things Journal*, *11*(21), 34337–34348. https://doi.org/10.1109/JIOT.2024.3398055

Somantri, M., Fauzan, M. R., & Surya, I. (2025). Optimization of IoT-based monitoring system for automatic power factor correction using PZEM-004T sensor. *Indonesian Journal of Electrical Engineering and Computer Science*, 39(2), 860. https://doi.org/10.11591/ijeecs.v39.i2.pp860-873

Surya, I., & Kustija, J. (2022). Implementation of the Electricity Load Monitoring Trainer and Internet of Things-based Power Factor Improvement. *International Journal of Scientific and Research Publications*, *12*(11), 206–215. https://doi.org/10.29322/IJSRP.12.11.2022.p13127

Surya, I., & Kustija, J. (2023). Dashboard for Industrial Load Control and Remote Power Factor Correction Based on Adafruit ' s MQTT. *Buletin Ilmiah Sarjana Teknik Elektro*, *5*(1), 76–85.

https://doi.org/10.12928/biste.v5i1.7494

Surya, I., Kustija, J., Eka Pawinanto, R., Pramudita, R., Adli Rizqulloh, M., Wahyudin, D., & Haritman, E. (2023). Sistem monitoring beban listrik dan perbaikan faktor daya menggunakan PZEM004T dan dashboard Adafruit berbasis IoT. *JITEL (Jurnal Ilmiah Telekomunikasi, Elektronika, Dan Listrik Tenaga)*, *3*(3), 235–246. https://doi.org/10.35313/jitel.v3.i3.2023.235-246

Villegas, V. M., Capó, H., Cavuoto, K., McKeown, C. A., & Berrocal, A. M. (2014). Foveal structure-function correlation in children with history of retinopathy of prematurity. *American Journal of Ophthalmology*, *158*(3), 508-512.e2. https://doi.org/10.1016/j.ajo.2014.05.017

Wang, T. (2015). Adaptive Fuzzy Backstepping Control for A Class of Nonlinear Systems with Sampled and Delayed Measurements. *IEEE Transactions on Fuzzy Systems*, *23*(2), 302–312. https://doi.org/10.1109/TFUZZ.2014.2312026

Zhao, C., Wang, Y., Qi, B., & Wang, J. (2015). Global and local real-time anomaly detectors for hyperspectral remote sensing imagery. In *Remote sensing*. mdpi.com. https://www.mdpi.com/2072-4292/7/4/3966

Zhou, Q. (2017). Adaptive Fuzzy Control of Nonlinear Systems with Unmodeled Dynamics and Input Saturation Using Small-Gain Approach. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *47*(8), 1979–1989. https://doi.org/10.1109/TSMC.2016.2586108

Zhou, Q. (2018). Prescribed Performance Observer-Based Adaptive Fuzzy Control for Nonstrict-Feedback Stochastic Nonlinear Systems. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *48*(10), 1747–1758. https://doi.org/10.1109/TSMC.2017.2738155