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Preface

Jurnal Ecotipe (Electronics, Control, Telecommunication, Information, and Power Engineering), published by the Department of Electrical Engineering at Bangka Belitung University, is accredited by the Ministry of Higher Education, Science, and Technology of the Republic of Indonesia—covering the period from Volume 12, Number 1 (April 2025) through Volume 16, Number 2 (April 2029)—based on Decree No. 295/C/C3/KPT/2026, attaining a Rank of 2 (SINTA2). Hopefully, in the future, Jurnal Ecotipe can improve the quality and quantity of publishing quality scientific articles and improve its accreditation ranking

Currently, Jurnal Ecotipe volume 13, issue 2, October 2026, has been published. In this edition, the journal articles are entirely in English and consist of 20 articles by authors from outside the institution, numbered from pages 161-357. Hopefully, in the future, articles included in the journal's next edition will come from outside academia, both domestically and internationally.

Our highest appreciation goes to the Reviewers, Editorial Board, Authors, and all parties involved in the preparation and publication of the Jurnal Ecotipe volume 13 issue 2 October 2026. Hopefully, this journal can provide benefits and add scientific insight into the field of Electrical Engineering in particular and engineering in general. Therefore, we still hope for suggestions and constructive criticism for improvements and improvements for the progress of this journal.

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Table of Content

Editorial Board & Preface Table of Content

i
ii

Performance Evaluation of a Machine Learning for Image-Based Waste Management Using Convolutional Neural Networks <i>Dandy Cahyo Purnomo, Eka Aprilia Saputri, Ahmad Hasib Satiri, Luluk Khatimah, Hartono</i>	161-168
Android-Based Smart Centrifuge with PID Speed Control <i>Roichatun Nashichah, Deenda Putri Duta Natalia, Muhammad Kashif</i>	169-179
Parasitic Ringing Suppression in FPGA-Controlled Three-Phase Voltage Source Inverter Using RC Snubber Circuit <i>Angga Wahyu Aditya, Fathur Zaini Rachman, Andi Sri Irtawaty, Desak Made Ristia Kartika, Indra Ferdiansyah, Muhammad Rizani Rusli</i>	180-190
Fuzzy Expert System for Condition Assessment of Medium-Voltage Distribution Cable Insulation in Saline Environments <i>Saepul Rahmat, Riyani Prima Dewi, Erna Alimudin</i>	191-201
Development and Diagnostic Performance Evaluation of A Wireless Digital Fetal Heart Rate Monitoring System Using Ultrasonic Doppler with Digital Filter-Based Noise Reduction <i>Muhammad Ridha Mak'ruf, Roichatun Nashichah, Lusiana, Verry Angriawan</i>	202-211
Single-Camera Flood Monitoring Using YOLOv5 for Water Level and Turbidity Detection <i>Gamma Aditya Rahardi, Sherly Apta Maharani, Hasanur Mohammad Firdausi, Satryo Budi Utomo, Dani Hari Tunggal Prasetyo</i>	212-221
Adaptive PLC Scan-Time Optimization in a Unified PLC–SCADA Architecture <i>Yuda Bakti Zainal</i>	222-232
Low-Cost AIS Vessel Tracking System for Real-Time Web Visualization Using Software Defined Radio and Leaflet.js <i>Inka Trisna Dewi, Tri Budi Santoso, Rini Satiti, Fabria Alieftya Yusvianti, Nafilah Aqlatuz Zuhroh</i>	233-242
Design and Implementation of an IoT-Based Web Server System for Real-Time Vital Signs Monitoring <i>Alamsyah, Tan Suryani Solli, Catur Prasetyo, Mohammed Ikhlayel</i>	243-250
Voltage–Frequency Stability of a 300W Portable Cross-Flow Pico-Hydropower System under Low-Flow Conditions <i>Zulka Hendri, Akbar Abadi, Wiwik Wiharti, Yudia Meka Seftiani</i>	251-260
Performance Comparison of RTL-SDR and HackRF as ADS-B Signal Receivers at 1090 MHZ <i>Sholihin, Siswandi, Eka Susanti, Herman Yani, Sopian Soim</i>	261-270
Design and Performance Evaluation of a Hybrid Photovoltaic System Integrated with Battery Storage and Utility Grid for Residential Applications <i>Muhammad Reza Fahlevi, Syah Alam, Dianing Novita Nurmala</i>	271-282
Implementation of On-Device Convolutional Neural Network Inference for Indoor Occupancy Detection on the ESP32-S3 <i>Ade Aditya Ramadha, Felix Corputty, Naufal Hanan Lutfianto</i>	283-292
Adaptive Grasp Force Control for Robotic Gripper Based on Force Sensitive Resistor Sensor <i>Riky Tri Yunardi, Nasa Zata Dina, Deny Arifianto, Muchamad Sholakhuddin Al Fajri, Celya Intan Kharisma Putri</i>	293-302
Comparing Deep Learning and Ensemble Models for Photovoltaic Power Forecasting <i>Edris Shamsulhaq and Fikri Arif Wicaksana</i>	303-312
Evaluation of STIESIA E-Learning User Experience Using User Experience Questionnaire in the Implementation of Blended Learning <i>Achmad Fakhri Dzulfikar</i>	313-320
Optimal Solar PV Capacity Planning in Bangka Power System using Grey Wolf Optimizer <i>Wahri Sunanda, Rika Favoria Gusa, Euis Asriani, Firllya Rosa</i>	321-330
Intelligent Mobile-Spatial System for Small Business Digital Innovation in Lubuk Linggau <i>A. Taqwa Martadinata, Joni Karman, Herman Paleni, Aprilia Nadiella, Ariel Pratama</i>	331-340
Design and Development of a Smart Energy Management System Based on Hybrid Demand Side Management for 1100 Wp Off Grid Solar Power Plant Battery Optimization <i>Rivael Glenvil, Henry Candra, Dianing Novita N.P.</i>	341-347
Review on Resilience-Oriented Strategies Power Systems Facing Extreme Natural Disaster <i>Arfita Y Dewi, Adrianti, Muhammad Nasir, Asnal Effendi</i>	348-357

Performance Evaluation of a Machine Learning for Image-Based Waste Management Using Convolutional Neural Networks

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ABSTRACT

Waste management is still a significant environmental problem, especially in developing countries with high population density. The waste sorting process, which is still mostly done manually, causes low efficiency and consistency of sorting. Previous studies generally focused on binary classification, while research on lightweight CNN architectures for multi-class waste classification, particularly in simulation-based scenarios with per-class performance analysis, remained relatively limited. This study aims to evaluate the performance of the waste image classification model using a lightweight Convolutional Neural Network architecture, namely MobilNetV2 based on the transfer learning approach. The dataset used consists of four categories of waste (metal, plastic, paper, organic) obtained from public datasets. The flow of this research includes the dataset collection stage, preprocessing in the form of resize and rescale, training model and evaluation model using accuracy, confusion matrix, precision, recall, and F1-Score metrics. The test results showed that the model achieved an accuracy of 92.02% with relatively consistent performance in each class. The misclassification that appears is limited and shows a similar pattern between classes. These findings show that MobileNetV2 is able to provide stable classification performance and has the potential to be used as a supporting model in the development of automated waste sorting systems in the future.



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1. INTRODUCTION

Waste management is one of the environmental problems that is still a challenge in various countries. The world's waste is expected to increase to 3.4 billion tonnes per year by 2050, with most of it generated in developing countries that lack the infrastructure to recycle waste and divert resources to collect it [1]. Indonesia is one of the most densely populated developing countries. Population growth and increased public consumption activities contribute to the increase in the volume of household waste every year [2].

One of the important stages in waste management is the process of sorting by material type, such as organic waste, plastic, paper, and metal, which aims to support recycling and advanced processing

processes more effectively. In practice, the waste sorting process is still mostly done manually. This method requires a lot of time and effort and relies heavily on human precision so that many are still unable to sort waste properly. Technologies such as bins that can automatically separate waste were developed to address this problem [3]. One of the findings of waste image classification provides a new direction for waste classification problems is the use of Convolutional Neural Network (CNN) to train waste image classification models [4]. The model is trained to recognize different types of waste through visual analysis such as color, shape, and texture.

In several studies, deep learning, especially Convolutional Neural Networks, has been used for digital image-based waste classification. Compared to conventional methods that rely on manual sorting, this method has proven to be effective in extracting visual features automatically and improving classification accuracy [5]. As demonstrated by Zheng et al., the integration on lightweight CNN architecture with an attention mechanism is highly effective for achieving accurate object localization, particularly in identify the spatial position of insect pests[1].

In addition, a deep learning approach has also been used in smart and sustainable urban waste management; This shows that the classification of waste based on images is still relevant and constantly evolving [7]. However, some previous research has still concentrated on the use of binary systems or classifications. Meanwhile, studies evaluating the performance of light CNN architecture in simulation-based multi-class waste classification scenarios with performance analysis per class are still relatively limited.

Based on the research gap, this study aims to evaluate the performance of the MobileNetV2 architecture in conducting multi-class classification of image-based waste in a simulation scenario. The evaluation was carried out using accuracy, precision, recall, and F1-score metrics to analyze the consistency and balance of model performance in each waste class. This research is expected to contribute in the form of a deeper understanding of the capabilities and limitations of MobileNetV2 as a lightweight classification model, as well as its potential to be used as a supporting module in the development of intelligent waste management systems in future research.

2. RESEARCH METHOD

This study uses the *applied experimental research* method with the Convolutional Neural Network *model transfer learning approach* for the classification of waste images. This method aims to evaluate the performance of the machine learning model in classifying images into four categories of waste based on test data. The experimental approach was chosen because it allows for controlled measurement of model performance through quantitative metrics as well as prediction error analysis. The results of the model's performance measurement are expected to be able to be implemented as an intelligence component in the automatic waste classification system. The research workflow is illustrated in **Figure 1**. First, the dataset is collected and categorized into four classes: metal, plastic, paper, and organic. The dataset is subsequently partitioned into three subsets: 80% for training, 10% for validation to prevent overfitting, and 10% for testing. Prior to training, preprocessing is applied through resizing and rescaling to standardize image dimensions and normalize pixel values. The MobileNetV2 architecture is then trained on the prepared subsets, after which model evaluation is conducted to assess classification performance.

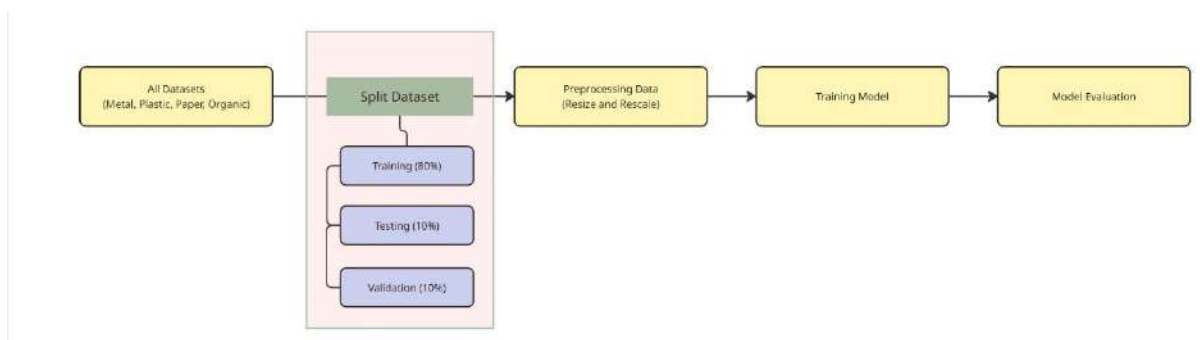


Figure 1. Research workflow

2.1. Dataset Collection

The dataset was taken from the Kaggle public dataset [2][3], which was divided into four categories, namely metal, organic, paper and plastic with a total of 410 in each class. The images are taken from various angles with diverse backgrounds. The dataset is then stratified into 80% for data training, 10% for testing, and 10% validation. Table 1 shows the distribution of the dataset ratios used. An example of the dataset used is in “Figure 2”. Due to the limitations of the dataset, an augmentation technique was carried out to increase the variety of the dataset, namely in the form of random horizontal or vertical reversals with a rotation of 15° [4].

Table 1. Dataset distribution

	Total	Train (80%)	Test (10%)	Val (10%)
Metal	410	328	41	41
Organic	410	328	41	41
Paper	410	328	41	41
Plastic	410	328	41	41
	1.640	1.312	164	164

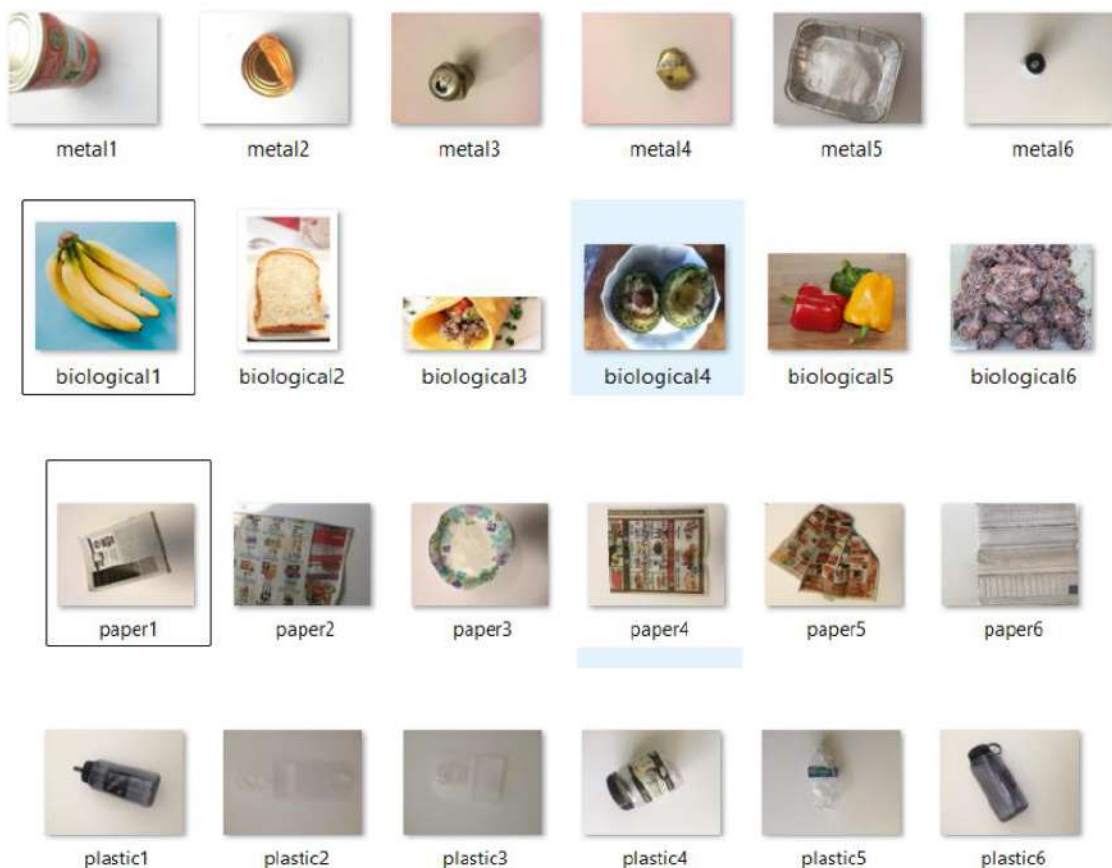


Figure 2. Example of the dataset used in the study is divided into four classes, namely metal, organic, paper and plastic

2.2. Preprocessing Data

Image preprocessing is done by resize the entire image size to 224 x 224 pixels to meet the input layer specifications of the MobilNetV2 architecture. This process is important in the data preprocessing stage because it ensures that the neural network can process each image consistently without changing

its key visual features [5]. Furthermore, the pixel value is normalized to a floating value of 0 to 1 to accelerate the convergence of the training process [6].

2.3. Training Model

The model runs on the MobilNetV2 architecture. The MobilNetV2 was chosen because it is lightweight and can balance performance and computing efficiency [7]. The MobileNetV2 model is initialized from ImageNet, which is transfer learning so that the model can leverage knowledge from big data such as ImageNet to improve image classification tasks [13].

The model was trained using the Adam optimizer with a learning rate of 0.0001, a batch size of 32, and a number of epochs of 20. The relatively small learning rate selection aims to ensure that the weight update process takes place stably at the classification layer. During the training process, data augmentation is applied to the training data to improve visual variation of the image. This augmentation is based on the ImageDataGenerator class provided by the Keras deep learning neural network library [9][10]. Meanwhile, validation data is used to monitor model performance and detect potential overfitting through the observation of accuracy and loss values.

2.4. Model Evaluation

The evaluation of model performance was carried out using a confusion matrix. The confusion matrix represents the actual value and predicted value of the model [11]. The model is then evaluated by calculating precision, recall, and F1-score metrics for each of its classes defined in Equations (1) – (4). The main components of the confusion matrix consist of True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). The four components are calculated for each class where one class is treated as a positive class and the other class as a negative class. As an illustration, in the paper class, the TP value represents the number of paper images that are correctly predicted to be papers. The FP value indicates the number of images from other classes (e.g. plastic or metal) that are incorrectly predicted to be paper. The FN value represents the number of paper images that are incorrectly classified as other classes, while TN represents the number of images from other classes that are correctly predicted as non-paper. The same approach is applied to the metal, organic, and plastic classes.

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

It is used to measure the level of reliability of a model's prediction of a class, i.e. the extent to which the resulting positive prediction is correct.

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

To measure the model's ability to detect all actual samples of a class.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (3)$$

To provide a measure of balance between precision and recall in order to be able to represent model performance in more detail.

3. RESULTS AND DISCUSSION

The test results on the test data showed that the model achieved an accuracy of 92.02% with a low loss value. These results show that the transfer learning approach with MobileNetV2 is able to classify waste images well even though the model is not fine-tuned. This high performance indicates that the visual features learned from ImageNet are representative enough to distinguish categories of garbage that have clear visual differences.

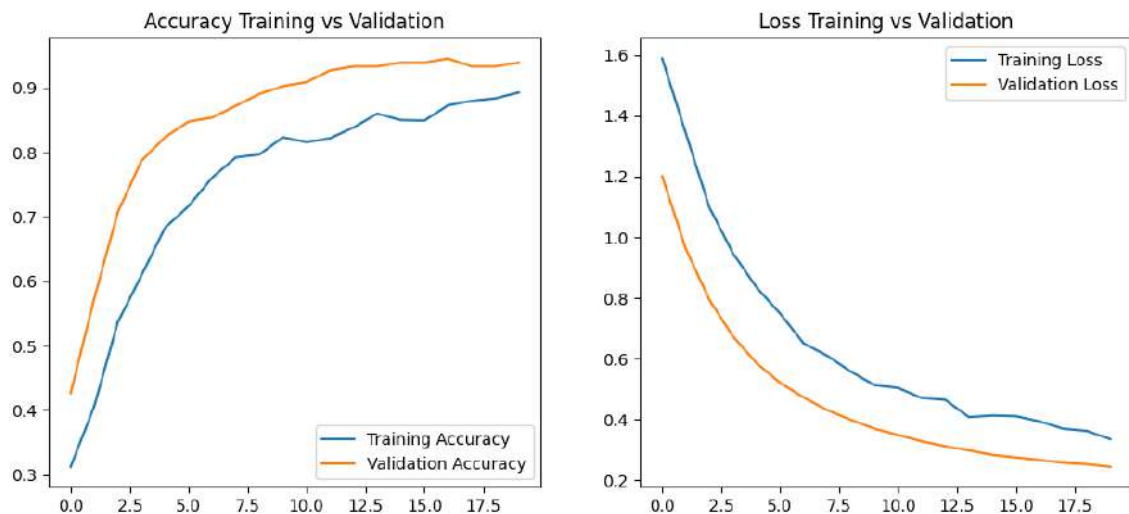


Figure 3. Training or validation loss and accuracy

In “Figure 3,” the model's performance shows an overall improvement trend during the training process, although it is accompanied by fluctuations between epochs. The accuracy of the training data which at the beginning of the training was at 0.2982 increased to a range of 0.85, with some temporary decreases at certain epochs. The accuracy of the validation data also increased gradually and reached a high value of 0.94 in the 17th epoch, but did not increase monotonically throughout the training. The lowest validation loss was recorded at 0.26 in the 17th epoch. The achievement of the highest validation accuracy value in conjunction with the lowest validation loss indicates that the performance of the model at the epoch represents the most optimal learning conditions based on the validation data, according to the pattern shown by the graph and table of training results.

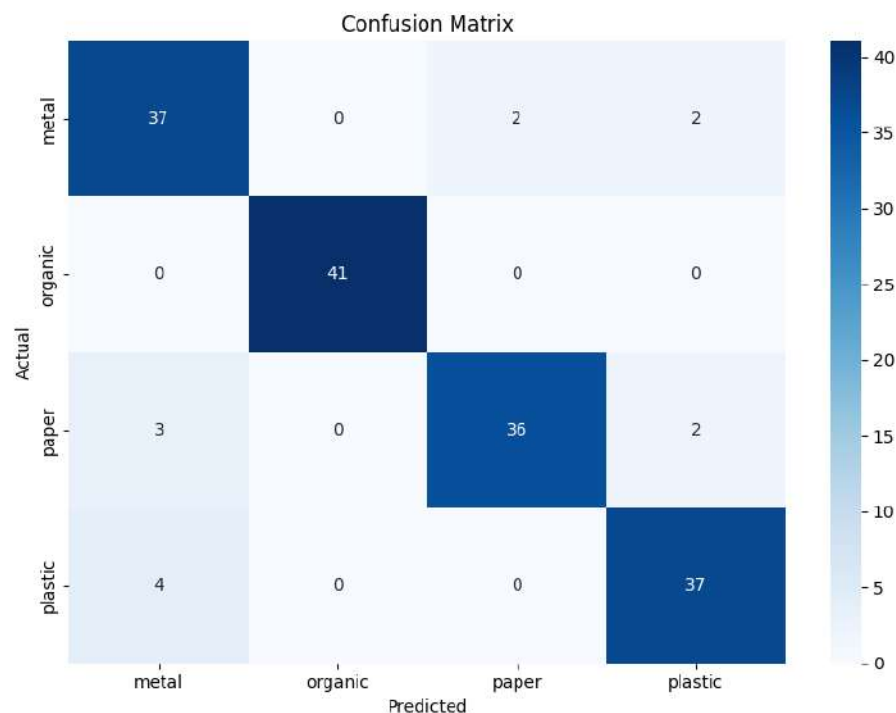


Figure 4. Confusion Matrix

The confusion matrix shows that most of the test data is correctly classified, with a relatively consistent pattern of error between classes. The organic class exhibits the highest consistency, where all 41 data are predicted precisely without errors. In the metal class, out of 41 data, there are 4 prediction errors that are consistently divided into paper (2 data) and plastic (2 data) classes. The paper class

showed 5 prediction errors, with a similar pattern of errors, namely 3 data misclassified as metal and 2 data as plastic. Meanwhile, in the plastic class, out of 41 data, there are 4 data that are consistently incorrectly predicted as metals. A pattern of repeating errors that are concentrated in specific class pairs indicates that the model has stable predictive behavior, where errors are not random, but rather appear in classes with potentially intersecting visual characteristics. Thus, this confusion matrix not only indicates the level of accuracy of the model, but also reflects the consistency of the prediction pattern and the resulting error.

Table 2. Evaluation Matrix in the form of Precision, Recall and F1-Score

	Precision	Recall	F1-Score
Metal	0,8409	0,9024	0,8705
Organic	1,0000	1,0000	1,0000
Paper	0,9474	0,8780	0,9114
Plastic	0,9024	0,9024	0,9024
Macro Avarage	0,9226	0,9207	0,9211
Weighted Average	0,9226	0,9207	0,9211

In the evaluation metrics, the model showed consistent performance across the class. The organic class obtained a precision, recall, and F1-score of 100%, which indicates a perfect level of prediction consistency in the test data so that it is easily recognized by the model. Meanwhile, the metal, paper, and plastic classes also showed varied performance, with F1-score values of 87.05%, 91.13% respectively; and 90.24%. This difference in performance between classes indicates a certain level of visual similarity, especially in the paper and plastic classes. Nonetheless, the F1-Score score obtained still shows a good balance between precision and recall in each class. Overall, the average value of the evaluation metrics reached 92%, which shows that the model is able to consistently classify waste on the dataset used. However, it should be noted that the dataset used was under controlled conditions, so the model's performance under real conditions with variations in lighting, object deformation, and more diverse levels of waste cleanliness could not be fully represented in this study.

In addition to quantitative evaluation, qualitative inference testing was conducted using a Gradio-based interface, as demonstrated in Figures 5 through 8. Figure 5. shows a plastic wrapper sample correctly classified as plastic, Figure 6. depicts a beverage can correctly predicted as metal, Figure 7. presents bread waste classified as organic, and Figure 8. shows a newspaper correctly identified as paper. This test aims to verify the predictive behavior of the model on the input image individually outside of the batch testing scheme. The test results showed that the model was able to provide class predictions that were consistent with the performance patterns obtained in quantitative evaluations, especially in images with clear visual characteristics. These findings indicate that the model not only performs well numerically, but also performs stably in simulated use scenarios, which is relevant for the development of automated waste classification systems in the future.

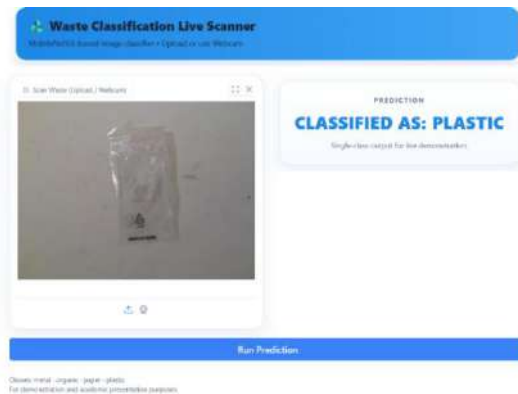


Figure 5. Plastic wrapper waste predicted as plastic

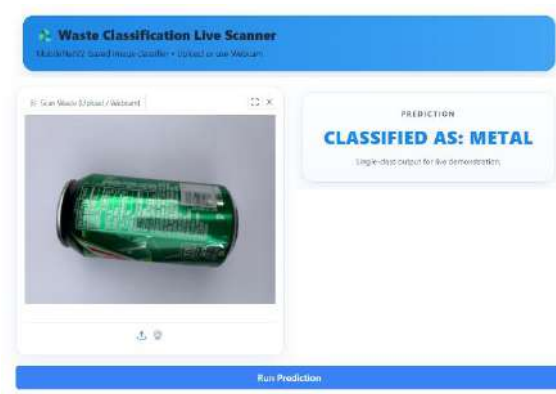


Figure 6. Beverage can waste predicted as metal

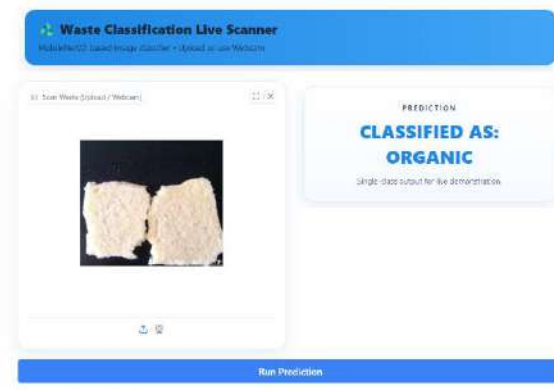


Figure 7. Bread waste predicted as organic

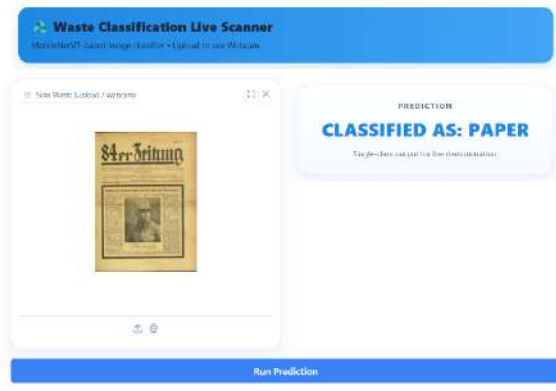


Figure 8. Newspaper waste predicted as paper

4. CONCLUSION

The MobileNetV2 model achieved an accuracy of 92.02% in multi-class waste image classification, demonstrating balanced performance across all categories. Per-class analysis revealed consistent predictive behavior, with misclassification patterns concentrated among visually similar classes. These results confirm that lightweight CNN architectures are capable of delivering stable classification performance, both in terms of overall accuracy and inter-class prediction distribution. The primary contribution of this study lies in the systematic evaluation of per-class performance consistency and misclassification pattern analysis in lightweight models, aspects that have received limited attention in prior literature. From a practical standpoint, the findings suggest that MobileNetV2 holds considerable potential as a classification module in automated waste sorting systems and image-based educational applications. However, validation under real-world environmental conditions and deployment on resource-constrained devices remain important directions for future research.

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Android-Based Smart Centrifuge with PID Speed Control

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ABSTRACT

This study aimed to design and implement an Android-based centrifuge monitoring system with Proportional Integral Derivative (PID) speed control to improve rotational speed stability and monitoring flexibility in laboratory applications. The system utilized a DC motor as the driving unit, a speed sensor for feedback acquisition, and an Android application developed using MIT App Inventor for real-time monitoring. PID parameters were determined using the Ziegler–Nichols open-loop tuning method based on the process reaction curve. From the experimental response, a dead time of 0.5 s and a time constant of 3.65 s were obtained, resulting in PID parameters of $K_p = 8.76$, $K_i = 8.76$, and $K_d = 2.19$. Experimental testing was performed using a tachometer to evaluate rotational speed performance. The results showed that the implemented PID controller provided stable speed regulation with improved response characteristics and low steady-state error. In addition, the Android application successfully displayed real-time operational data and maintained reliable communication with the centrifuge system. The proposed system demonstrated that the integration of PID control and Android-based monitoring can enhance both control accuracy and operational convenience for laboratory centrifuge applications.



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1. INTRODUCTION

Centrifuges are essential laboratory instruments used to separate components of a sample based on differences in density through the application of centrifugal force [1][2][3]. These devices are widely utilized in clinical laboratories, pharmaceutical industries, biological research, and chemical analysis, particularly for blood sample processing and other biological fluid separations. The effectiveness of the separation process is strongly influenced by the rotational speed of the centrifuge, making speed accuracy and stability important factors in achieving reliable laboratory results.

Despite their widespread application, conventional centrifuge systems often experience difficulties in maintaining stable rotational speeds under varying operating conditions. Load variations, external disturbances, and fluctuations in power supply may affect rotational performance and reduce the accuracy of the separation process[4]. In addition, many laboratory centrifuges still employ limited user interfaces and require direct manual operation, making real-time monitoring and control less practical. These limitations may reduce operational efficiency and create challenges in educational laboratory environments where interactive and user-friendly equipment is required.

Various control strategies have been developed to improve the performance of rotational systems. Among these methods, the Proportional Integral Derivative (PID) controller remains one of the most widely used control techniques because of its simple implementation, robustness, and ability to improve system stability while reducing steady-state error[5][6]. The effectiveness of PID control is highly dependent on the selection of appropriate controller parameters. One of the most commonly used tuning approaches is the Ziegler–Nichols method, which determines controller parameters based on the dynamic characteristics of the system response and has been successfully applied in various motor speed control applications[7][8].

The advancement of mobile technology has enabled the integration of laboratory instruments with Android-based applications, allowing real-time monitoring and control through smartphones[9]. In addition, MIT App Inventor facilitates rapid Android application development with minimal programming requirements[10]. Although previous studies have explored PID-based speed control and Android-based monitoring separately, their integration in centrifuge systems for clinical laboratory practicum applications remains limited. Therefore, this study aims to develop a centrifuge system that combines accurate PID speed control with an intuitive Android-based monitoring interface to enhance both performance and usability. This study proposes a PID-controlled centrifuge integrated with an Android-based monitoring application. The PID parameters were tuned using the Ziegler–Nichols open-loop method[11][12], while the Android interface was developed using MIT App Inventor. The proposed system aims to provide stable speed control, real-time monitoring, and a portable, user-friendly, and cost-effective solution for clinical laboratory practicum applications.

2. RESEARCH METHOD

a. System Design

The proposed system consists of a centrifuge unit, a PID-based speed controller, and an Android monitoring application. Speed feedback from a rotational sensor is processed by a microcontroller, which adjusts the DC motor through PID control and transmits data to an Android device via Bluetooth. The application enables real-time monitoring and setpoint control, while the PID controller minimizes speed error by continuously regulating the motor drive signal.

b. PID Controller Design

A Proportional Integral Derivative (PID) controller was implemented to regulate the rotational speed of the centrifuge. The controller generates a control signal based on the difference between the desired speed and the measured speed. The PID control law is expressed as:

$$u(t) = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt}$$

where $u(t)$ is the controller output, $e(t)$ is the speed error, and K_p , K_i , and K_d are the proportional, integral, and derivative gains, respectively.

c. PID Parameter Tuning

The PID parameters were determined using the Ziegler–Nichols open-loop tuning method. The tuning process was performed by applying a step input to the motor system and observing the resulting process reaction curve. The dead time (L) and time constant (T) were identified from the response characteristics. Based on the experimental results, the dead time was measured as 0.5 s and the time constant was determined as 3.65 s. The PID parameters were calculated according to the Ziegler–Nichols open-loop tuning rules. The obtained controller parameters were: $K_p = 8.76$, $K_i = 8.76$, $K_d = 2.189$. These parameters were applied to all speed settings during system testing.

d. Android Application Development

The Android monitoring application was developed using MIT App Inventor and connected to the centrifuge via Bluetooth. It enables users to set speed targets, monitor real-time rotational speed, and check connection status through a simple and user-friendly smartphone interface.

e. Experimental Procedure

System performance was evaluated through experimental testing under several rotational speed setpoints. During each experiment, the rotational speed was measured using a tachometer and compared with the desired setpoint. The system response was recorded to evaluate the effectiveness of the PID controller. In addition, Bluetooth communication tests were conducted to evaluate the stability of the wireless connection and the operational range between the centrifuge system and the Android application.

f. Data Collection and Analysis

The dataset consisted of experimental data collected from the developed centrifuge system, including rotational speed (RPM), speed setpoints, response time, PID parameters, and Bluetooth communication performance. The data were analyzed to evaluate speed control accuracy, PID controller performance, and the reliability of the Android-based monitoring system by comparing the measured speed with the desired setpoint and assessing communication stability during operation.

2.1. Data Collection

Data collection was conducted through experimental testing of the developed centrifuge prototype operating under a closed-loop control system, as shown in Fig. 1. Rotational speed (RPM) was measured using a calibrated tachometer at several predefined setpoints to evaluate system performance and dynamic response. For each test, the centrifuge was operated until steady-state conditions were reached, and the RPM data were recorded for analysis. An Android application developed using MIT App Inventor was used to set the desired rotational speed and monitor system performance in real time via Bluetooth communication. Wireless communication performance was also evaluated by varying the distance between the mobile device and the centrifuge system to determine the effective operating range and communication stability.

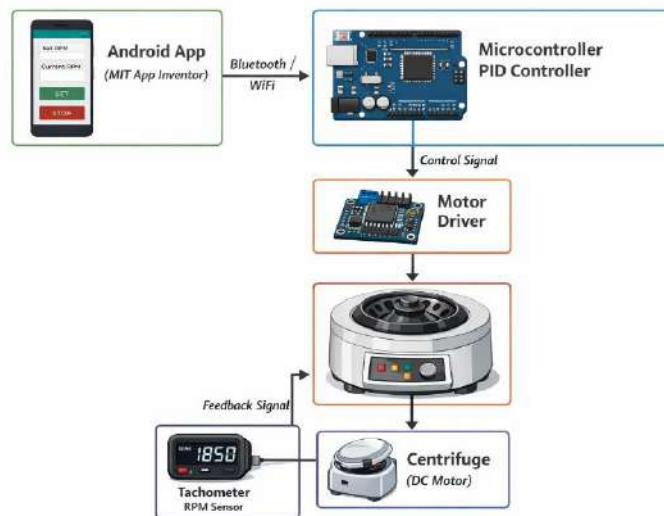


Figure 1. Block diagram of the PID-based closed-loop centrifuge control system with wireless interface and tachometer

2.2. Data Processing

The collected experimental data were processed to evaluate the performance of the centrifuge closed-loop control system under PID regulation. The recorded rotational speed (RPM) data were categorized based on different setpoint conditions and experimental runs. Both transient and steady-state responses were analyzed to characterize the dynamic behavior of the system.

Steady-state performance was evaluated by identifying the interval where the RPM output remained within a stable fluctuation band. The steady-state error (SSE) was computed as :[13]

$$SSE = r - y_{ss} \quad (1)$$

where r is the reference setpoint and y_{ss} is the measured steady-state output.

The centrifuge system was approximated using a first-order plus dead-time (FOPDT) model, as it provides a simple yet effective representation of real process dynamics and is widely applied in control system analysis and design [14][15][16][14]:

$$G(s) = K \cdot \frac{e^{-Ls}}{\tau s + 1} \quad (2)$$

where K is system gain, L is dead time, and τ is the time constant. The model parameters were identified from the step response curve obtained experimentally.

The control strategy for the centrifuge system was implemented using a Proportional–Integral–Derivative (PID) controller to regulate the rotational speed according to the desired setpoint[17]. The controller generates a control signal based on the error between the reference input and the measured output [18].

$$u(t) = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt} \quad (3)$$

where K_p , K_i , and K_d represent the proportional, integral, and derivative gains, respectively. The proportional term provides an immediate response to the current error, the integral term eliminates steady-state error by accumulating past errors, and the derivative term predicts future error trends to improve system stability and damping. The initial tuning of the PID parameters was performed using the Ziegler–Nichols closed-loop method. In this approach, the proportional gain was gradually increased while the integral and derivative gains were set to zero until the system reached a condition of sustained oscillation. The corresponding gain at this condition is defined as the ultimate gain (K_u), and the oscillation period is referred to as the ultimate period (P_u)[19].

Based on these experimentally obtained parameters, the: These initial values provide a baseline controller configuration that typically yields a fast response with acceptable stability[20]. However, due to the nonlinear characteristics and disturbances present in the centrifuge system, further fine-tuning was carried out experimentally. The tuning process aimed to minimize overshoot, reduce settling time, and improve overall stability while maintaining a small steady-state error.

The final PID parameters were selected based on the best trade-off between response speed and system stability under various setpoint conditions[21]. System performance was evaluated using standard time-domain parameters, including rise time (t_r), settling time (t_s), overshoot (M_p), and steady-state error (SSE). Rise time indicates response speed, settling time reflects stability within a $\pm 2\%$ tolerance band, overshoot measures the maximum response exceeding the setpoint, and SSE represents steady-state accuracy. Stability was assessed from response convergence and damping behavior, ensuring asymptotically stable responses at all tested setpoints.[22].

2.3. Calibration and Measurement Uncertainty

This is how to start another subsection Calibration of the tachomete based RPM measurement system was performed to ensure the accuracy and reliability of rotational speed measurements. The calibration process was conducted by comparing the tachometer readings with reference rotational speed values at several predefined setpoints. At each calibration point, repeated measurements were carried out under identical operating conditions to minimize external disturbances and random errors. For each reference point, a set of n repeated measurements was collected. The statistical parameters, including the mean value ($\bar{x}$), standard deviation (SD), and number of observations (n), were calculated to characterize the measurement distribution. The mean value represents the best estimate of the measured RPM, while the standard deviation indicates the spread or variability of the data. The standard uncertainty due to random effects (Type A uncertainty) was evaluated using[23]:

$$u = \frac{SD}{\sqrt{n}} \quad (4)$$

This value reflects the uncertainty associated with measurement repeatability. To express the uncertainty at a higher confidence level, the expanded uncertainty was calculated using a coverage factor $k = 2$, corresponding to a confidence level of approximately 95%:

$$U = k \cdot u = 2 \frac{SD}{\sqrt{n}} \quad (5)$$

The expanded uncertainty provides an interval within which the true value of the measured RPM is expected to lie with a 95% level of confidence[24]. In addition to Type A uncertainty, the calibration procedure also considered potential sources of systematic error, such as instrument resolution and calibration reference limitations. These components can be incorporated into a combined uncertainty analysis if required. An uncertainty budget table was constructed to summarize the calibration results for each reference point. The table includes the reference RPM, measured mean RPM, standard deviation, standard uncertainty, and expanded uncertainty. This comprehensive evaluation ensures traceability and supports the validity of the measurement system used in the experimental analysis[25].

Type B uncertainty was estimated based on instrument characteristics, such as the resolution of the tachometer and manufacturer specifications. Assuming a rectangular (uniform) distribution, the Type B uncertainty can be expressed as[23]:

$$u_B = \frac{a}{\sqrt{3}} \quad (6)$$

where a represents the half-width of the measurement interval (e.g., instrument resolution or tolerance). The combined standard uncertainty (u_c) was then calculated using the root-sum-square (RSS) method[24]:

$$= \sqrt{u_A^2 + u_B^2} \quad (7)$$

To express the uncertainty with a higher confidence level, the expanded uncertainty (U) was calculated using a coverage factor $k = 2$, corresponding to a confidence level of approximately 95%:

$$U = K \cdot U_c \quad (8)$$

The combined uncertainty provides a more realistic estimation of the measurement error by incorporating both random and systematic components. This approach ensures that the reported RPM measurements are supported by a rigorous uncertainty analysis, improving the reliability and credibility of the experimental results[24]. An uncertainty budget table was constructed to summarize all contributing components, including Type A uncertainty, Type B uncertainty, combined uncertainty, and expanded uncertainty for each calibration point.

2.4. Wireless Communication Performance

Wireless communication between the Android application and the centrifuge system was evaluated by varying the transmission distance[26]. The effective control range was defined as the maximum distance at which the system maintained stable command execution without packet loss or significant delay[27][28]. Communication latency and stability were qualitatively observed to assess real-time control feasibility.

3. RESULTS AND DISCUSSION

a. Result

The centrifuge system was successfully transformed from an open-loop control system into a closed-loop control system by integrating an optocoupler sensor and a Proportional-Integral-Derivative (PID) controller. In the original open-loop configuration, the microcontroller generated Pulse Width Modulation (PWM) signals based solely on user-defined speed and time settings. Since no feedback mechanism was available, the system could not detect or correct deviations between the desired rotational speed and the actual motor speed. After the implementation of the closed-loop architecture, the optocoupler sensor continuously measured the motor rotational speed and transmitted the feedback signal to the controller. The PID controller processed the measured speed and adjusted the PWM output according to the calculated error between the setpoint and the actual speed.

Experimental testing was conducted at three setpoints: 1500 RPM, 2000 RPM, and 3000 RPM. The results showed that the centrifuge successfully reached all target speeds and maintained stable operation throughout the testing period. The response curves indicate that the motor speed increased rapidly toward the desired setpoint and remained within an acceptable tolerance range after reaching steady-state conditions. Furthermore, the system demonstrated low steady-state error and stable speed regulation. The measured speed fluctuations remained within $\pm 2\%$ of the setpoint, indicating effective control performance. The dynamic response characteristics obtained from the experiments included a short rise time, low overshoot, and fast settling time. The response characteristics for all tested setpoints are illustrated in Fig. 2.

b. Discussion

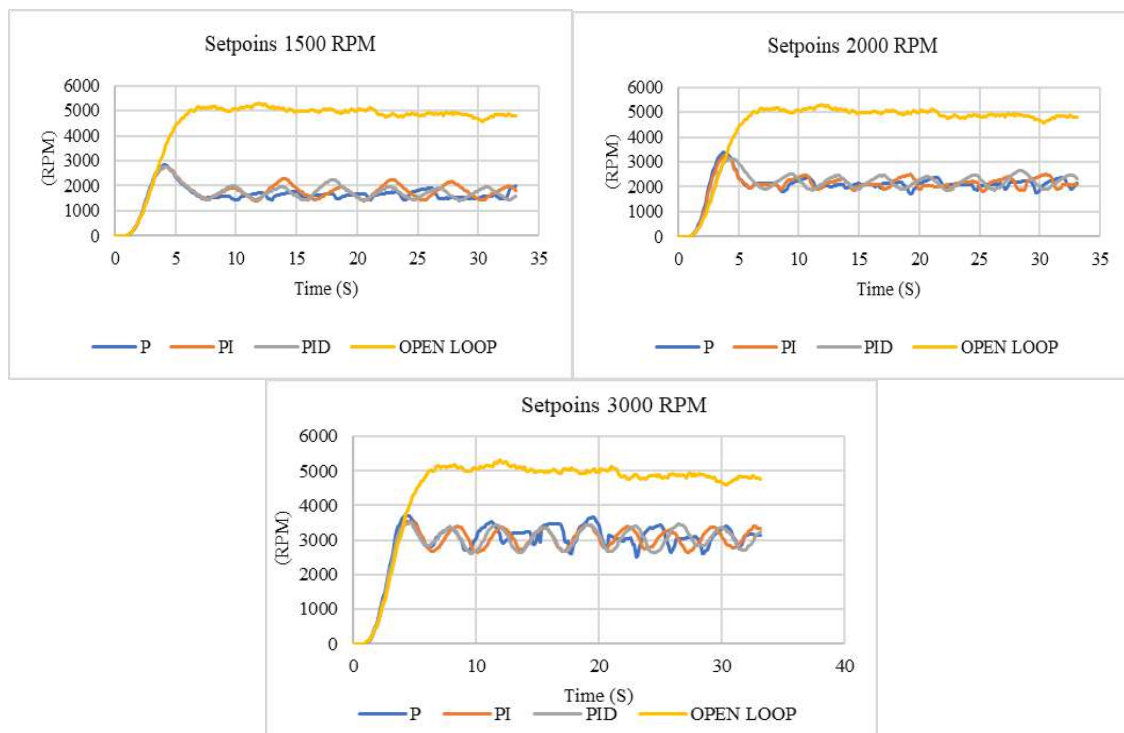


Figure 2. Dynamic responses of P, PI, PID, and open-loop controls at setpoints of (a) 1500 RPM, (b) 2000 RPM, and (c) 3000 RPM

The main finding of this study is the successful conversion of the centrifuge from an open-loop to a closed-loop control system using a PID controller. By integrating an optocoupler sensor as feedback, the controller continuously adjusted the PWM signal based on the error between the setpoint and measured speed, resulting in improved accuracy and stability. As shown in Fig. 2, the system achieved fast setpoint tracking, low overshoot, short settling time, and stable operation within a $\pm 2\%$ tolerance band. Consistent performance at 1500, 2000, and 3000 RPM demonstrates the robustness and reliability of the implemented PID controller under varying operating conditions.

3.1. System Response of the Centrifuge

The dynamic response of the centrifuge system was first analyzed to observe its general behavior under operating conditions. As shown in Fig. 2, the centrifuge system exhibits a gradual increase in rotational speed from the initial condition until it approaches the steady-state region. The response shows a relatively smooth rise without abrupt changes, indicating stable system behavior. However, slight oscillations are observed near the steady-state region, suggesting that the system experiences minor fluctuations before reaching full stability. This behavior highlights the importance of implementing an appropriate control strategy to improve response stability and reduce oscillations.

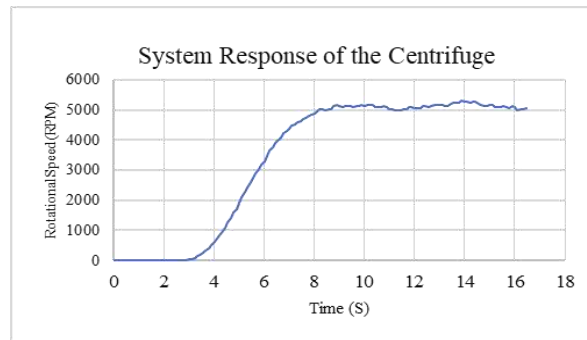


Figure 3. System response of the centrifuge

3.2. The performance comparison of P, PI, and PID controllers

As shown in Table 1, all controllers exhibit similar rise times, indicating comparable initial response speeds. However, differences are observed in overshoot and stability. The PI controller achieves the lowest overshoot at 1500 RPM, while the PID controller performs best at 2000 and 3000 RPM by reducing overshoot and oscillations. Overall, the PID controller provides the most stable and balanced performance across all operating conditions, demonstrating greater robustness for a wide range of rotational speeds.

Table 1. Performance comparison at various setpoints

Setpoint (RPM)	Controller	Rise Time (s)	Overshoot (RPM)	Oscillation (RPM)
1500 RPM	P	2.6	2798	400
	PI	2.6	2210	500
	PID	2.6	2235	500
2000 RPM	P	3.0	3364	500
	PI	3.0	3191	500
	PID	3.0	3127	500
3000 RPM	P	3.5	3686	800
	PI	3.5	3548	700
	PID	3.5	3489	700

3.3. Experimental Validation of Sample Separation

To validate the practical performance of the centrifuge, a separation experiment was conducted using a mixture of water, milk, and food coloring as a blood-like fluid model. Two identical 5 mL samples were prepared: one processed using open-loop PWM control and the other using closed-loop PID control. The PWM system operated at the minimum duty cycle required for rotation ($T_{ON} = 5.8\%$), while the PID system was set to 3000 RPM. Both experiments were conducted for 30 minutes.

The results, shown in Fig. 4, indicate that both control methods produced comparable separation outcomes, likely due to similar average rotational speeds and processing times. However, the PID-controlled system provided superior speed regulation and operational stability by continuously maintaining the desired rotational speed. This improves process consistency, repeatability, and robustness against disturbances, making the closed-loop approach more reliable for centrifugation applications. Future studies should evaluate the system using fluids with different viscosities or real biological samples.



Figure 4. Sample separation result using PWM control (TON = 5.8%, 30 minutes)

3.4. Centrifuge Calibration Result (RPM Measurement)

The calibration of the centrifuge was performed using a tachometer at three predefined setpoints: 1500 RPM, 2000 RPM, and 3000 RPM. The performance was evaluated in terms of average measured rotational speed, correction value, standard deviation (STDEV), and expanded uncertainty (U95).

Table 2. Centrifuge calibration results

Setpoint (RPM)	Average (RPM)	Correction (RPM)	STDEV (RPM)	U95 (RPM)
1500	1511	+11	1.50	±1.5
2000	2031	+31	1.98	±1.5
3000	3012	+12	1.45	±1.5

The calibration results in Table 2 indicate a consistent positive deviation from the setpoints, showing that the centrifuge tends to slightly overestimate rotational speed. The largest correction was observed at 2000 RPM (+31 RPM). Despite this systematic error, the system demonstrated high precision, with standard deviations below 2 RPM and a constant expanded uncertainty (U95) of ±1.5 RPM across all test points. These results confirm that the centrifuge provides stable and repeatable measurements. However, applying calibration correction factors is recommended to improve accuracy, especially at critical operating speeds. Overall, the system is reliable in terms of precision but requires calibration adjustment to enhance accuracy.

3.5. Wireless Communication Performance

Table 3 presents the Bluetooth communication performance at various distances. The system operated reliably without noticeable delay up to 7 m under minimal obstruction conditions. When the signal passed through a concrete wall, a delay of approximately 0.2 s was observed at distances of 10–15 m, while the connection was lost at 20 m. These results indicate that the Bluetooth-based control system provides stable communication within typical laboratory environments, with an effective range of up to 15 m under obstructed conditions.

Table 3. Bluetooth communication performance at various distances

Distance Range	Environment	Connection Status	Delay (s)
1–7 m	Indoor	Stable	0
10–15 m	Outdoor	Slight delay	0.2
20 m	Outdoor	Disconnected	—

The transition from an open-loop to a closed-loop centrifuge system significantly improved speed control accuracy and stability. By integrating optocoupler-based feedback and a PID controller, the system was able to continuously minimize speed error and maintain operation within a ±2% tolerance band. The PID controller provided the best overall performance, particularly at higher setpoints, where derivative action effectively reduced oscillations and improved damping. Although a consistent measurement bias was observed during calibration, the low standard deviation values (<2 RPM) indicate high precision and repeatability. Experimental validation demonstrated that the proposed system achieved reliable sample separation and stable speed regulation throughout operation. While visual separation results were similar between PWM and PID control methods, PID control ensured

greater consistency and reproducibility. Wireless communication tests showed that Bluetooth-based monitoring remained functional within a typical laboratory range, although communication delays increased in the presence of physical obstacles. These findings are consistent with previous studies showing that closed-loop PID control outperforms open-loop and PI-based approaches in accuracy, stability, and disturbance rejection. The results also demonstrate that low-cost embedded systems can provide reliable centrifuge performance for laboratory applications. However, this study is limited by the use of simplified fluid samples, the presence of systematic measurement bias, and Bluetooth range constraints. Future work should focus on advanced calibration methods, testing with real biological samples.

4. CONCLUSION

This study successfully transformed a conventional centrifuge system from an open-loop control configuration into a closed-loop control system integrated with a Proportional-Integral-Derivative (PID) controller. The implementation of feedback control enabled the system to continuously monitor and adjust the motor speed, thereby improving rotational speed regulation and overall system performance. The experimental results demonstrated that the proposed PID-based control system achieved the desired objectives by providing accurate and stable speed control. The centrifuge maintained operation within $\pm 2\%$ of the target speed, exhibited low steady-state error, and showed favorable dynamic response characteristics, including fast settling behavior and minimal overshoot. Calibration and validation tests further confirmed the reliability and repeatability of the speed measurement system. In addition, the wireless Android-based control interface operated successfully within the tested communication range, allowing remote monitoring and control with minimal delay. These findings indicate that the developed system offers improved stability, accuracy, and operational convenience compared with the previous open-loop configuration. Therefore, the proposed closed-loop PID-controlled centrifuge can be considered an effective solution for applications requiring precise and consistent rotational speed control. Future research may focus on evaluating performance using real biological samples and implementing advanced control algorithms to further enhance system adaptability and accuracy.

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Parasitic Ringing Suppression in FPGA-Controlled Three-Phase Voltage Source Inverter Using RC Snubber Circuit

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ABSTRACT

Parasitic phenomena in inverter circuits, arising from semiconductor switching devices, are a well-recognized challenge that causes voltage spikes, high-frequency oscillations, and PWM signal distortions, thereby reducing the reliability of electric motor drive systems. Unlike prior studies that address snubber design without explicitly deriving parasitic parameters, this work presents a systematic approach to RC snubber design based on analytically derived parasitic inductance and resonance frequency parameters. A series-parallel RC snubber is designed for each semiconductor switch using mathematical models for spike voltage, resonant frequency, snubber capacitance, and damping resistance. Experimental validation is conducted using a three-phase inverter with a switching frequency of 25 kHz, controlled by a Field Programmable Gate Array, and connected to an electric motor. Without the snubber, ringing reaches approximately 70–75% of the nominal PWM voltage, and current spikes exceed 33% of the peak value. After applying the designed snubber, oscillations are reduced to approximately 1.5–1.8% of the nominal PWM voltage, and current spikes are confined below 10% with an oscillation duration of less than 1 millisecond. These results demonstrate that the analytically designed snubber effectively suppresses parasitic ringing, reduces switching stress, and improves inverter stability and motor control accuracy under high-frequency PWM operation.



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1. INTRODUCTION

The era of global energy transformation and industrial digitalization has indirectly made power conversion systems a crucial component of modern technological transformation, including new renewable energy generation systems, green energy-based vehicles, and artificial intelligence-driven industrial optimization [1], [2], [3], [4]. It necessitates efficient, reliable, responsive, and high-performance power conversion systems to achieve significant increases, particularly in electrical energy conversion, electric vehicles, and industrial motor drive systems. A DC to AC Converter, also known as a Voltage Source Inverter (VSI), is one of the power conversion systems widely used in power

conversion systems because it has a primary output in the form of AC power, which can be implemented in electrical energy conversion systems and drive systems in electric vehicles and industries. In addition, VSI offers high performance and accuracy, as well as ease of controlling the output voltage [5]. The primary factors contributing to the optimal performance and high accuracy of VSI are circuit design, component quality, and real-time control capabilities [6], [7]. The biggest challenge in operating VSI is that during switching conditions, switching losses are caused by overlapping voltages and currents [8], [9]. In addition, other phenomena that occur during switching losses, such as voltage overshoot, ringing, and increased dv/dt , can damage components and produce high electromagnetic interference [10], [11], [12].

The use of soft switching to replace hard switching in VSI switching systems offers a practical solution to reduce switching losses caused by overlapping voltages and currents, as well as other phenomena [13], [14]. However, the application of soft switching in VSI has its own challenges, especially in terms of circuit complexity, controller capabilities, and high costs. It makes soft switching in VSI very difficult to apply to the needs of the industrial sector. Another approach used is the application of a snubber circuit in the VSI. The snubber circuit can reduce switching losses and mitigate transient phenomena [15], [16].

The approach to improving VSI performance in controllers involves applying digital modulation techniques, such as space vector modulation or sinusoidal pulse-width modulation, which offer various advantages, including reduced total harmonic distortion, improved efficiency, and high performance [17], [18]. However, to implement it, a microprocessor-based control device, such as a microcontroller or a Field-Programmable Gate Array (FPGA), is required, providing high flexibility in adjusting the control architecture. Microprocessor implementation in VSI is used for simple computations, such as controlling the Speed of a three-phase induction motor using a square-wave pulse-width modulation signal or flux control [19], [20]. Microprocessors have a weakness in terms of high latency compared to microcontrollers and FPGAs. On the other hand, microcontrollers can provide high Speed, power efficiency, and ease of integration with different hardware, making them very suitable for real-time processing-based control applications, albeit within a limited scope. Meanwhile, FPGAs have advantages over microprocessors and microcontrollers for implementing high-performance systems in real time, precise synchronization, and high control-flow complexity, as they can run multiple processes simultaneously with very low latency.

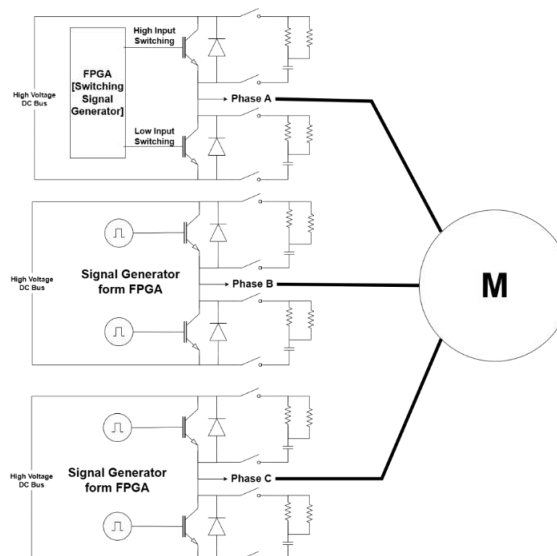


Figure 1. Voltage source inverter-based FPGA

The implementation of suppression and mitigation techniques for parasitic effects arising from switching components is essential in motor drive systems, as these effects can introduce voltage spikes, current oscillations, and electromagnetic interference, degrading motor current quality and distorting PWM control signals. Uncontrolled parasitic elements may lead to increased switching losses, reduced efficiency, and unreliable operation of both the power devices and the control circuitry. **Figure 1**

illustrates the architecture of an FPGA-controlled three-phase motor drive system with a clear separation between the control and power stages. On the FPGA side, high-side and low-side gate control signals for each phase are generated using digitally implemented control algorithms. These signals are then delivered to an isolated gate driver stage that provides electrical isolation between the low-voltage control domain and the high-voltage power domain, while ensuring sufficient drive strength for reliable switching of the power devices. In the power inverter stage, the semiconductor switches are arranged as a three-phase inverter to convert the DC supply into a three-phase AC voltage for motor operation. R–C snubber circuits are integrated to attenuate voltage transients and switching-induced disturbances, thereby improving current stability, signal integrity, and overall system reliability.

2. RESEARCH METHOD

2.1. The Snubber Circuit

A VSI device enables control of a three-phase induction motor. Inverters generally use IGBT or MOSFET semiconductor devices. Inverter topologies typically employ a two-level topology with complex controls to generate an AC voltage that approximates the sinusoidal shape depicted in Figure 2. In controlling a three-phase induction motor, the inverter uses a switching control principle, with the output voltage adjusted to meet specific needs. This switching control allows the inverter to control the Speed, voltage, current, flux, and power consumption of the induction motor. In addition, the implementation of advanced control methods for induction motors, such as Field-Oriented Control and Direct Torque Control, enables more complex controls for stability, robustness, and optimization of induction motor performance [21], [22].

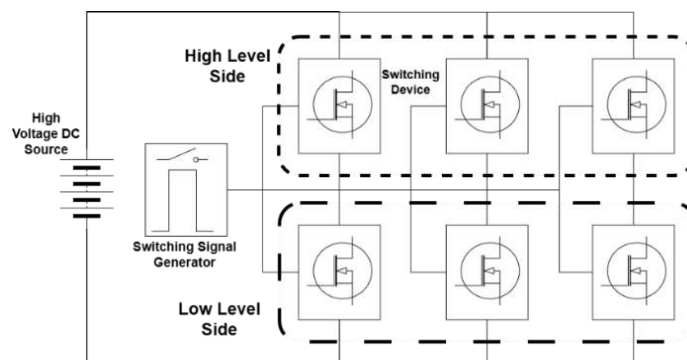


Figure 2. Three-phase inverter topology

The design of a snubber circuit in power electronics is intended to reduce phenomena that cause losses, especially switching losses. The snubber circuit controls voltage during transients and current surges that occur during the switching process in semiconductor devices. A basic snubber circuit consists of a resistor, a capacitor, and a diode. The snubber circuit can reduce voltage overshoot (surge voltage, V_{surge}), resonant oscillation, and electromagnetic interference by flowing energy stored in inductive elements.

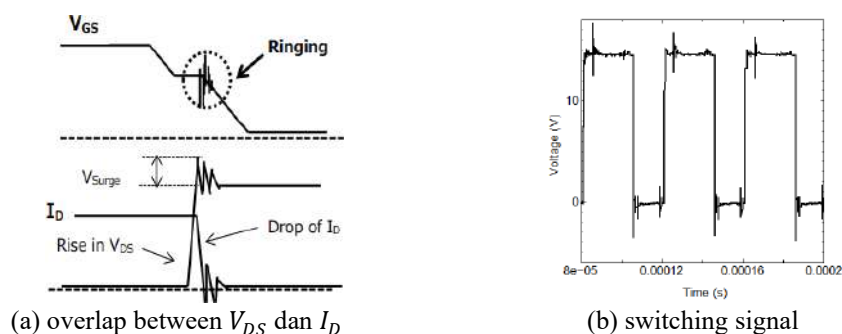


Figure 3. Inductance parasitic phenomena

Semiconductor components in switching devices and inverter circuit designs can cause parasitic inductance to trigger voltage spikes during significant transient conditions in the switching signal. It is sufficient to trigger ringing or voltage overshoot, as shown in **Figure 3(a)**. The overlap between current and voltage, as shown in **Figure 3(a)**, causes energy losses during switching that depend on the shape of the switching signal, as illustrated in **Figure 3(b)**. The implementation of a snubber circuit in an inverter, as shown in **Figure 4**, can significantly reduce voltage overshoot, enabling the inverter to operate at high frequencies while maintaining reliability [25]. Additionally, a snubber circuit design that accounts for parasitic inductance effects provides DC voltage stability, increased efficiency, and reduced energy losses [26].

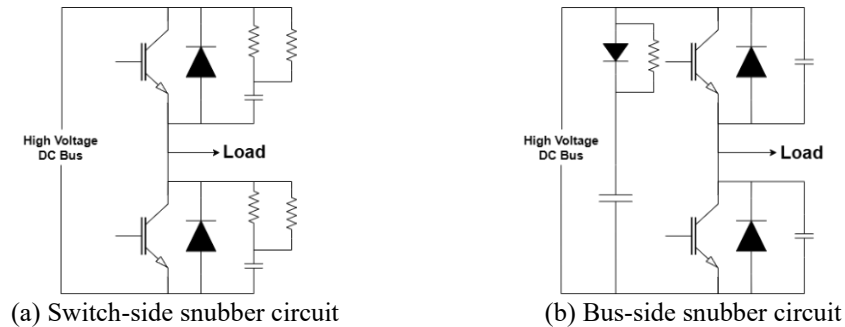


Figure 4. Classification of the snubber circuit

2.2. The Parasitic Element Phenomena

In modern motor drive systems that employ high-speed switching devices, parasitic electrical elements inherent in semiconductor devices and circuit layouts play a crucial role in determining switching behavior and waveform integrity. Figure 3(a) and Figure 5 illustrate the physical origins and dynamic behavior of parasitic effects that commonly occur during the switching operation of power semiconductor devices. As shown in Figure 3(a), the rapid transition of the drain–source voltage (V_{DS}) and drain current (I_D) during turn-on and turn-off excites unavoidable parasitic inductances and capacitances, resulting in voltage overshoot, current drop, and oscillatory ringing in the gate–source voltage (V_{GS}). These phenomena are primarily caused by the interaction between device parasitic capacitances and stray inductances in the gate loop, power loop, and load path, leading to increased electromagnetic interference, switching losses, and distortion of the intended PWM waveform [27].

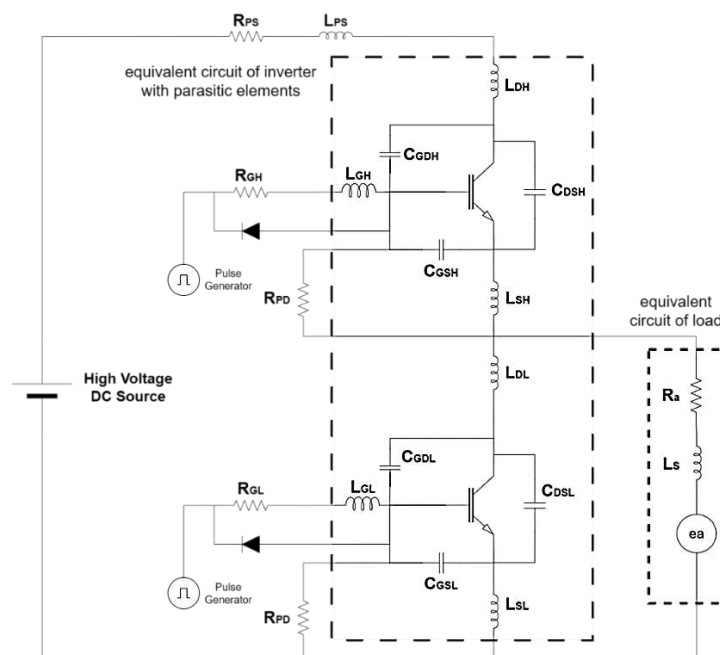


Figure 5. Parasitic elements phenomena

Figure 5 further represents an equivalent circuit model that explicitly includes parasitic gate inductances, source inductances, and intrinsic capacitances of the switching devices, as well as the parasitic resistance and inductance of the load. This model explains how rapidly switching edges can couple energy into parasitic elements, forming resonant circuits that amplify voltage spikes and ringing. The presence of a common-source inductance, in particular, introduces negative feedback into the gate drive, affecting the effective gate voltage and slowing or destabilizing the switching process. Consequently, these parasitic-induced phenomena directly affect motor current quality, control accuracy, and system reliability, underscoring the need for effective suppression techniques, such as optimized layout, gate resistance tuning, and snubber networks, in high-performance motor drive applications.

The VSI design, utilizing an FPGA as a switching signal generator, is illustrated in Figure 1. The inverter circuit is equipped with a switch-side snubber circuit, which is connected to the switch for testing its performance. The FPGA generates an SVPWM switching signal, which is connected to the gate after signal conditioning, as shown in Figure 6. The signal conditioning is performed to obtain a peak value that matches the semiconductor device's characteristics. The switching signal conditioning circuit consists of an optocoupler and a semiconductor device driver. The optocoupler device, in addition to serving as a signal conditioner, also acts as a safety device for the FPGA, protecting it from electromagnetic interference and short circuits that may occur during VSI operation [28].

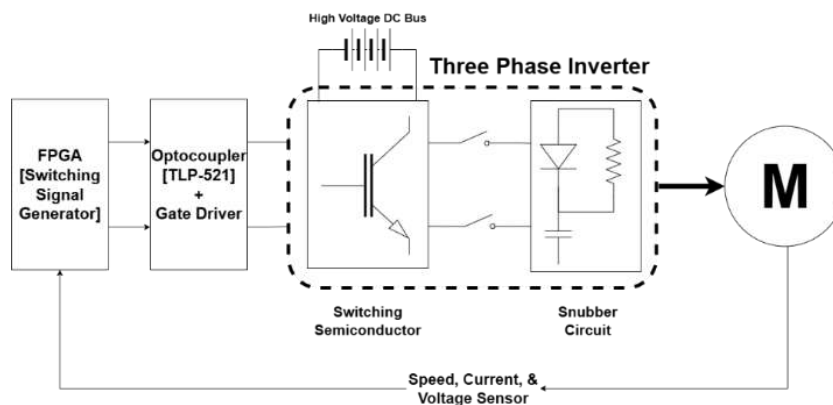


Figure 6. Three-phase inverter-based FPGA

The design of a three-phase induction motor control based on an FPGA is shown in Figure 7. The three-phase inverter circuit uses SV-PWM modulation with a switching frequency of 25 kHz. The FPGA Z7-20 generates the switching signal. The switching method, combined with the SV-PWM modulation technique, was chosen for its ability to minimize switching losses [29]. The generated SV-PWM signal is connected to the TLP521 optocoupler circuit. The switching signal from the optocoupler circuit has a 15-volt voltage level and will be connected to the IGBT FGA25N120 driver circuit. The IR2110 driver circuit maintains the switching signal voltage level within the tolerance limits of the semiconductor components.

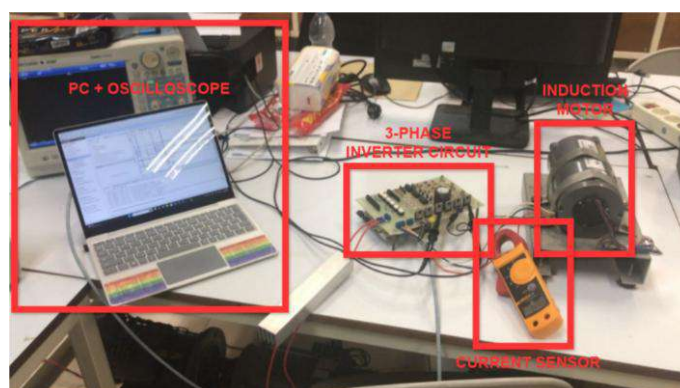


Figure 7. Experimental setup of VSI-based FPGA

A three-phase VSI is designed with a switch-side RC snubber. The snubber circuit is designed with a switch that allows testing its performance and its effect on parasitic inductance. The performance testing of the three-phase VSI is conducted with a load in the form of an induction motor. The gate signal switching response and stator current on the three-phase VSI are measured using an oscilloscope connected to a personal computer, allowing oscilloscope data to be read and processed directly.

3. RESULTS AND DISCUSSION

3.1. Analysis of Snubber Circuit, and Parasitic Element Phenomena

High-speed switching in power electronics can generate parasitic phenomena arising from semiconductor components, interconnections, and circuit layouts. Parasitic element phenomena cause voltage spikes, current oscillations, and ringing during switching transitions, leading to increased switching losses, electromagnetic compatibility issues, and degradation of electric motor current waveforms [30], [31]. An effective snubber circuit design can mitigate the adverse effects of parasitic element phenomena, thereby enhancing the overall stability and reliability of the power conversion system. The development of capacitance and resistance parameters for the snubber circuit in the power conversion system is based on calculating the spike voltage and switching transition. During the switching transition, voltage overshoot caused by parasitic effects or spike voltage (V_{SPIKE}) can be expressed in (1).

$$V_{SPIKE} = V_{LP} + V_S \quad (1)$$

$$V_{LP} = L_P \frac{dI_D}{dt}$$

Where I_D is the drain current, V_{LP} is inductance parasitic voltage and V_S is a high-voltage DC source. The parasitic inductance in the inverter circuit induces resonant behavior during high-speed switching, leading to oscillations in both voltage and current. This resonance equation is expressed in (2).

$$\omega_{SPIKE} = \sqrt{\frac{1}{L_P C_P}} \quad (2)$$

$$F_{SPIKE-H} = \frac{1}{2\pi \sqrt{L_P C_{OSS}}} \sqrt{1 - \left(\frac{\sqrt{\frac{L_P}{C_{OSS}}}}{2R_{PD}} \right)^2} ; F_{SPIKE-L} = \frac{1}{2\pi \sqrt{L_P (C_{OSS} + C_{in})}} \sqrt{1 - \left(\frac{\sqrt{\frac{L_P}{C_{OSS} + C_{in}}}}{2R_{PD}} \right)^2} \quad (3)$$

$$L_P = \frac{1}{4\pi^2 (F_{SPIKE-H} F_{SPIKE-L})^2 C_{in}} \quad (4)$$

Where the parameters ω_{SPIKE} , $F_{SPIKE-H}$, and $F_{SPIKE-L}$, represent the resonant frequency associated with the ringing phenomenon, the natural ringing frequency due to the intrinsic device capacitance, and the modified ringing frequency resulting from the addition of external capacitance, respectively.

The effect of parasitic inductance on spike voltage and resonant behavior is evaluated by adding a capacitor and a damping resistor to the circuit. The ringing frequency equation ($F_{SPIKE-H}$ and $F_{SPIKE-L}$) shown in (3) can be used to estimate the parasitic inductance. Based on these frequency components, the parasitic inductance (L_P) can be calculated using (4). In addition, ringing current occurs when the switching device transitions to the ON state and the DC source excites the equivalent series LC network formed by the parasitic elements. Given the desired damping ratio and switching frequency, the capacitance and resistance values of the ringing suppression circuit can be determined using (5) and (6), respectively.

$$C_{SP} = \frac{(L_P I_F)^2}{(V_{SPIKE} + V_S)^2} \quad (5)$$

$$R_{SP} = \frac{2\epsilon \sqrt{L_P}}{F_S} \quad (6)$$

Where, I_F is the floating current under the OFF condition, C_{SP} is the snubber capacitance, R_{SP} is the snubber resistance, C_{OSS} is the intrinsic output capacitance of the semiconductor devices, C_{in} is the

external parasitic capacitance, R_{PD} is the pull-down resistance, ε is the damping factor used for suppression design, and F_s is the switching frequency. Based on the analysis, the gate driver circuit design must explicitly account for parasitic element effects to suppress ringing-induced switching losses, thereby enhancing system efficiency, stability, and overall reliability in motor drive applications. Based on the experimental measurements of ringing frequencies in the fabricated inverter circuit, the parasitic inductance is estimated as $L_p \approx 120$ nH using (4). The snubber capacitance is calculated as $C_{SP} \approx 4.7$ nF from (5) using this value along with the floating current and the DC bus voltage. The snubber resistance is obtained from (6) with a damping factor $\varepsilon = 0.5$, yielding $R_{SP} \approx 10 \Omega$. These calculated values represent analytically derived design parameters validated against experimental measurements.

3.2. Experimental Validation

The switch-side RC snubber is tested in a three-phase inverter circuit to validate its effectiveness in mitigating parasitic inductance. The inverter circuit is designed as a prime mover for an electric motor, featuring a high switching frequency and rapid voltage transitions. The main electrical parameters, switching characteristics, and protection features of the inverter are summarized in Table 1. These specifications define the operational limits of the inverter and ensure compatibility with both the control platform and the driven motor during experimental evaluation.

The control and signal generation tasks are implemented using an FPGA-based platform to ensure precise timing, high-resolution PWM generation, and reliable gate signal control. The FPGA enables flexible implementation of control algorithms and facilitates real-time adjustment of switching parameters, which is essential for evaluating parasitic effects and snubber performance. The main specifications of the FPGA platform, including logic resources, clock frequency, and interfacing capabilities, highlight its suitability for high-speed motor drive control applications.

Table 1. The parameter value of IGBT (FGA25N120)

The Parameter	Value
Maximum Voltage	1200 V
Maximum Current	25 A
Rated Power	260 watt
Isolated-driver side	Optocoupler + IGBT Driver

Based on experimental observations of the switching signal behavior of a three-phase inverter, the switching signal shape without a snubber circuit is shown in Figure 8(a), which exhibits ringing due to parasitic inductance on the switching gate signal. This ringing phenomenon results in high-frequency oscillations in the shape of the PWM switching signal. Based on (7), the ringing phenomenon (RP) for this condition can reach 70% to 75%, indicating imperfect damping of parasitic energy during the switching transition. The switching signal shape after using a resistive-capacitive snubber circuit is shown in Figure 8(b), indicating oscillation damping and eliminating ringing during the switching transition. The residual voltage spike is effectively reduced and remains within approximately 1.5–1.8% of the nominal PWM voltage, demonstrating strong attenuation of high-frequency oscillations. This improved damping behavior confirms that the proposed snubber configuration effectively suppresses parasitic resonance, thereby reducing switching losses, minimizing electrical stress on power devices, and enhancing the overall reliability of the inverter system under high-frequency PWM operation.

$$RP = \frac{V_{ringing\ high} - V_{ringing\ low}}{V_{PWM}} \times 100\% \quad (7)$$

Figure 8(c) shows that, under the no-snub condition, the inverter output current waveform connected to the motor experiences an average current spike of more than 33%, corresponding to a peak current of over 1 A. In this case, the spike persists for approximately 4 ms within one cycle period. These results indicate that parasitic effects in power inverter components, as discussed earlier, induce a ringing switching loop that directly affects the inverter's PWM waveform, as illustrated in Figure 8(a).

In contrast, the effectiveness of the proposed system is demonstrated in Figure 8(d), where improved performance is observed. When the inverter output current connected to the motor is 3 A, the

voltage spike in the PWM signal driving the IGBT power inverter is effectively suppressed. Furthermore, as shown in Figure 8(b), the output current waveform becomes consistently smoother. In the presence of a current spike, the maximum magnitude does not exceed 10% of the 3 A peak current, and the oscillation duration is reduced to less than approximately 1 ms. Moreover, minimizing current distortion in phases A and B helps maintain the accuracy and stability of the motor control performance.

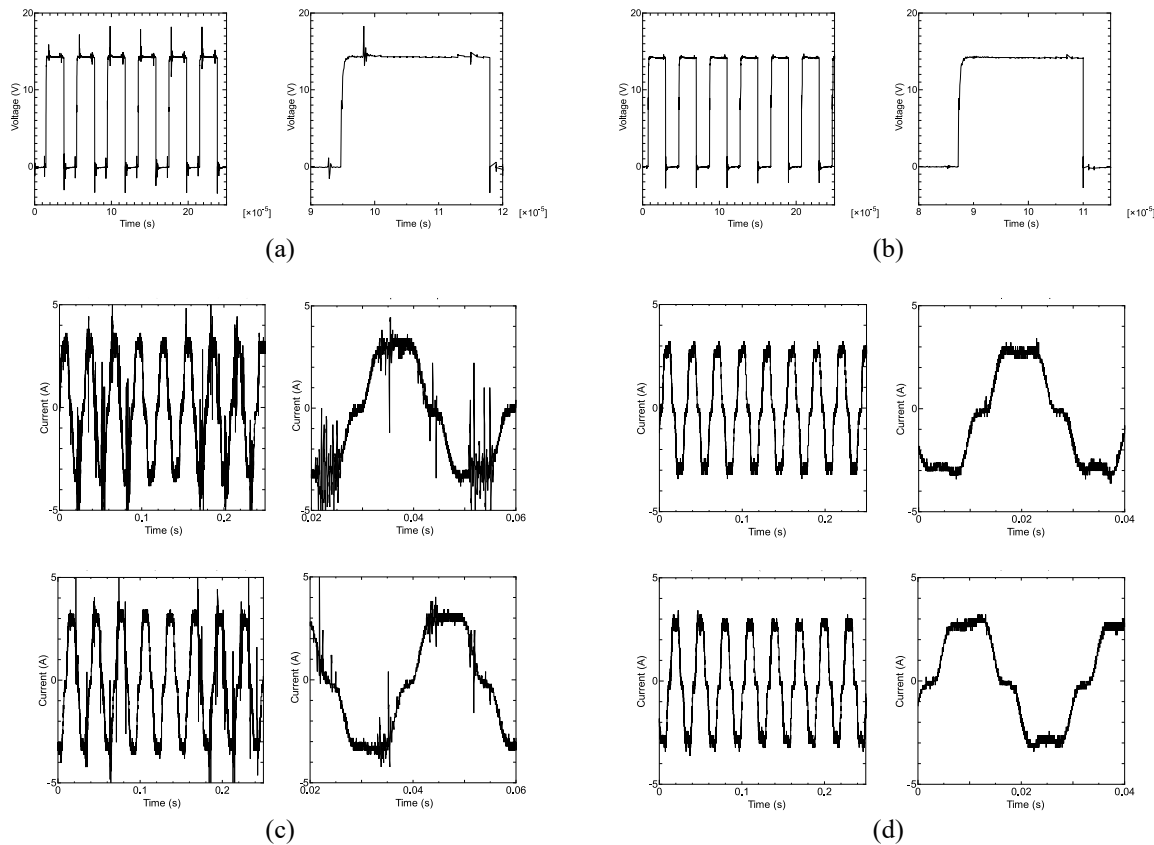


Figure 8. The effect of parasitic elements (a) PWM – gate signal switching without the snubber circuit; (b) PWM – gate signal switching with the snubber circuit; (c) stator current of the electric motor without the snubber circuit; (d) stator current of the electric motor with the snubber circuit.

4. CONCLUSION

This study presents an experimental analysis of parasitic ringing phenomena in an FPGA-controlled three-phase VSI and demonstrates the effectiveness of an analytically designed RC snubber circuit. The principal contribution is a model-based snubber design procedure that extracts parasitic inductance from measured ringing frequencies and derives snubber parameters using closed-form equations. Experimental results confirm that the designed snubber reduces gate-signal ringing from 70–75% to 1.5–1.8% of the nominal PWM voltage and motor stator current spikes from above 33% to below 10% of the peak value, with oscillation duration reduced from approximately 4 ms to less than 1 ms per cycle. These results demonstrate the effectiveness of the proposed approach in suppressing parasitic resonance and improving inverter signal integrity under high-frequency PWM operation. A limitation of the present study is that direct switching-loss measurements and frequency-domain analysis were not performed; these represent important directions for future work. Extending the validation to MOSFET-based inverters would further assess the generality of the proposed design framework.

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Fuzzy Expert System for Condition Assessment of Medium-Voltage Distribution Cable Insulation in Saline Environments

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ABSTRACT

One cause of damage to medium-voltage cables is electrical treeing. This forms channels resembling tree branches in the cable insulation due to excessive electrical voltage. Electrical treeing can harm cable performance and cause short circuits between phase conductors. Short circuits in medium-voltage power networks increase fire risk and endanger electrical operators. This study aims to develop a non-destructive method for detecting defects in medium-voltage cables. The Arduino Mega and ESP32 microcontrollers were used because of the numerous parameters used to determine cable health and the need for a portable diagnostic tool that can be controlled from a safe distance for the user. This method enables faster damage identification, uses more accessible technology, and achieves greater accuracy through multi-parameter measurements. The research output is a prototype system that assesses the quality of medium-voltage cable insulation into six test parameters and six fuzzy rules based on mechanical and chemical data, resulting in a total of 216 unique rule combinations. The tested cable samples are assessed by an expert system with an accuracy rate of 95% from actual conditions and show a decrease in insulation quality from mechanical and electrical perspectives, which affects the distribution cable's service life.



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1. INTRODUCTION

In the electric power distribution system, medium-voltage cables play a crucial role in delivering electrical energy from substations to consumers. One of the main problems in medium-voltage cables is damage or defects in the cable insulation—an insulating layer that prevents unwanted current flow—which can degrade the quality of the electric current or even cause failure of the distribution system [1]. One cause of damage to medium-voltage cables is electrical treeing, a process that forms branching channels within the cable's insulating material due to excessively high electrical voltage [2]. This high voltage causes a breakdown of the insulation's molecular structure through a carbonization reaction, in which the material is locally converted to carbon, creating microscopic channels that lead to the surface and causing the insulation layer to shrink, as shown in Figure 1.

Damage caused by electrical treeing is often not detected early using electrical methods alone; it also requires consideration of other interrelated parameters, including mechanical stress-induced cable damage, which increases the risk of infrastructure failure, as shown in Figure 2 [3]. The time-consuming

process of monitoring mechanical failures, due to the need for specialized equipment, limits the scope of use of treeing detection technology in medium-voltage cables. To address the aforementioned issues, this study proposes several steps to develop a method for assessing medium-voltage cable defects. These include applying a Fuzzy Logic algorithm for quicker, more accurate condition prediction[4]. The method also establishes a non-destructive monitoring procedure that enables defect detection without direct intervention. Electrical test data will be clustered using fuzzy logic and correlated with other parameters, such as chemical parameters measured by Fourier Transform Infrared Spectroscopy (FTIR), which can indicate insulation damage [5].

Conventional methods for detecting defects in medium-voltage cables are generally destructive or require expensive, difficult-to-access measurement equipment[6]. This poses significant challenges, particularly in terms of cost and time efficiency for routine inspections. This research aims to develop a non-destructive method for assessing medium-voltage cable defects that identifies defects more quickly, uses more accessible technology, and achieves greater accuracy through multi-parameter measurements. Thus, this research will contribute to improving the reliability of the power distribution system and to minimizing losses caused by damage to medium-voltage cables.

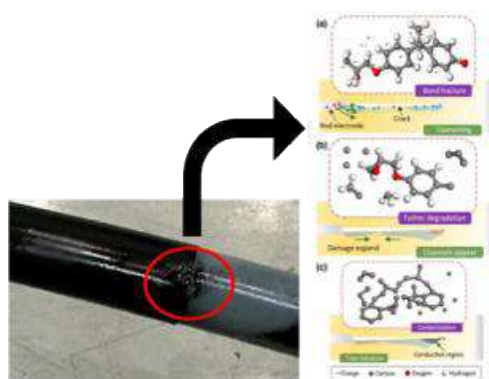


Figure 1. The beginning of the formation of electrical treeing on cable insulation

Despite significant advancements in power asset management, existing condition monitoring systems for medium voltage (MV) cables heavily rely on localized, single-source electrical diagnostics such as partial discharge (PD) or insulation resistance measurements [7]. While these standalone parameters offer valuable insights into immediate insulation defects, they often fail to capture the multi-stress aging mechanisms that simultaneously degrade the cable structure over time. Current fuzzy-based expert systems typically process these diagnostic metrics in isolation without accounting for their non-linear cross-interactions [8]. Consequently, a prominent research gap remains in establishing a unified fuzzy expert system capable of synthesizing diverse electrical parameters into a cohesive, multi-variable health index rather than relying on isolated indicators. Furthermore, the majority of conventional fuzzy logic diagnostic models are developed under controlled laboratory settings or standardized operational assumptions, largely ignoring the severe impact of site-specific environmental stressors [9]. In practical field environments—particularly in tropical, high-humidity, or coastal industrial regions—MV cables suffer from accelerated thermal, chemical, and mechanical degradation due to ambient temperature fluctuations, moisture ingress, and salinity [10]. Existing expert systems lack the necessary environmental input variables and tailored fuzzy membership functions to dynamically adjust asset health assessments based on these geographic factors.

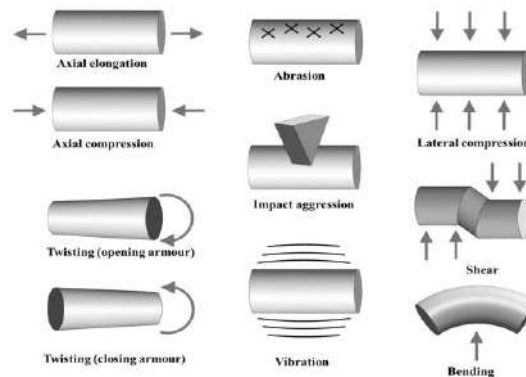


Figure 2. Variations in the form of mechanical stress on cable insulation

Previous research has examined electrical treeing in cables. For example, [11] analyzed applied voltages associated with partial discharge pulses and the effects of treeing damage on medium-voltage substation cables with SF6 gas insulation. A similar study by [12] aimed to determine the effect of insulation degradation on medium-voltage cables in offshore wind power plants. Another study on insulation degradation was conducted by [13]. This study analyzed a decrease in the insulation breakdown voltage in cables exhibiting electrical treeing, caused by their placement around a boiler pump. Research on cable insulation under mechanical stress has also been conducted by researchers [14]. Their title revealed that mechanical stress alters the morphology of the insulation network, thereby initiating electrical treeing and reducing the cable insulation voltage drop. This study will develop an expert assessment system using an Arduino Mega and an ESP32 as the main controllers to assess cable insulation condition. The system will create clusters from mechanical test data (tensile strength and degree of polymerization) and chemical test data (Fourier Transform Infrared Spectroscopy and Scanning Electron Microscopy). The study introduces an IoT-based system using an Arduino Mega, an ESP32, and a fuzzy logic algorithm to assess cable insulation using test data.

2. RESEARCH METHOD

This research is experimental, with tests based on earlier hypotheses. The process follows Figure 3 and includes: (1) planning—identify the problem, review the literature, and draft the design; (2) design and manufacturing—gather tools and materials, and create a prototype (mechanical and electrical); (3) testing—test hardware and software, then analyze results for product development; (4) finalization—use test analysis to make improvements and prepare a report or journal.

2.1. Block Diagram

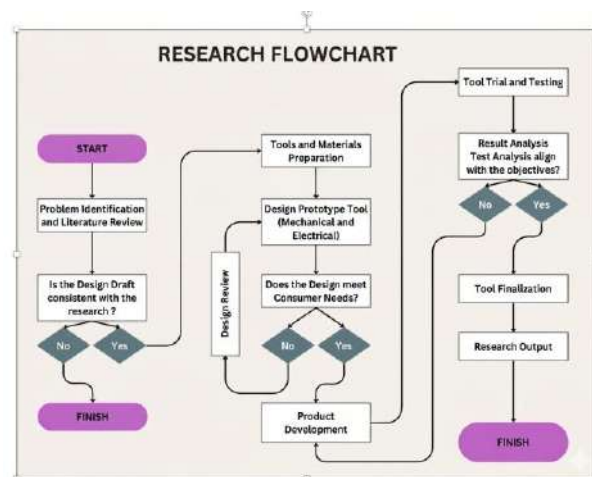


Figure 3. Block diagram

Cable specimens underwent a series of tests to create a fuzzy-logic cluster. Cable specimens underwent a series of tests as follows: first, electrical properties were evaluated using a pre-set circuit, determining the minimum partial-discharge inception voltage and the maximum breakdown voltage after electrical treeing [15]. After electrical testing, tensile strength was measured using a universal testing machine (Autograph) in the PNC Mechanical Engineering Materials Laboratory. The cable insulation specimen was cut with care to avoid defects, then its length, width, and thickness were measured as specified [16] before testing. This research uses N2XSY and A3C-S cables with XLPE insulation. These cables are commonly used for distributing load flows up to 20 kV, as shown in Table 1 below. To assess damage effects, changes in the cable insulation's chemical structure were measured. Fourier-transform infrared spectroscopy in the PNC Environmental Chemistry Laboratory revealed these changes. Scanning electron microscopy revealed microscopic defects due to reduced insulation integrity. Results were correlated with changes in molecular structure [17]. Absorption values within a specific wavelength range indicated the presence of microchannels, leading to electrical treeing and insulation failure. After testing, the data identified clusters in the fuzzy logic algorithm. Insulation quality was assessed with Arduino and ESP32 microcontrollers, and the results appeared via IoT.

Table 1. Specification of X2XSY and A3C-S cable samples.

No	Parameter	X2XSY	A3C-S
1	Conductor Diameter (mm ²)	13,1	13,9
2	Insulation Material	XLPE Insulation, Copper wire/tape screened, PVC Sheathed cable	Extruded XLPE
3	Insulation diameter thickness (mm)	5.5	3,0
4	AC Voltage Test (kV/5 min.)	42	13
5	Max. Current Carrying Capacity at 30°C (Ampere)	320	275
6	Max. DC Conductor Resistance (ohm/km)	0,153	0,438

2.2. Prototype Design

Figure 4 shows a prototype design for a medium-voltage cable insulation condition assessment system. The materials and tools needed to create a prototype of an expert system for detecting insulation quality include an Arduino Mega microcontroller, ESP 32, power supply, HFCT sensor, Rogowski coil, RTC DS3231, Nextion 2.8" LCD, Voltage Divider, 2N3094 Transistor, RC Detector, Lipo Battery, and Mini USB Connector.

The prototype test of the cable insulation condition assessment system includes physical and chemical testing. Results of physical tests, such as tensile strength, are compared with IEC 60227 or SNI 04-6629 standards. Chemical tests follow SNI 046629.3, IEC 60502-1:2009, IEC 840-1987, and SPLN 42-1 standards [18]. If requirements are not met, components are replaced with higher-specification ones to reach minimum standards. This research is conducted on a laboratory scale at the Electrical Machinery Laboratory of the Cilacap State Polytechnic. If the system works and passes lab tests, it can serve as a reference for corona-detection tools for electrical equipment in Cilacap Regency.

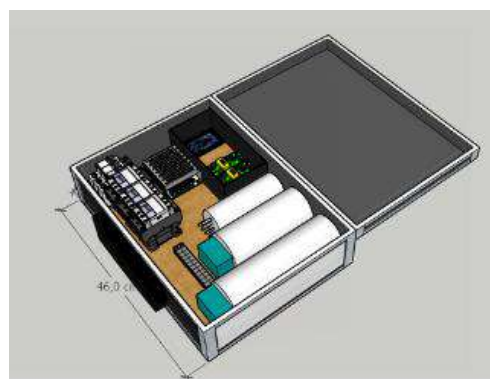


Figure 4. Prototype design

2.3. Fuzzy Clustering

Fuzzy clustering is used as a decision-making system to evaluate various test parameters against predetermined standard limits. The control program is created on a computer and then uploaded to the microcontroller. The Arduino ATmega 2560 microcontroller processes input data, stores it in memory, and uses a set of fuzzy-logic rules to determine whether equipment insulation quality has decreased. These fuzzy rules, defined in the program, establish criteria for determining when parameters indicate reduced insulation quality[19]. If the measured data exceeds the preset values, the Nextion HMI displays the cable insulation condition, the value of each parameter, and recommendations for improvement.

All parameters were then clustered to determine the condition of the cable insulation. Based on the test data, the test was conducted using six inputs: DP, Tensile Strength, CH₄ gas, C₂H₂ gas, % Transmittance, and % Adsorption. The 3x3x2x2x3x2 rule [20] was as follows:

- DP = 3 clusters
- Tensile Strength = 3 clusters
- CH₄ gas = 2 clusters
- C₂H₂ gas = 2 clusters
- % Transmittance = 3 clusters
- % Adsorption = 2 clusters

First, all parameters were tested using the same input parameters while varying membership function values. The results were used to assess the condition of the cable insulation by identifying at least 3 critical parameters that showed significant changes during testing.

3. RESULTS AND DISCUSSION

3.1. Prototype Research Product

Figure 5 illustrates a cable-damage detection prototype utilising a fuzzy-logic algorithm. The control program is developed on a computer and uploaded to a microcontroller. The Arduino ATmega 2560 receives input data, processes it, and stores it in memory. Data is evaluated against predefined fuzzy rules to determine if parameters indicate reduced insulation quality. If measured values exceed set thresholds, the Nextion HMI displays cable insulation status, parameter values, and repair recommendations.



Figure 5. Prototype research product

3.2. Degree of Polymerisation Testing

The degree of polymerisation is the number of monomer units in a polymer chain, which directly affects cellulose's mechanical strength by determining the chain length. Cellulose is a linear polymer composed of glucose units linked at the first and fourth carbon atoms by glycosidic bonds. The degree of polymerisation test was conducted at the Bandung Pulp and Paper Centre (BBPK).

The degree of polymerisation was tested using an intrinsic viscosity method, which included a capillary viscometer and cupryethylene diamine solvent. The procedure followed the ES ISO 5351 standard [21]. Measurement results are presented in Table 1.

Table 1. Degree of Polymerisation Testing

No	Sample	Aging treatment	Degree of Polymerisation
1	T0	Initial state	1909
2	T1	Temperature 120C for 336 hours	1546
3	T2	Temperature 150C for 336 hours	1133
4	T3	Temperature 120C for 672 hours	1023
5	T4	Temperature 150C for 672 hours	1012

The Degree of Polymerization (DP) is a fundamental metric that represents the average number of repeating monomer units in a polymer chain. During the operational lifecycle of an electrical cable, its insulation materials (whether traditional cellulose paper or synthetic polymers like XLPE, EPR, and PVDF) are subjected to continuous environmental and operational stressors. Over time, these stressors break down the macro-molecular chains, leading to a stark decrease in DP. The DP limit value of 200 is relevant because it corresponds to 50% of the insulation's tensile strength. Schoff demonstrated that ageing causes a decrease in DP to 250 and a reduction in tensile strength to 50% of its original value. This relationship, combined with the IEEE insulation strength limit curve, shows that a DP decrease to 200 and tensile strength reaching 50% of its original value marks the insulation's normal operating condition for 180,000 hours (20.5 years).

According to the table, the decrease in the degree of polymerisation indicates a change in the structure of the cellulose bonds in the insulation compared to its initial condition. The cellulose bonds in the insulation break under heat, forming flammable gases that degrade the insulation. The degree of polymerisation curve generally decreases, showing the same characteristic catalytic and environmental acceleration as research by [22], that declare damaged cables for synthetic polymers. The diffusion of transition copper ions from the inner conductor into the insulation matrix acts as a major catalyst that lowers the activation energy required for oxidative chain scission. In subsea cables, ingress of seawater anions similarly attacks the microstructure, causing rapid chain breakage.

3.3 Tensile Strength Testing

Tensile strength testing was conducted with an Autograph tool in the PNC Mechanical Engineering Materials Laboratory. Insulation samples were cut into uniform rectangular shapes using continuous motion to avoid defects. Sample length, width, and thickness were measured before tensile testing. After the fracture, load and elongation values from the Autograph and the fracture area were documented. Insulation service life is often marked by a reduction in tensile strength to 50% or 25% of its initial value. Test results for the tensile strength test are provided in Table 2.

Table 2. Tensile Strength Testing

No	Sample	Aging treatment	Tensile Strength (MPa/mm)
1	T0	Initial state	45,73
2	T1	Temperature 120C for 336 hours	43,55
3	T2	Temperature 150C for 336 hours	32,66
4	T3	Temperature 120C for 672 hours	29,40
5	T4	Temperature 150C for 672 hours	27,22

The test results show that the insulation sample's tensile strength decreased under both the 336-hour and 672-hour ageing conditions. This decrease means the cellulose bonds in the insulation changed, reducing its ability to maintain these bonds in the cable material. As a result, there is excessive heating and reduced insulation strength, especially the axial tensile strength.

3.4 Dissolved Gas Analysis & Fourier Transform Infrared Spectroscopy Testing

Dissolved Gas Analysis (DGA) is a test performed to detect the presence of dissolved gases resulting from temperature or environmental changes that can degrade insulation quality. The effect of thermal ageing on insulation can break down chemical bonds in the insulation. FTIR testing shows that the highest absorption peak occurs in the C-H (aliphatic) group. The graph shows a decrease in %T (% Transmittance) for the C-H (aliphatic) functional group over the wavelength range 3000-2850 cm⁻¹. A

decrease in %T indicates an increase in %Absorption [23]. An increase in %Absorption indicates an increase in the concentration of the C-H (aliphatic) functional group, which is the main component of cable insulation.

Changes in the C-H functional group are caused by the formation of combustible gas when the insulation is thermally aged. In all samples, the most dominant component, the C-H bond, breaks and combines to form a flammable gas. Table 3 shows an increase in combustible gas concentration without a corresponding increase in C-O concentration, because the C-O concentration is formed not from the breakdown of the C-H bonds of the insulation sample used, but from the cellulose paper insulation.

Table 3. Dissolved Gas Analysis Testing

Sample	Combustible Gas Concentration (ppm)					
	H ₂	CH ₄	C ₂ H ₂	C ₂ H ₄	C ₂ H ₆	CO
T0	0	0	0	0	0	0
T1	0	68,52	0	11,16	73,43	92,35
T2	0	21,74	0	29,17	45,40	94,10
T3	0	41,22	0	11,83	39,95	110,30
T4	0	267,39	0	33,45	293,14	438,15

Fourier Transform Infrared Spectroscopy (FTIR) testing was conducted to determine the effect of ageing on changes in the functional group composition of the samples. This testing was conducted at the PNC Environmental Chemistry Laboratory. All samples were tested, and the FTIR results are presented in a graph showing the percentage of infrared transmittance at specific wavelengths.

In the FTIR graph, the vertical axis, %T, represents the percentage transmittance, which is the ratio of the infrared light not absorbed by the sample to the infrared light delivered to the sample. The horizontal axis represents the wavenumber in 1/cm. The infrared region used is 4000–5001/cm, as in the Nieman reference [24].

Table 4. Dissolved Gas Analysis Testing

Sample	%Transmittance	% Absorption
T0	850,61	2,097
T1	565,14	0,161
T2	536,21	1,398
T3	441,70	3,577
T4	437,84	3,257

From Table 4, the FTIR test data result in the % Transmittance parameter, allowing us to determine the condition of the insulation sample. The accepted condition in this study was an increase in the concentration of C-H functional groups (aliphatic), which are the main components of cable insulation. Knowing that an increase in C-H functional groups will occur, it is certain that the DGA test will also show an increase in the concentration of C-H groups. This is evidenced by the test results above, which show increased concentrations of CH₄, C₂H₄, and C₂H₆.

The concentration of C-O bonds also increased, but this was not related to the increase in the concentration of C-H groups. This increase in C-O bonds may be due to changes in the cellulose bond structure in the insulation due to heating [25]. The amount of heat the insulation receives can affect the concentration of CO compounds formed. The higher the temperature and the longer the heating time, the greater the change in the cellulose bond structure in the tested insulation[26].

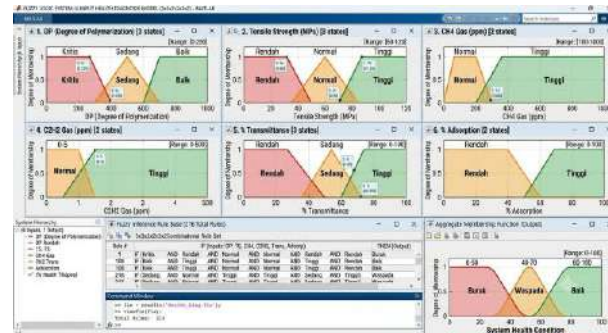


Figure 6. Fuzzy Logic Membership Function

The results of the study indicate that the prototype of the medium voltage cable insulation quality assessment system is capable of clustering various test result parameters with a total of 6 parameters and 6 fuzzy rules as shown in Figure 6. This notation dictates that the system has 6 input variables with varying numbers of membership functions (linguistic states), resulting in a total of 216 unique rule combinations. Based on the test data, the test was conducted using six inputs: DP, Tensile Strength, CH₄ gas, C₂H₂ gas, % Transmittance, and % Adsorption.

This expert system contains six parameters that can be divided into 3 parameters with three membership functions and 3 parameters with two membership functions, and mathematically, it can be achieved through a combination of multiplying the factor numbers $3 \times 3 \times 3 \times 2 \times 2 = 216$ total rules. Writing all 216 combinations out individually is redundant, so they are structured here systematically from equations (1) and (2) below:

$$R = |MF(X1)| \times |MF(X2)| \times |MF(X3)| \times |MF(X4)| \times |MF(X5)| \times |MF(X6)| \quad (1)$$

$$\text{IF } (X1 \text{ is } A1, p) \text{ AND } (X2 \text{ is } A2, q) \text{ AND } (X3 \text{ is } A3, r) \text{ AND } (X4 \text{ is } A4, s) \text{ AND } (X5 \text{ is } A5, t) \text{ AND } (X6 \text{ is } A6, u) \text{ THEN } (y \text{ is } Bk) \quad (2)$$

Equations 1 and Equation 2 are ruled for every combination, with each k rule based on the standard criteria. For example, Rule 45 uses this formula: IF Degree of Polymerization is Critical (A1,1) AND Tensile Strength is Low (A2,1) AND CH₄ Gas is Danger (A3,3) AND C₂H₂ Gas is Abnormal (A4,2) AND % Transmittance is Low (A5,1) AND % Adsorption is Saturated (A6,2) THEN Cable Health Status is Very Poor / Breakdown Risk (B45). The reasoning uses a worst-case dominance logic; for example, if PD is High and DP is Critical, the outcome naturally skews to Critical regardless of environmental factors. The Python code is uploaded to the Arduino to be evaluated against predefined fuzzy rules to determine if parameters indicate reduced insulation quality. If measured values exceed set thresholds, as shown in Figure 10, the Nextion HMI displays cable insulation status, parameter values, and repair recommendations. Recommendations were given according to the standard of each criterion, for example, tensile strength with IEC 60811-501, DP with IEC 60450, and other standards.

The tested cable samples show that the cable has experienced a decrease in insulation quality on both mechanical and electrical fronts, thereby affecting the distribution cable's service life. The ageing condition of the sample will affect the insulation strength of the material tested through a series of electrical tests, namely mechanical test data (tensile strength and degree of polymerisation) and chemical test data (Dissolved Gas Analysis (DGA) and Fourier Transform Infrared Spectroscopy (FTIR).



Figure 7. Interfacing cable's health index

Based on the input test results, several conditions were identified that indicate the cable's health index. Table 5 clearly shows that different conditions and health index values serve as a reference for other tests and determine repair or maintenance recommendations for the tested cables, and are also directly proportional to the interfacing shown in Figure 7. The test results based on the health index are as follows:

Table 5. Cable health index

Sample	Output Fuzzy Value	Output Fuzzy Expert Condition	Recommended Action	Actual Sample Condition
T0	64,8747	Normal	Schedule regular inspections and monitoring.	New MV cable
T1	60,7776	Normal	Schedule regular inspections and monitoring.	New-aged MV cable
T2	40,5833	Poor	Inspect immediately and prepare for repairs	Damaged MV cable
T3	57,25	Normal	Schedule regular inspections and monitoring.	New-aged MV cable
T4	46,3779	Poor	Inspect immediately and prepare for repairs	Damaged MV cable

The results of the study indicate that the prototype of the medium-voltage cable insulation quality assessment system can cluster various test result parameters into 6 parameters and 6 fuzzy rules. The ageing condition of the sample will affect the insulation strength of the material tested through a series of electrical tests, as well as mechanical test data (tensile strength and degree of polymerisation) and chemical test data (Dissolved Gas Analysis (DGA) and Fourier Transform Infrared Spectroscopy (FTIR)). The tested cable samples are assessed by an expert system with an accuracy rate of 95% compared to actual conditions. This result also showed that the cable had experienced a decrease in insulation quality on both mechanical and electrical fronts, thereby affecting the service life of the distribution cable.

4. CONCLUSION

The results of the study indicate that the prototype of the medium voltage cable insulation quality assessment system is capable of clustering various test result parameters with a total of 6 parameters and 6 fuzzy rules. The tested cable samples show that the cable has experienced a decrease in insulation quality on both mechanical and electrical fronts, thereby affecting the distribution cable's service life. This study aims to develop a non-destructive method for detecting defects in medium-voltage cables. The ageing condition of the sample will affect the insulation strength of the material tested through a series of electrical tests, namely mechanical test data (tensile strength and degree of polymerisation) and chemical test data (Dissolved Gas Analysis (DGA) and Fourier Transform Infrared Spectroscopy (FTIR)).

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Development and Diagnostic Performance Evaluation of A Wireless Digital Fetal Heart Rate Monitoring System Using Ultrasonic Doppler with Digital Filter-Based Noise Reduction

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ABSTRACT

Early fetal heart rate (FHR) monitoring is essential for assessing fetal well-being and enabling the early detection of fetal distress during pregnancy. However, existing fetal Doppler systems commonly rely on wired communication and remain susceptible to signal noise, limiting monitoring flexibility and measurement reliability. This study aimed to develop and evaluate a wireless fetal heart rate monitoring system with enhanced signal quality and reliable real-time communication. The proposed system integrates an ultrasonic Doppler sensor, ESP32 microcontrollers communicating through the ESP-NOW protocol, and digital signal processing using a Butterworth low-pass filter and a smoothing algorithm to suppress noise and improve signal clarity. System performance was evaluated using sampling frequencies ranging from 200 to 1000 Hz and baud rates from 300 to 250,000 bps. Communication reliability was assessed by transmitting 1,500 ADC packets for each sampling-frequency configuration and 1,000 ADC packets for each baud-rate configuration while monitoring packet sequence numbers to identify transmission loss. Experimental results showed that no packet loss was observed under all tested configurations. The developed system achieved BPM measurement errors ranging from 0.56% to 0.89% and improved signal quality, with the highest signal-to-noise ratio of 18.70 ± 0.17 dB obtained using a 0.5–20 Hz Butterworth filter. Higher sampling frequencies produced more detailed waveform representations, whereas higher baud rates improved transmission responsiveness without affecting waveform integrity within the tested range. These findings demonstrate that the proposed system provides an accurate, reliable, and portable solution for real-time wireless fetal heart rate monitoring.



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1. INTRODUCTION

Fetal heart rate (FHR) is one of the most important physiological indicators used to assess fetal well-being during pregnancy. Continuous and accurate FHR monitoring enables early detection of fetal abnormalities and distress, thereby supporting timely clinical intervention. Despite advances in maternal

healthcare, infant and perinatal mortality rates remain relatively high in many developing countries, including Indonesia [1][2]. A considerable proportion of neonatal deaths is associated with delayed identification and management of fetal complications. Therefore, reliable FHR monitoring systems are essential for improving prenatal care and supporting preventive healthcare strategies. The availability of monitoring devices that are accurate, responsive, and convenient to use is increasingly important in both healthcare facilities and home-based monitoring environments[3][4].

Fetal Doppler technology is widely utilized for fetal heartbeat detection by employing the Doppler effect to capture blood flow movement in the fetal heart and convert it into audible signals [5][6][7]. Various studies have developed fetal monitoring systems using microcontroller-based platforms to improve portability and reduce system complexity [8][9]. Signal amplification circuits and display modules have been integrated into these systems to provide real-time fetal heart rate information. Furthermore, recent developments have introduced wireless communication technologies and digital signal processing methods to enhance data transmission efficiency and signal quality [10][11]. These advancements have contributed to the development of more practical and accessible fetal monitoring systems.

However, several limitations remain unresolved in existing fetal Doppler monitoring systems. Many systems still rely on wired communication, which restricts user mobility and reduces monitoring flexibility[12], [13], [14]. In addition, beats-per-minute (BPM) measurements may become unstable due to noise contamination and inadequate signal processing techniques [1], [15], [16]. Environmental interference, electromagnetic disturbances, and motion artifacts generated by body movement can further degrade signal quality and reduce measurement reliability [17][18]. Consequently, there is a need for a fetal monitoring system that provides reliable wireless communication, improved signal quality, and stable real-time BPM measurements[19].

To address these limitations, this study proposed a wireless fetal Doppler monitoring system integrated with digital signal processing techniques. The system utilized ESP32 microcontrollers and the ESP-NOW communication protocol to enable fast and efficient wireless data transmission without requiring Wi-Fi infrastructure. Fetal heart rate signals acquired from the Doppler sensor were processed using a digital low-pass filter and a smoothing algorithm to suppress noise and improve signal clarity[16]. By combining wireless communication and digital filtering, the proposed system was expected to enhance both transmission reliability and measurement accuracy.

This study aimed to develop and evaluate a wireless fetal Doppler-based fetal heart rate monitoring system capable of providing reliable real-time signal acquisition, wireless transmission, and improved signal quality. Unlike previous fetal Doppler systems, which primarily focused on either wireless communication or signal processing separately, the proposed system integrates ESP-NOW-based wireless communication with digital signal processing using a Butterworth low-pass filter and a smoothing algorithm within a single real-time monitoring platform. In addition, this study provides a comprehensive performance evaluation by investigating the effects of baud rates (300–250,000 bps) and sampling frequencies (200–1,000 Hz) on communication reliability and signal quality. The proposed system was further validated using a fetal simulator through packet transmission analysis, BPM measurement accuracy, and signal-to-noise ratio.

2. RESEARCH METHOD

Research Methods: This study employed a research and development approach to design and evaluate a wireless digital fetal heart rate (FHR) monitoring system based on the ultrasonic Doppler method. The system consisted of a Doppler ultrasound sensor, signal conditioning circuit, digital noise reduction filter, and ESP32-based wireless communication modules for real-time data transmission. The acquired Doppler signals were processed using digital filtering techniques to reduce noise and motion-related artifacts before fetal heart rate extraction. System performance was evaluated through experimental testing using multiple fetal heart rate conditions. The measured FHR values were compared with reference values to determine measurement accuracy. Communication performance was assessed by analyzing transmission reliability, baud rate stability, packet delivery, and communication range. Signal quality was evaluated based on waveform clarity and noise suppression effectiveness.

Sampling frequency analysis was also conducted to determine its influence on BPM measurement accuracy and real-time monitoring performance. The collected data were analyzed quantitatively using percentage error and transmission success rate metrics to assess the overall effectiveness of the proposed system. Wireless communication performance was evaluated by transmitting 1,000 ADC packets for each baud-rate configuration (300–250,000 bps). Each experiment was conducted for 30 s in an indoor laboratory environment with transmitter–receiver separation distances of 1 m and 3 m under line-of-sight conditions. Packet loss was determined by comparing the sequence numbers of transmitted and received packets at the end of each transmission session.

2.1. Dataset

This study aims to evaluate the effectiveness of a wireless fetal Doppler system in improving the accuracy and reliability of fetal heart rate monitoring data, particularly for clinical decision-making applications. By analyzing the performance and limitations of the proposed system, this research is expected to provide an effective solution for minimizing data loss, thereby enhancing safety and efficiency in practical use. Furthermore, this study aims to ensure that innovations in fetal monitoring technology not only emphasize portability and ease of use, but also maintain high standards of data accuracy and transmission reliability, as illustrated in Figure 1.



Figure 1. Implementation of fetal heart rate (FHR) monitoring using a wireless fetal doppler with FHR sound enhancement and digital filter for noise reduction

During the system design process, a piezoelectric sensor was used to detect fetal heart rate signals, while an ESP32 microcontroller served as the main processing unit. The measurement results were displayed on an OLED screen. To ensure accurate BPM measurements, system calibration was performed using a fetal simulator with predefined BPM variations. Data observations were conducted by comparing the BPM values obtained from the transmitter and receiver units to evaluate data consistency. The system was tested under five BPM conditions, namely 60, 90, 120, 150, and 180 BPM. Furthermore, data loss analysis was carried out by comparing ADC values between the transmitting and receiving units to determine the presence of any mismatch or information loss during wireless data transmission under different sampling frequency and baud rate configurations.

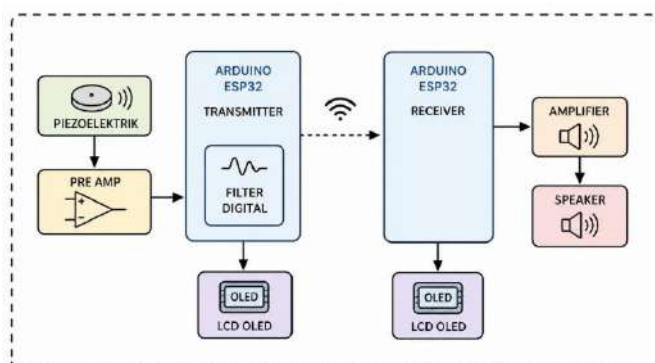


Figure 2. Block diagram of wireless fetal doppler with Djj Voice Enhancement and digital filter for noise reduction

Figure 2 shows a block diagram of the system that starts with a piezoelectric transducer attached to the pregnant woman's abdomen. This transducer functions to send ultrasonic waves into the body, which

are then reflected by the fetal heart and received back as reflected waves. These reflected waves are converted into electrical signals, then processed by a demodulator circuit to extract the information signal from the carrier signal. After that, the signal is amplified using a pre-amplifier circuit, converted from analog to digital, then digitally filtered to remove noise. Furthermore, the signal that has been processed by the ESP32 microcontroller on the sending side is converted into BPM data and displayed on the OLED screen. The BPM data is also sent wirelessly to the receiving ESP32 to be displayed again for comparison. In addition, the data is converted back into an analog signal, amplified using the main amplifier, and finally output through the speaker as an audio signal.

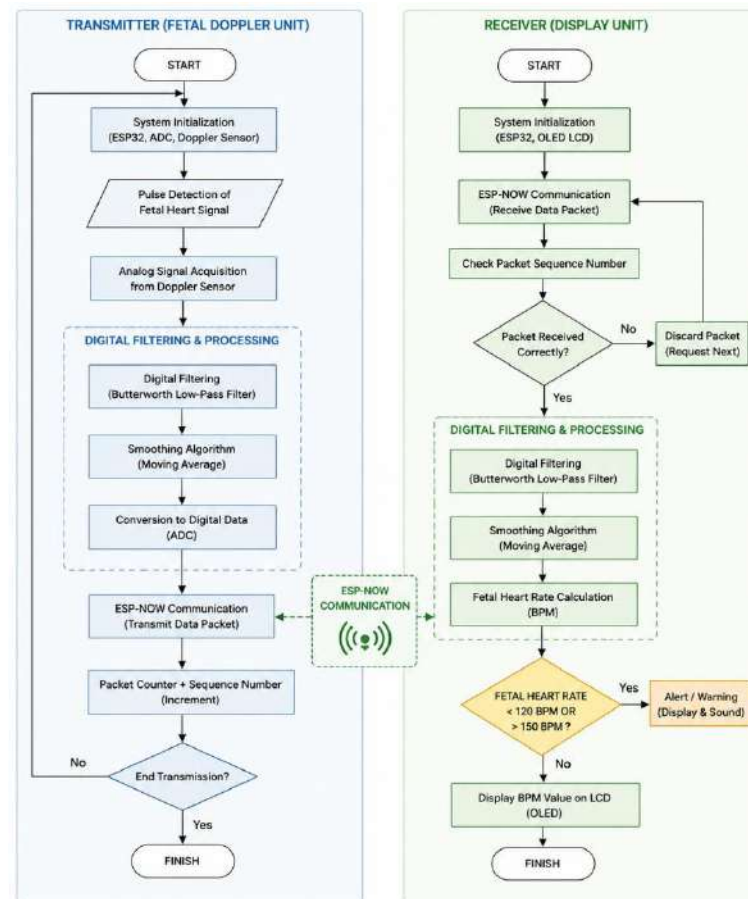


Figure 3. Flowchart of the ESP-NOW-Based wireless fetal heart rate monitoring system

Figure 3 illustrates the operational flow of the proposed wireless fetal heart rate monitoring system, which consists of separate transmitter and receiver processes. The process begins when the Doppler transducer is placed on the pregnant woman's abdomen to acquire fetal heart signals. In the transmitter unit, the ESP32 is initialized, and the analog Doppler signal is acquired and converted into digital data through the analog-to-digital converter (ADC). The acquired signal is then processed using a Butterworth low-pass filter followed by a smoothing algorithm to suppress noise and improve signal quality. The processed digital data are subsequently transmitted wirelessly to the receiver unit using the ESP-NOW communication protocol. At the receiver side, the received data are used to calculate the fetal heart rate in beats per minute (BPM). The calculated BPM value is compared with the predefined normal range (120–160 BPM). If the measured value falls outside this range, the system identifies the condition as abnormal; otherwise, it is considered normal. Finally, the BPM value is displayed on the OLED LCD for real-time monitoring.

2.2. Data Processing

The acquired fetal heart rate (FHR) data were analyzed offline to evaluate the performance of the proposed wireless monitoring system. For each fetal simulator setting (60, 90, 120, 150, and 180 BPM),

six repeated measurements were performed to assess the accuracy and repeatability of the system. The measured BPM values obtained from the receiver unit were compared with the corresponding reference values provided by the fetal simulator.

The arithmetic mean of the repeated measurements was calculated using Equation (1):

$$\bar{x} = \frac{X_1 + X_2 + \dots + X_n}{n} \quad (1)$$

where $\bar{x}$ is the average of the measured BPM values, X_i represents each individual measurement, and n is the total number of measurements.

The percentage error between the measured BPM and the simulator reference value was calculated using Equation (2):

$$\text{Error \%} = \frac{BPM_{ref} - BPM_{meas}}{BPM_{ref}} \times 100\% \quad (2)$$

where BPM_{ref} is the reference value generated by the fetal simulator and BPM_{meas} is the average BPM measured by the proposed system. Measurement repeatability was evaluated using the sample standard deviation, calculated as follows:

$$stdev = \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{x})^2}{n - 1}} \quad (3)$$

where SD denotes the standard deviation, $\bar{x}$ is the mean value, and X_i represents each measurement.

To evaluate the effectiveness of digital signal processing, the signal-to-noise ratio (SNR) was calculated before and after filtering using Equation (4):

$$SNR = 10 \log_{10} \left(\frac{P_{signal}}{P_{noise}} \right) \quad (4)$$

where P_{signal} is the power of the useful fetal heart signal and P_{noise} is the power of the noise component. The calculated SNR values were used to compare the performance of different cutoff frequencies and determine the optimal filtering configuration for fetal heart rate monitoring.

3. RESULTS AND DISCUSSION

The developed wireless fetal heart rate monitoring system was successfully implemented and evaluated to analyze its performance in detecting fetal heart signals, transmitting data wirelessly, and improving signal quality through digital filtering techniques. Several tests were conducted to assess system performance, including BPM measurement accuracy, data transmission reliability, baud rate performance, and sampling frequency evaluation. The experimental results demonstrated that the proposed system was capable of transmitting data reliably without significant loss while maintaining stable and clear fetal heart rate signals. Furthermore, the implementation of digital filtering and wireless communication using the ESP-NOW protocol contributed to improved signal clarity and overall system effectiveness for real-time fetal heart rate monitoring applications.

3.1. Accuracy

The module is designed using a piezoelectric sensor to detect the fetal heart rate, using an ESP32 microcontroller and displaying the readings on an OLED LCD. Figure 4. shows the entire circuit used to create the tool module.

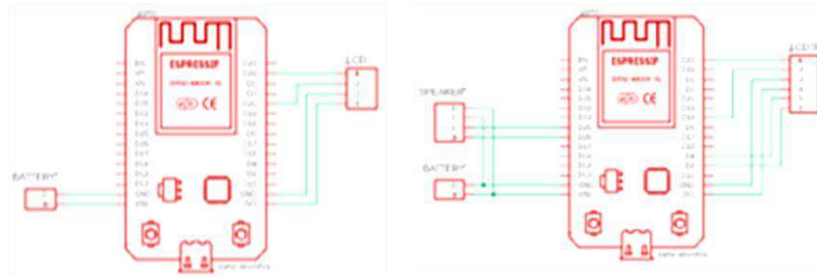


Figure 4. Wireless fetal doppler system circuit with Djj Voice Enhancement and digital filter

Tabel 1. Test results and calculation of percentage of data loss with different F sampling

No	F sampling	Jumlah Paket ADC Dikirim	Jumlah Paket ADC Diterima	Paket Hilang	Persentase Loss (%)
1	200 hz	1500	1500	0	0%
2	400 hz	1500	1500	0	0%
3	600 hz	1500	1500	0	0%
4	800 hz	1500	1500	0	0%
5	1000 hz	1500	1500	0	0%

To find out if any data is lost during the wireless transmission process using ESP-NOW, a test is conducted where each data sent from the sending device is given a sequence number (packet number) that keeps increasing one by one. For example, the first packet is numbered 1, then 2, 3, and so on. The receiving device will display the successfully received packet number along with the ADC (analog-to-digital converter) data value sent. If the receiving device skips a number, for example from packet 101 directly to 103 (without receiving packet 102), then this is considered a lost packet. This test was conducted using different sampling frequencies and baud rates.

In Table 1, Based on the tests I tried, the system was tested using several variations of sampling frequency (F sampling) to determine its effect on transmission performance and the quality of the resulting signal. I tried F sampling ranging from 200 Hz to 1000 Hz to ensure that the system can transmit and receive data stably at various sampling rates. As a result, all tests showed no data loss (0% loss), indicating that the transmission was running well. However, the sampling frequency still affects the shape and sharpness of the signal. At low sampling frequencies such as 200 Hz, the signal looks less detailed and does not capture rapid changes as a whole, because the amount of data sent per second is less. Conversely, at high sampling frequencies such as 1000 Hz, the signal looks more detailed and sharp because more data points are recorded, so the waveform looks clearer and closer to the original shape. Therefore, although the system is able to transmit data stably at various sampling frequencies, choosing the right sampling frequency is still important to ensure that the signal remains accurate and does not lose important details.

Table 2 presents the packet transmission performance of the proposed ESP-NOW communication system under different baud-rate configurations. For each baud rate, 1,000 ADC data packets were transmitted from the ESP32 transmitter to the ESP32 receiver over a testing period of 30 s. The communication tests were conducted in an indoor laboratory environment with transmitter–receiver separation distances of 1 m and 3 m under line-of-sight conditions. Packet loss was evaluated by comparing the sequence numbers of transmitted and received packets after each transmission session. As shown in Table 2, all 1,000 transmitted packets were successfully received at every tested baud rate, resulting in no observed packet loss (0%) across all communication configurations. These results demonstrate that the proposed ESP-NOW communication system provides reliable wireless data transmission for real-time fetal heart rate monitoring within the tested indoor distances.

Tabel 2. Packet transmission performance at Different Baud Rates using the ESP-NOW protocol

No	Baud Rate	ADC Packets Sent	ADC Packets Received	Lost Packets	Packet Loss (%)
1	300 bps	1000	1000	0	0
2	1200 bps	1000	1000	0	0
3	2400 bps	1000	1000	0	0
4	4800 bps	1000	1000	0	0
5	9600 bps	1000	1000	0	0
6	19200 bps	1000	1000	0	0
7	38400 bps	1000	1000	0	0
8	57600 bps	1000	1000	0	0
9	115200 bps	1000	1000	0	0
10	230400 bps	1000	1000	0	0
11	250000 bps	1000	1000	0	0

Although no packet loss was observed, the baud rate affected the responsiveness of real-time data visualization. At lower baud rates (300–9600 bps), data transmission was slower, causing the waveform to appear intermittent on the display. Increasing the baud rate to 115,200 bps and 250,000 bps enabled smoother and more continuous waveform visualization without affecting signal integrity. However, preliminary experiments at baud rates higher than 250,000 bps (500,000 and 1,000,000 bps) produced corrupted data, most likely due to hardware communication limitations. Therefore, baud rates of 115,200 bps and 250,000 bps are recommended because they provide an appropriate balance between transmission speed and communication reliability.

Figure 5. shows the display of BPM values read by the fetal doppler device when connected to the fetal simulator. In this process, the fetal simulator is used as a source of artificial heartbeat signals that can be adjusted for testing and calibration purposes. In the example in the figure, the fetal simulator is set at 60 BPM, then the probe of the fetal doppler is placed directly on the output port of the fetal simulator to detect the signal. The fetal doppler device will read the signal from the simulator and display it in the form of a BPM value on the device screen.

The data collection process is carried out systematically with variations in BPM settings on the fetal simulator, ranging from 60 BPM, 90 BPM, 120 BPM, 150 BPM, to 180 BPM. For each BPM value, measurements were taken six times to ensure the accuracy and stability of the readings, in accordance with standard medical device calibration procedures. The results of each measurement are then averaged and compared with the reference value of the simulator, so that it can be seen how much error or deviation occurs in each BPM setting. The average error value of each BPM setting is presented in the Table 3 as a result of the device performance evaluation.



Figure 5. Measurement results with different bpm settings using fetal simulator

Table 3. Test results and calculation of percentage of data loss with different F sampling

Setting (BPM)	Error (Mean $\pm$ SD)
60	0.84 $\pm$ 0.96
90	0.56 $\pm$ 0.61
120	0.83 $\pm$ 0.55
150	0.89 $\pm$ 0.66
180	0.56 $\pm$ 0.47

From the data Table 3 presented, it can be seen that system was tested at five different BPM settings, namely 60, 90, 120, 150, and 180. The test results show that the resulting error rate is quite small and within a narrow range, which is between 0.56% and 0.89%. In detail, at BPM 60, an error of 0.84% was recorded, BPM 90 was 0.56%, BPM 120 was 0.83%, BPM 150 was 0.89%, and BPM 180 was 0.56%. From these data, I can conclude that although there is a slight variation, all error values are still relatively low and show the stability of the system's performance in detecting BPM in various conditions.

3.2. Performance

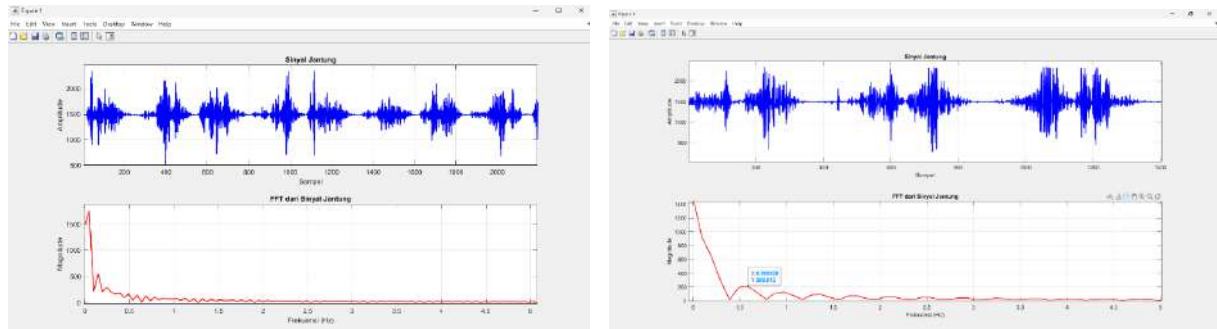


Figure 6. Heartbeat signal analysis using FFT on signals before and after filtering

In the graphic image shown in Figure 6. I performed the acquisition and analysis of the heart signals displayed in two domains, time and frequency. The upper signal shows the shape of the heart signal that I acquired based on the number of samples against the amplitude, while the lower part is the result of analyzing the frequency spectrum using fast Fourier transform (FFT). In processing this signal, I applied an IIR Butterworth bandpass filter with a cutoff frequency of 0.5 Hz to 20 Hz. I used this filter to eliminate low-frequency noise such as baseline wander below 0.5 Hz and also eliminated high-frequency noise above 20 Hz that is irrelevant to the main information of the heart signal.

From the FFT results I obtained, it can be seen that the dominant frequency component of the heart signal is at a frequency below 2 Hz, which corresponds to the physiological range of normal human heart rate, which is about 60-120 beats per minute (bpm)[20]. In the second graph, I marked one of the dominant frequency peaks at about 0.58 Hz with a magnitude of about 209.313, which shows the success of the filter in retaining the main components of the signal. By using the IIR Butterworthfilter, I got a smoother and cleaner spectrum shape as it has gradual transition characteristics as well as a stable frequency response within the bandpass I specified. Through this filtering process, I managed to improve the quality of the heart signal so that it is easier to analyze and more representative of real conditions. This is very important for further analysis, such as peak detection heart rate calculation.

Table 4. Test results and calculation of percentage of data loss with different F sampling

FC filter	Mean $\pm$ SD (dB)
0.5-20hz	18.70 $\pm$ 0.17
0.5-50hz	16.16 $\pm$ 0.08
0.5-100hz	10.83 $\pm$ 0.12
0.5-150hz	8.13 $\pm$ 0.37
0.5-200hz	6.19 $\pm$ 0.48

Table 4 is a the measurement results show that the application of a digital filter with a variation in

cutoff frequency (FC) affects the SNR value. At a narrower FC, such as 0.5–20 Hz, the SNR increases to 18.70 ± 0.17 dB, indicating that noise is effectively suppressed. Conversely, when the FC range is expanded to 0.5–200 Hz, the SNR decreases drastically to 6.19 ± 0.48 dB due to the entry of high-frequency noise. The low standard deviation value (0.08–0.48 dB) indicates that the filtering process is stable and consistent. The decreasing trend in SNR as the FC increases reflects the working principle of the low-pass filter, which only passes low-frequency signals and reduces noise outside that limit. Overall, these data indicate that the digital filter is able to effectively improve signal quality through selective and efficient noise suppression. The performance of the digital filter is proven to be effective in reducing noise. At narrow FC (0.5–20 Hz), high SNR (18.70 ± 0.17 dB) indicates noise is successfully suppressed, while at wide FC (0.5–200 Hz), SNR drops drastically (6.19 ± 0.48 dB) because high-frequency noise is also included. The pattern of decreasing SNR as FC increases is consistent with the working principle of the low-pass filter. The small standard deviation value reflects the stability of the results. This indicates that the filter works optimally in improving signal quality through selective and consistent noise suppression.

4. CONCLUSION

This study successfully developed and evaluated a wireless ultrasonic Doppler-based fetal heart rate (FHR) monitoring system integrating ESP32 microcontrollers, ESP-NOW wireless communication, and digital signal processing using a Butterworth low-pass filter and a smoothing algorithm. The proposed system demonstrated reliable wireless communication, with no packet loss observed during the transmission tests conducted at sampling frequencies of 200–1000 Hz and baud rates ranging from 300 to 250,000 bps. The system achieved BPM measurement errors between 0.56% and 0.89% and improved signal quality, obtaining the highest signal-to-noise ratio (SNR) of 18.70 ± 0.17 dB using a 0.5–20 Hz Butterworth filter. Furthermore, higher sampling frequencies produced more detailed waveform representations, whereas higher baud rates improved transmission responsiveness without compromising communication reliability within the tested range. These findings demonstrate that the proposed system provides an accurate, reliable, and portable solution for real-time wireless fetal heart rate monitoring. Future work will focus on integrating cloud-based monitoring, IoT connectivity, and automatic fetal heart rate abnormality detection to further enhance the system's clinical applicability.

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Single-Camera Flood Monitoring Using YOLOv5 for Water Level and Turbidity Detection

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ABSTRACT

Floods are one of the most common natural disasters and require efficient early warning systems to mitigate their effects on infrastructure and communities. Conventional flood monitoring systems generally consist of many physical sensors, which may incur higher maintenance cost and reduce the system robustness in a severe river environment. The purpose of this study is to create a single-camera flood monitoring system that is capable of detecting water level and water turbidity in real-time using YOLOv5. An initial dataset containing 1,711 original images was collected and augmented to 4,104 images for model training and evaluation. Four YOLOv5 variants (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) were trained for 50 and 150 epochs. Experimental results show that all models have high detection performance with precision, recall and mAP values above 0.98. YOLOv5s achieved the best real-time performance with 4.26 FPS and maintained competitive accuracy. Detection failures due to overexposure were observed at high illumination levels and illumination analysis indicated that detection can be reliably performed under lighting conditions below 25,000 lux. The proposed system provides a vision-based alternative for real-time inundation early warning applications.



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1. INTRODUCTION

Floods are among the most destructive natural disasters worldwide, causing significant losses of human life, economic activities, and infrastructure. In Indonesia, floods frequently occur due to rapid urbanization, high-intensity rainfall, land-use changes, and inadequate drainage systems. They are commonly characterized by rising water levels, increased sediment transport, debris movement, and higher water turbidity, which serve as important indicators of flood occurrence and severity. Recent studies have highlighted the growing need for advanced flood monitoring and forecasting systems to improve disaster preparedness and mitigation [1] - [3].

Timely information is essential for effective flood Early Warning Systems (EWS). Modern EWS increasingly integrate artificial intelligence, hydrological modeling, and real-time sensing technologies to improve prediction accuracy and response capability [4] - [6]. However, developing a reliable and scalable monitoring system remains challenging, particularly in river environments where sensor

installation and maintenance are difficult. Therefore, continuous monitoring approaches capable of operating under varying environmental conditions are highly desirable [1], [7].

Various methods have been proposed for flood monitoring. Ultrasonic sensors are widely used for water level measurement because of their simplicity and low cost [8], while turbidity sensors monitor suspended particles and water quality changes associated with flood events [9] - [11]. IoT technologies further support environmental monitoring through automatic warning dissemination, cloud data transmission, and remote monitoring [12] - [14]. More recently, deep learning and computer vision have enabled camera-based flood monitoring, including water level estimation using single-camera systems [15] - [20] and flood detection or inundation segmentation from images [21] - [23].

Despite these advances, existing flood monitoring systems still face several limitations. Many studies focus on a single flood indicator, such as water level, flood extent, or water quality [7], [22], [23]. Sensor-based approaches require multiple devices, increasing installation complexity and maintenance while remaining vulnerable to debris, sedimentation, and extreme weather [8], [10], [11]. Some systems also demand substantial computational resources or cannot operate in real-time [4], [5], [24], whereas camera-based methods are sensitive to illumination and adverse weather conditions [20]. Furthermore, only a few studies have investigated simultaneous detection of water level and water turbidity using a single-camera, and comparative evaluations of different YOLOv5 variants under varying environmental conditions remain limited [1], [3], [7], [17].

To address these limitations, this study proposes a single-camera flood monitoring system based on the YOLOv5 object detection algorithm for simultaneous water level and water turbidity detection. Four YOLOv5 variants (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) are evaluated under different training configurations. YOLOv5 was selected because of its strong performance in lightweight and real-time object detection applications [25] - [27]. Ultrasonic and turbidity sensors are used as reference measurements to validate the proposed vision-based system.

The main contributions of this study are: (1) developing a single-camera flood monitoring framework; (2) enabling simultaneous detection of water level and water turbidity; (3) comparing multiple YOLOv5 variants for real-time monitoring; and (4) analyzing the effect of illumination on detection performance. The proposed approach provides a vision-based alternative for real-time flood monitoring and early warning applications in river environments, complementing recent advances in computer vision-based hydrological monitoring and flood management systems [1], [2], [6], [12].

2. RESEARCH METHOD

2.1 System Architecture

The proposed flood monitoring system employs a single-camera vision-based framework integrated with reference sensors for system validation, as illustrated in Figure 1. A webcam continuously captures river images, which are processed by a laptop running the YOLOv5 object detection model to determine water turbidity and water level conditions in real-time. Camera-based monitoring has gained increasing attention because of its non-contact measurement capability and suitability for flood monitoring applications [1], [15], [17] - [19].

An ultrasonic sensor and a turbidity sensor are used as references to measure water level and turbidity (NTU), respectively. YOLOv5 predictions are compared with the sensor measurements to evaluate detection accuracy and system reliability. This hybrid approach enables validation of the vision-based system while reducing reliance on physical sensors in practical flood monitoring applications [8], [9], [12]. Similar integrations of computer vision and sensor-based systems have been reported to improve the reliability of environmental monitoring applications [2], [11].

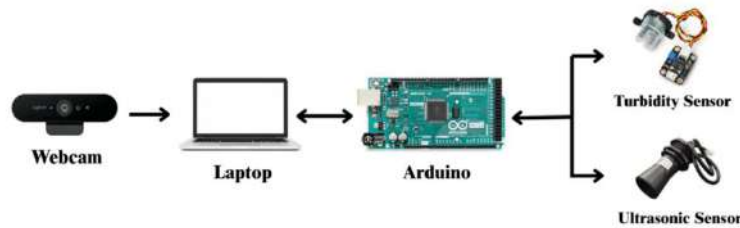


Figure 1. Overall architecture of the proposed flood monitoring system

2.2 Dataset Preparation

The dataset consisted of 1,711 original images captured under various environmental conditions, representing different water turbidity and water level scenarios. Data augmentation was applied to improve model generalization and reduce overfitting, resulting in a total of 4,104 images. Dataset diversity enhances the robustness of deep learning models under varying environmental conditions, including illumination changes and water appearance [21] - [23]. The augmented dataset was divided into training, validation, and testing sets with a ratio of 88:8:4. The training set was used for model optimization, while the validation and testing sets were used to evaluate model performance and generalization capability. Similar dataset partitioning strategies have been widely adopted in computer vision studies for flood monitoring and object detection [16], [20], [22].

Table 1. Dataset distribution

Dataset	Images
Training	3591
Validation	343
Testing	170
Total	4104

2.3 Data Annotation and Augmentation

Image annotation and dataset management were performed using the Roboflow platform. Each image was manually annotated with predefined classes representing water turbidity and water level conditions, while bounding boxes were generated for object localization during YOLOv5 training. Accurate annotation is essential for improving object localization and classification in deep learning-based monitoring systems [22], [27]. To improve model robustness and generalization, data augmentation techniques including horizontal flipping, image rotation, and blur transformation were applied. These augmentations simulate variations in camera viewpoints and illumination commonly encountered in river environments. Data augmentation has been shown to improve the generalization capability and detection accuracy of deep learning models for environmental monitoring applications [21], [25], [26].

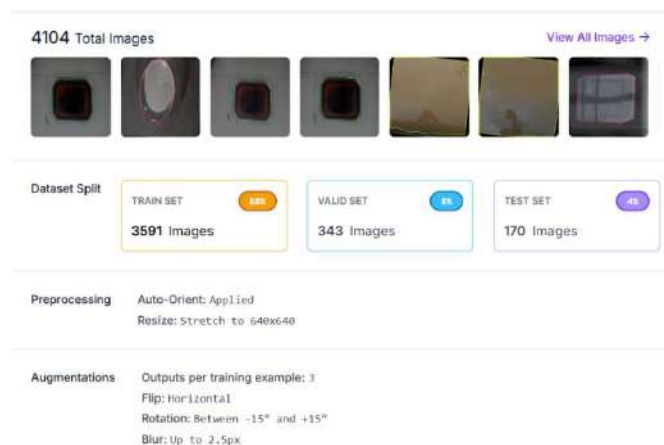


Figure 2. Dataset annotation and augmentation using Roboflow

2.4 YOLOv5 Training

This study evaluated four YOLOv5 variants (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) to analyze the trade-off between detection accuracy and computational efficiency. Although newer object detection models have recently been introduced, YOLOv5 was selected because of its balanced accuracy, computational efficiency, and maturity for real-time vision-based monitoring applications [13], [25] - [27]. Model training was conducted on the Google Colab and Kaggle cloud platforms using two training settings (50 and 150 epochs). The trained models were evaluated using standard object detection metrics and processing speed (FPS). Real-time inference and FPS evaluation were performed on a Lenovo ThinkPad T470 laptop equipped with an Intel Core i7-6600U processor, 16 GB RAM, Intel HD Graphics 520, and connected to a Logitech BRIO 4K webcam.

2.5 Water Level Detection Strategy

Water level monitoring was implemented using a Region of Interest (ROI)-based approach, in which the monitoring area was divided into three warning zones: Normal, Alert, and Danger. The ROI boundaries were established through an initial calibration after the camera was installed at a fixed position, using ultrasonic sensor measurements to align the corresponding waterline positions in the captured images. Thus, the system classifies the detected water level based on calibrated ROI boundaries rather than performing continuous pixel-to-centimeter conversion. Methods based on ROI are widely used for image-based water level estimation because of their simplicity and effectiveness [15], [17], [18]. Water levels below 370 cm were classified as Normal, levels between 370 cm and 610 cm as Alert, and levels above 610 cm as Danger, providing actionable information for flood early warning applications [4], [6], [8]. Since the calibration assumes a fixed camera position, significant camera displacement would require recalibration of the ROI boundaries.



Figure 3. ROI-based water level monitoring strategy

2.6 Performance Evaluation

The proposed system was evaluated using standard object detection metrics, including Precision, Recall, mean Average Precision at an Intersection over Union (IoU) threshold of 0.5 (mAP@0.5), and mean Average Precision over IoU thresholds from 0.5 to 0.95 (mAP@0.5:0.95). These metrics are widely used to evaluate deep learning models for flood monitoring and computer vision applications [7], [21], [22]. Precision measures the proportion of correctly detected objects, while Recall measures the ability to detect all relevant objects. The mAP metrics evaluate the overall localization and classification performance and have been widely adopted for flood detection and water level estimation systems [17], [18], [23]. Real-time performance was evaluated using Frames Per Second (FPS), which indicates the number of images processed per second. Higher FPS values indicate greater suitability for real-time flood monitoring applications [1], [5], [27]. The evaluation metrics are defined as:

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i \quad (3)$$

where (TP), (FP), and (FN) represent true positive, false positive, and false negative detections, respectively, while (N) denotes the number of object classes.

3. RESULTS AND DISCUSSION

3.1 Sensor Calibration

The turbidity sensor was calibrated using three reference turbidity levels (10, 100, and 500 NTU) before system validation, as shown in Figure 4. The sensor exhibited different measurement errors across the turbidity range. The highest error occurred at 10 NTU (22.28%), indicating lower sensitivity to small changes in water clarity, whereas the errors at 100 NTU and 500 NTU were 1.49% and 5.33%, respectively, demonstrating better performance at medium and high turbidity levels. The calibration curve showed an inverse linear relationship between turbidity and sensor output (ADC value), expressed as:

$$y = -0.2625x + 856.04 \quad (4)$$

where x represents turbidity (NTU) and y is the ADC value. The coefficient of determination ($R^2 = 0.8285$) indicates a good correlation between the reference turbidity values and the sensor readings, demonstrating that the regression model is suitable for converting ADC values into turbidity measurements.

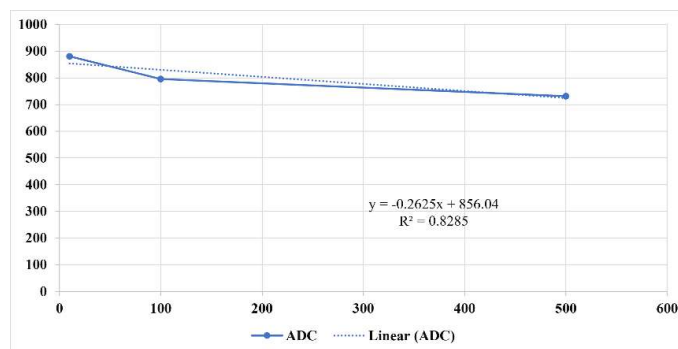


Figure 4. Turbidity sensor calibration curve

3.2 YOLOv5 Performance Comparison

The four YOLOv5 variants (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) were evaluated using two training settings (50 and 150 epochs), and the results are summarized in Table 2. All models achieved excellent detection performance, with precision, recall, and mAP@0.5 values above 0.99. Increasing the training from 50 to 150 epochs resulted in comparable performance across all variants, with slight improvements in mAP@0.5 for YOLOv5m, YOLOv5l, and YOLOv5x, while YOLOv5s maintained similar performance. Overall, the performance differences among the four variants were small, indicating that all models were capable of accurately detecting the water turbidity classes. Although YOLOv5m achieved marginally higher overall accuracy, YOLOv5s was selected for deployment because of its superior real-time processing speed.

Table 2. Best model performance

Model	Epoch	Precision	Recall	mAP@0.5
YOLOv5s	50	0.994	0.996	0.991
	150	0.992	0.997	0.991
YOLOv5m	50	0.995	0.997	0.990
	150	0.994	0.997	0.991
YOLOv5l	50	0.995	0.997	0.990
	150	0.994	0.997	0.991
YOLOv5x	50	0.995	0.997	0.990
	150	0.994	0.997	0.992

3.3 Loss Analysis

The training loss curves for object loss, classification loss, and box loss are shown in Figure 5. All YOLOv5 variants exhibited a rapid loss reduction during the first 20 epochs, followed by gradual convergence to stable values. YOLOv5s showed slightly larger fluctuations during the early training stage, whereas YOLOv5m, YOLOv5l, and YOLOv5x converged more smoothly. Stable box loss and decreasing object and classification losses indicate improved object localization, successful class learning, and no significant overfitting.

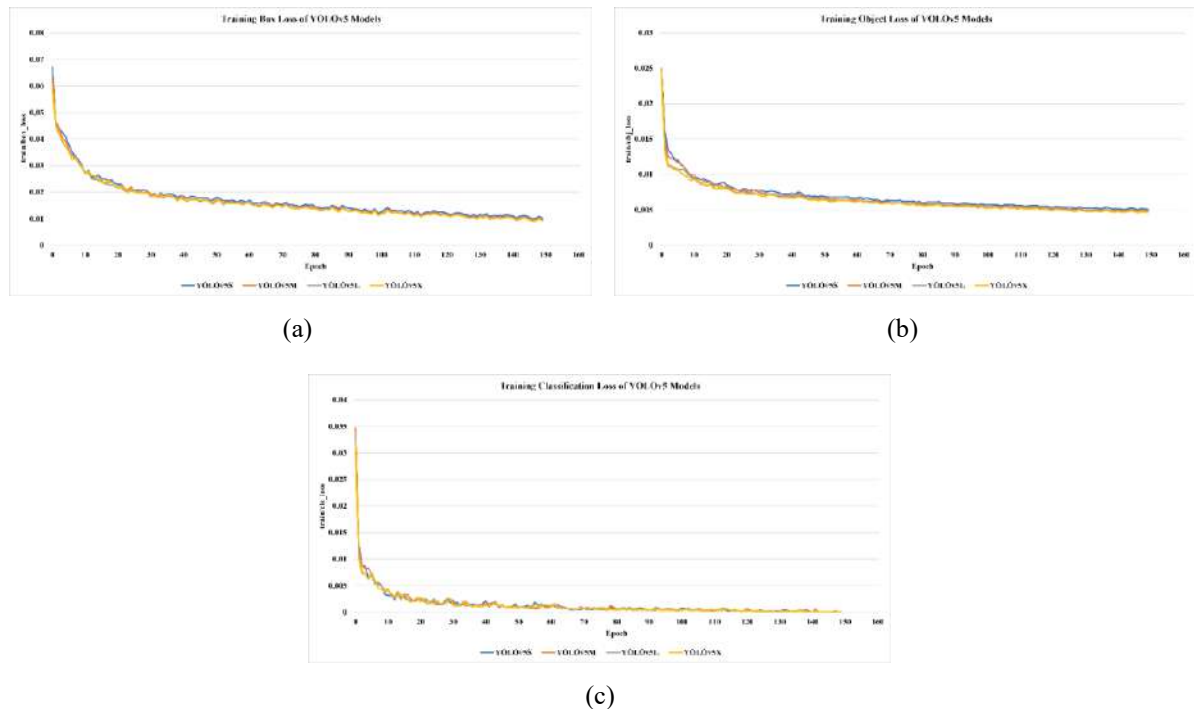
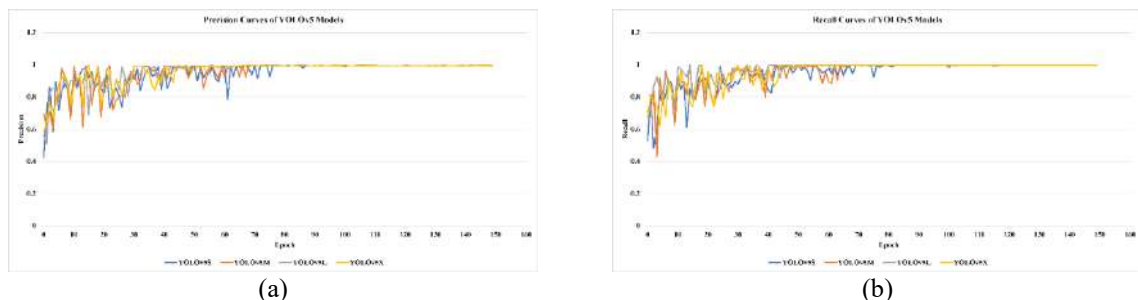


Figure 5. a. Training box loss; b. Training object loss; c. Training classification loss of YOLOv5 models

3.4 Detection Performance

Figure 6 shows the changes of precision, recall, mAP@0.5 and mAP@0.5:0.95 during training. At the beginning of the learning process, all models showed fluctuations due to parameter adaptation. After 20-30 epochs the metrics were stabilized and optimal values were obtained. YOLOv5x and YOLOv5l, on the other hand, had more stable learning behavior and faster convergence, while YOLOv5s required more epochs to reach a similar performance level. At the end of the training process, all models obtained values for precision and recall close to 1.0, indicating their high efficiency in object detection. The mAP@0.5 and mAP@0.5:0.95 demonstrated good localization and classification ability and always exceeded 0.95. The stable metric curves suggest that the trained models generalized well to unseen data.



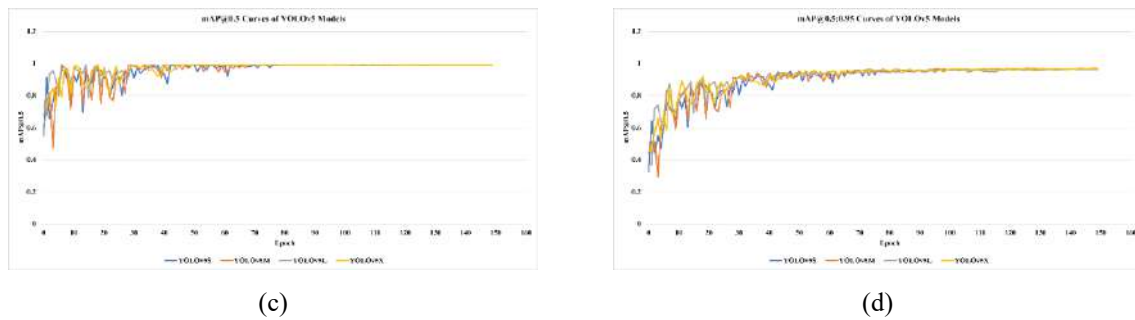


Figure 6. a. Precision curves; b. Recall curves; c. mAP@0.5 curves; d. mAP@0.5:0.95 curves of YOLOv5 models

3.5 Real-Time Performance

Frames Per Second (FPS) was used to evaluate the real-time performance of the proposed system, and the results are summarized in Table 3. A clear trade-off was observed between computational efficiency and detection accuracy. Larger models (YOLOv5l and YOLOv5x) achieved stable detection performance but at substantially lower processing speeds, whereas YOLOv5s achieved the highest speed of 4.26 FPS while maintaining competitive detection accuracy. The FPS measurements were obtained using a Lenovo ThinkPad T470 laptop equipped with an Intel Core i7-6600U processor, 16 GB RAM, Intel HD Graphics 520, and a Logitech BRIO 4K webcam. Although 4.26 FPS is lower than conventional video frame rates, it is sufficient for river flood monitoring because water level and turbidity change gradually rather than instantaneously. Therefore, YOLOv5s was selected as the most suitable model for real-time deployment of the proposed flood monitoring system.

Table 3. Real-time performance of YOLOv5 models.

Model	FPS
YOLOv5s	4.26
YOLOv5m	2.83
YOLOv5l	1.73
YOLOv5x	0.49

3.6 Illumination Analysis

The effect of the illumination on the detection efficiency was studied for different illumination conditions. The experimental results are summarized in Table 4. Detection failures were observed under extreme brightness conditions exceeding 25,000 lux. The webcam could not detect turbidity and water level at illumination levels of 39,400 lux and 87,040 lux due to overexposure and water surface reflection. On the other hand, the detections were effectively obtained under moderate and low illumination conditions below 25,000 lux, respectively. The model could detect the flood parameters accurately even with very low illumination (41 lux). Another contribution of this work is the results showing that illumination greatly affects vision-based flood monitoring systems. The findings suggest that illumination intensity is a critical factor affecting camera-based flood monitoring systems. Excessive brightness can lead to overexposure and reflection artifacts, reducing detection reliability.

Table 4. Illumination testing results.

No.	Light Intensity (Lux)	Sensor Testing		YOLO Testing		Success / Failure
		Water Turbidity (NTU)	Height (cm)	Turbidity (NTU)	Height Level	
1.	3940 x 10	216,99	206	-	-	Not Detected
2.	8704 x 10	236,04	206	-	-	Not Detected
3.	2394 x 10	243,66	203	26 – 250	Normal	Success Detected
4.	1795	247,47	202	26 - 250	Normal	Success Detected
5	41	239,85	202	26 - 250	Normal	Success Detected

3.7 Overall System Validation

The proposed vision-based system was validated by comparing YOLOv5 predictions with turbidity and ultrasonic sensor measurements. Measurements performed during field experiments showed that water turbidity values ranged between 216.99 NTU and 247.47 NTU, and water levels were between 202 cm and 206 cm. The YOLOv5 model correctly classified the water level into the Normal Region of Interest (ROI) and accurately predicted water turbidity within the 26–250 NTU category. The good agreement between the YOLOv5 predictions and the reference sensor measurements demonstrates the reliability of the proposed vision-based approach. Furthermore, the field validation confirms that the single-camera system can simultaneously monitor water turbidity and water level in real-time with results consistent with the reference sensors. These findings demonstrate the feasibility of using a single-camera vision-based approach for real-time flood monitoring and early warning applications.

4. CONCLUSION

In this work, a real-time single-camera flood monitoring system based on YOLOv5 is proposed to simultaneously detect water turbidity and water level. The experimental results demonstrate the effectiveness of the proposed vision-based approach for multi-parameter flood monitoring, with YOLOv5s identified as the most suitable model for real-time deployment due to its processing speed of 4.26 FPS while maintaining precision, recall, and mAP values generally above 0.98. Validation using turbidity and ultrasonic sensors showed good agreement between the YOLOv5 predictions and the reference sensor measurements, demonstrating the reliability of the proposed approach. In addition, illumination experiments indicated that the system operated reliably under lighting conditions below 25,000 lux, whereas detection performance degraded under severe overexposure. Overall, the proposed system demonstrates the feasibility of using a single-camera vision-based approach for simultaneous water level and turbidity monitoring to support real-time flood monitoring and early warning applications. Despite these promising results, the study was limited by reduced robustness under high illumination conditions and validation at a single river location. Future work will focus on evaluating the system in multiple river environments, improving robustness under challenging lighting conditions, and integrating the proposed approach with IoT-based early warning systems for practical flood monitoring applications.

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Adaptive PLC Scan-Time Optimization in a Unified PLC–SCADA Architecture

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ABSTRACT

Industrial automation systems require integrated intelligence to support Industry 4.0 manufacturing. However, PLC, IoT, predictive maintenance, and digital twin technologies are typically implemented independently, limiting system performance. This study proposes a unified adaptive PLC–SCADA architecture integrating adaptive PLC scan-time optimization, IoT monitoring, machine learning-based predictive maintenance, and digital twin synchronization within a cyber–physical framework. The proposed system was validated through a 14-day laboratory experiment using 40,320 time-stamped observations. Performance was evaluated in terms of energy consumption, PLC scan time, communication latency, and predictive maintenance accuracy. Compared with a conventional PLC architecture, the proposed framework reduced energy consumption by 25%, PLC scan time by 60.4%, and communication latency by 20.1%, while achieving 95.0% predictive maintenance accuracy. These results demonstrate the effectiveness of the proposed architecture for energy-efficient, intelligent, and data-driven industrial automation.



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1. INTRODUCTION

Industrial automation has become a key enabler of Industry 4.0 by integrating cyber–physical systems (CPS), the Industrial Internet of Things (IIoT), artificial intelligence, and data-driven decision-making to improve manufacturing productivity, reliability, and operational efficiency [1,6], [10], [12]. Programmable Logic Controllers (PLCs) remain the core real-time control platform because of their deterministic execution and high reliability. However, conventional PLCs generally employ fixed scan cycles that may increase computational overhead and energy consumption while limiting responsiveness under dynamic operating conditions [13, 15].

Recent studies have introduced IIoT monitoring, predictive maintenance, and digital twin technologies to enhance industrial intelligence [5, 9], [16], [17], [18, 22]. Nevertheless, these technologies are typically implemented as separate subsystems. Existing PLC–SCADA solutions mainly focus on supervisory monitoring, while predictive maintenance and digital twin applications are commonly deployed independently, resulting in limited closed-loop optimization and adaptive control capabilities. Consequently, adaptive PLC scan-time optimization integrated with predictive intelligence and digital twin synchronization remains insufficiently investigated.

Table 1 summarizes representative studies and demonstrates that most existing approaches do not simultaneously integrate adaptive PLC scan-time optimization, predictive maintenance, digital twin synchronization, and energy-aware closed-loop control.

To address this research gap, this study proposes a unified adaptive PLC–SCADA architecture integrating adaptive PLC scan-time optimization, IIoT monitoring, machine learning-based predictive maintenance, and digital twin synchronization within a cyber–physical framework. The proposed architecture enables continuous closed-loop optimization to improve energy efficiency, communication performance, controller responsiveness, and operational reliability. The proposed framework was validated through laboratory-scale experiments, demonstrating its feasibility as an integrated intelligent automation solution for Industry 4.0.

Table 1. Methodological comparison of previous studies and the proposed framework

Reference	Methodological Approach	Main Limitation	IM	PM	DT	APST	EO	Scientific Contribution
Lu and Cecil [18]	IIoT-enabled PLC monitoring	Fixed PLC scan cycle; no adaptive control or digital twin integration	✓	✓	✗	✗	✗	Real-time industrial monitoring
Lu et al. [5]	Digital Twin-based industrial monitoring	Digital twin used mainly for visualization; no adaptive PLC optimization	✓	✓	✓	✗	✗	Digital twin-assisted monitoring
Doke et al. [8]	Machine learning-based predictive maintenance	No PLC–SCADA integration and no closed-loop optimization	✓	✓	✗	✗	✗	Intelligent fault prediction
Proposed Method	Unified adaptive PLC–SCADA architecture integrating adaptive PLC scan-time optimization, IIoT monitoring, predictive maintenance, and digital twin feedback	Laboratory-scale validation (future large-scale industrial deployment required)	✓	✓	✓	✓	✓	Closed-loop adaptive industrial automation with energy-aware PLC optimization

Where:

IM = IoT Monitoring; PM = Predictive Maintenance; DT = Digital Twin; APST = Adaptive PLC Scan-Time; EO =Energy Optimization.

2. RESEARCH METHOD

2.1. System Architecture

Figure 1 presents the proposed unified adaptive PLC–SCADA architecture integrating adaptive PLC scan-time optimization, IIoT monitoring, predictive maintenance, digital twin synchronization, and closed-loop energy optimization. The architecture continuously adapts PLC operation using real-time process feedback to improve energy efficiency, controller responsiveness, and operational reliability for Industry 4.0 manufacturing environments [1], [3], [9], [22]. It consists of eight functional layers forming a closed-loop industrial automation ecosystem.

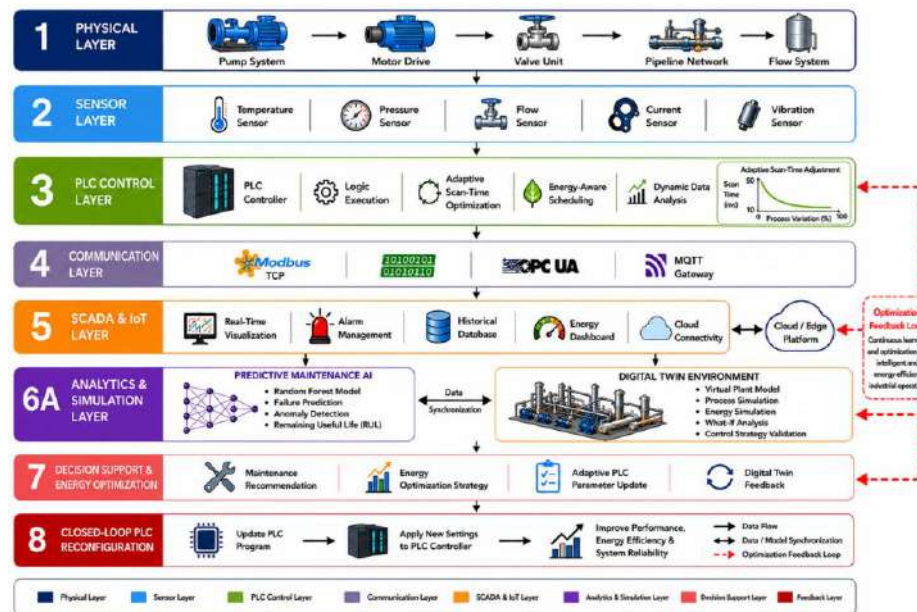


Figure 1. Proposed adaptive PLC–SCADA architecture for intelligent industrial automation

1. **Physical Industrial Process Layer**
The Physical Industrial Process Layer represents the industrial plant, including pumps, electric motors, valves, pipelines, and flow systems. Operational data acquired from these assets provide the foundation for adaptive PLC control, predictive maintenance, and digital twin synchronization within the proposed cyber–physical architecture [1], [3], [16].
2. **Sensor Acquisition Layer**
The Sensor Acquisition Layer continuously acquires real-time process variables, including temperature, pressure, flow rate, electrical current, and vibration. These measurements provide input for adaptive PLC control, predictive maintenance, digital twin synchronization, and scan-time optimization, enabling real-time monitoring in IIoT-based industrial automation [3], [14], [15].
3. **Adaptive PLC Control Layer**
The Adaptive PLC Control Layer serves as the real-time control unit of the proposed framework. Unlike conventional PLCs with fixed scan cycles, it dynamically adjusts the scan interval according to normalized process variability (Δx). The process-variability threshold was set to $\delta = 0.02$, corresponding to a 2% change on the Min–Max normalized scale, while the adjustment step was $\Delta T = \pm 5$ ms. These values were selected through preliminary experiments to balance controller responsiveness and computational efficiency [15], [17], [22].
4. **Industrial Communication Network Layer**
The Industrial Communication Network Layer provides reliable, low-latency communication between field devices, the PLC, SCADA, and cloud services using standard industrial protocols, including Modbus TCP, PROFINET, OPC UA, and MQTT. This layer enables interoperable real-time data exchange for the proposed adaptive PLC–SCADA architecture [3], [11].
5. **SCADA and IoT Platform Layer**
The SCADA and IoT Platform Layer provides real-time supervisory monitoring, alarm management, historical data storage, and cloud connectivity for remote monitoring and edge-to-cloud synchronization. It supports real-time data visualization and operational monitoring within the proposed adaptive PLC–SCADA architecture [3], [7], [11].
6. **Analytics and Simulation Layer**
The Analytics and Simulation Layer comprises two intelligent subsystems: (1) a Random Forest-based predictive maintenance module that analyzes real-time sensor data for anomaly detection, failure prediction, and Remaining Useful Life (RUL) estimation, and (2) a Digital Twin module

that synchronizes with the physical process to support process validation, control evaluation, and energy analysis. Together, these subsystems enable data-driven optimization within the proposed adaptive PLC–SCADA architecture [6], [8]–[10], [22].

7. Decision Support and Energy Optimization Layer

The Decision Support and Energy Optimization Layer integrates predictive maintenance and digital twin outputs to generate adaptive PLC settings, energy optimization strategies, and maintenance recommendations. These outputs enable data-driven operational optimization within the proposed adaptive PLC–SCADA architecture [6], [9], [22].

8. Closed-Loop PLC Reconfiguration Layer

The Closed-Loop PLC Reconfiguration Layer automatically updates PLC control parameters using optimization results from the Decision Support Layer, enabling continuous adaptive control under varying operating conditions [1], [6], [22].

Together, the eight functional layers establish a unified adaptive PLC–SCADA architecture that integrates real-time monitoring, industrial communication, predictive maintenance, digital twin synchronization, adaptive control, and energy optimization within a closed-loop cyber–physical framework for data-driven industrial automation [1], [3], [6], [22].

2.2. Mathematical Modeling

To quantitatively evaluate the proposed adaptive PLC–SCADA architecture, a mathematical model is developed to describe the relationships among energy consumption, PLC scan time, process variability, predictive maintenance, and digital twin simulation. The formulation is based on the following assumptions:

- (1) the industrial process operates under continuous monitoring;
- (2) the electrical power remains positive during operation;
- (3) the PLC executes cyclic scan operations;
- (4) sensor measurements are sampled at constant intervals; and
- (5) communication delays are assumed to be sufficiently stable during each PLC execution cycle and therefore do not affect the adaptive scan-time decision.

$$E = \int_0^T P(t)dt \quad (1)$$

Equation (1) represents the cumulative electrical energy consumed by the industrial system during the operating interval. Since electrical power varies continuously according to the operating condition of pumps, PLC execution, communication modules, and auxiliary devices, the total energy is obtained by integrating the instantaneous power over the entire operating period.

where :

E (kWh) = total energy consumption; $P(t)$ (kW) = instantaneous electrical power at time t ; T (h) = total operating duration.

$$T_{scan} = T_{input} + T_{logic} + T_{output} \quad (2)$$

The PLC scan cycle consists of three sequential execution stages: input acquisition, program execution, and output updating [17]. Therefore, the total scan time can be expressed as the summation of these three execution intervals, as shown in Equation (2). Reducing any of these components contributes directly to improving controller responsiveness and computational efficiency.

Where:

T_{scan} = total PLC scan time; T_{input} = input acquisition time; T_{logic} = ladder logic execution time; T_{output} = output update time.

Adaptive PLC scan-time adjustment is driven by the magnitude of process-variable variation between two consecutive sampling instants. The absolute difference is selected because it provides a simple yet effective indicator of process dynamics regardless of the direction of change.

$$\Delta x = |x(t) - x(t - 1)| \quad (3)$$

A small value of Δx indicates steady-state operation, allowing the PLC to increase its scan interval and reduce computational load. Conversely, a large Δx indicates rapid process dynamics requiring a shorter scan interval to improve control responsiveness.

where:

Δx represents the variation of the process variable between two consecutive sampling times; $x(t)$ denotes the current value of the process variable at time t ; $x(t-1)$ denotes the previous value of the process variable at time $t-1$; $|\cdot|$ represents the absolute value operator, which ensures that the magnitude of the variation is always non-negative.

If the variation is below a predefined threshold, the scan interval is increased to reduce computational overhead. Otherwise, the scan interval is decreased to improve responsiveness.

$$T_{scan}(k+1) = \begin{cases} T_{scan}(k) + \Delta T, & \Delta x < \delta \\ T_{scan}(k) - \Delta T, & \Delta x \geq \delta \end{cases} \quad (4)$$

with limits:

$$20 \text{ ms} \leq T_{scan} \leq 100 \text{ ms}$$

where:

$\delta = 0.02$ is the dimensionless process-variation threshold on the Min–Max normalized scale; $\Delta T = 5 \text{ ms}$ is the scan-adjustment step; $T_{scan}(k)$ is the current scan interval; and $T_{scan}(k+1)$ is the updated scan interval.

Equation (4) constitutes the core mathematical formulation of the proposed algorithm. The scan interval is increased during steady-state operation to reduce computational workload and energy consumption, whereas it is decreased during dynamic operating conditions to improve controller responsiveness. The scan interval is constrained between 20 ms and 100 ms to ensure deterministic PLC execution.

2.3. Adaptive PLC Scan-Time Optimization Algorithm

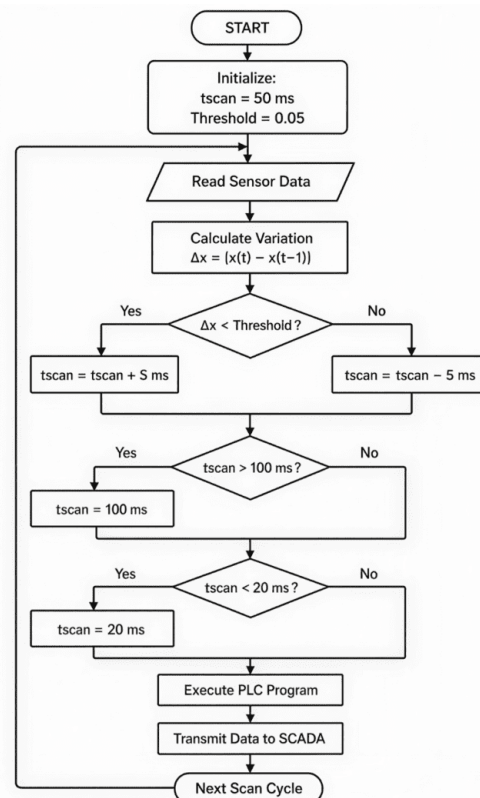


Figure 2. Adaptive PLC scan-time optimization algorithm

Figure 2 illustrates the proposed adaptive PLC scan-time optimization. The PLC adjusts the scan interval according to normalized process variability (Δx). When $\Delta x < \delta = 0.02$, the scan interval is increased to reduce computational load; otherwise, it is decreased to improve control responsiveness. The scan interval is constrained to 20–100 ms, with a 5 ms adjustment step, to maintain stable PLC operation. Compared with a fixed-cycle PLC, this strategy provides energy-aware control based on real-time process feedback [1], [15], [17].

2.4. Predictive Maintenance Model

Predictive maintenance was implemented using five operational features collected from the industrial pumping system:

$$X = \{\text{temperature, pressure, flow rate, vibration, current}\} \quad (5)$$

These features characterize the mechanical and electrical operating conditions [8], [9]. The dataset comprised 40,320 time-stamped observations collected at 30 s intervals over 14 days. After missing-value removal and Min–Max normalization, the data were divided into 80% training and 20% independent testing subsets. Binary labels comprised 34,272 normal observations (85%) and 6,048 fault observations (15%). A fault was assigned when at least one measured variable met the following criterion: temperature ≥ 60 °C, pressure outside 1.8–2.2 bar, flow rate < 18 L/min, vibration ≥ 4.5 mm/s RMS, or current ≥ 5.5 A. The thresholds were established from pump specifications and preliminary experiments.

A Random Forest classifier was selected because it can model nonlinear interactions, is comparatively robust to noisy measurements, and provides feature-importance estimates that support interpretation of multivariable industrial data [8], [9], [21]. The probability of equipment failure is expressed as:

$$P_{\text{failure}} = f(X) \quad (6)$$

Where $f(\cdot)$ denotes the trained Random Forest classifier. The model was implemented using 100 decision trees, a maximum tree depth of 10, and the Gini impurity criterion. Performance was evaluated using five-fold cross-validation and an independent testing dataset, with accuracy, precision, recall, and F1-score as evaluation metrics.

The five input features were selected based on their relevance to equipment health and their widespread use in industrial predictive maintenance.

2.5. Digital Twin Simulation

To further validate the proposed architecture, a Digital Twin was developed to estimate electrical power consumption (kW) and reproduce the behavior of the physical pumping system under real-time operating conditions.

$$Q = K \sqrt{\frac{P_{\text{in}} - P_{\text{out}}}{\rho}} \quad (7)$$

Motor power consumption is estimated using:

$$P = VI_{\cos\theta} \quad (8)$$

The Digital Twin continuously synchronizes its estimated electrical power consumption with physical-system measurements. Normalization was used only for Random Forest model inputs; Digital Twin outputs were evaluated in their original kW scale.

2.6. Experimental Setup

A laboratory-scale pumping platform comprising an Omron CP1E PLC, ESP32 IoT gateway, centrifugal pump, current, vibration, and temperature sensors, and Node-RED SCADA was used for validation (Figure 3 and Table 2). Data were sampled every 30 s for 14 days, producing 40,320 time-stamped observations. Three configurations were evaluated under the same pump load, supply voltage, environmental conditions, and experimental duration: (1) conventional PLC, (2) PLC with IoT monitoring, and (3) the proposed adaptive PLC with predictive maintenance and Digital Twin integration. Fault labels followed the operating thresholds defined in Section 2.4.

Table 2. Experimental hardware specifications

Component	Specifications
PLC	Omron CP1E
IoT Gateway	ESP32
Current Sensor	SCT013
Vibration Sensor	MPU6050
Temperature Sensor	DS18B20
SCADA	Node-RED
Communication	MQTT / Modbus TCP
Pump	Centrifugal Pump



Figure 3. Experimental setup of the proposed adaptive PLC-SCADA system

2.7. Statistical Analysis

Statistical inference was performed using 14 daily mean observations for each control configuration. Aggregation at the daily level reduced short-term temporal autocorrelation and avoided treating the 30 s samples as independent replicates. Although the configurations were evaluated under equivalent pump-load, supply-voltage, and environmental conditions, each configuration constituted a separately operated dataset; therefore, an independent two-sample t-test was used to compare configuration means at $\alpha = 0.05$ (95% confidence level). Means and standard deviations were also reported for each performance metric.

3. RESULTS AND DISCUSSION

The proposed architecture was evaluated experimentally using the laboratory-scale platform described in Section 2.6. Performance was assessed in terms of energy consumption, PLC scan time, predictive maintenance accuracy, communication latency, and Digital Twin validation.

3.1. Energy Consumption Analysis

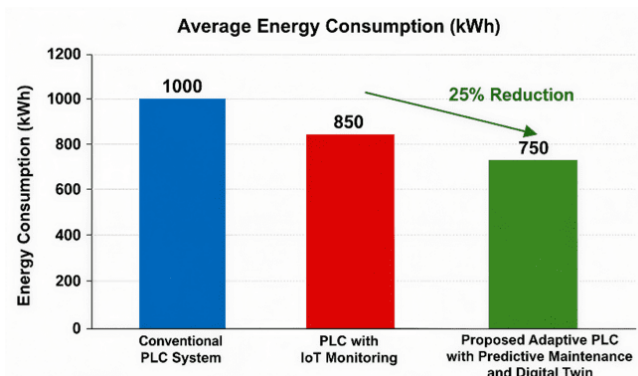


Figure 4. Energy consumption analysis

Figure 4 compares the energy consumption of three control configurations under identical operating conditions. The proposed adaptive PLC architecture reduced energy consumption from 1000 kWh (conventional PLC) to 750 kWh, corresponding to a 25% reduction (Table 3). This improvement is achieved by adaptive scan-time optimization, which increases the PLC scan interval during steady-state operation to reduce processor utilization and communication activity, while shortening the interval only when significant process variations are detected. Statistical analysis confirmed that the reduction was significant ($p = 0.003$), supporting the effectiveness of the proposed energy-aware control strategy. Similar energy-saving trends have been reported in adaptive industrial automation studies [15], [17], [22].

All three control configurations were evaluated under identical operating conditions, load profiles, and experimental duration to ensure a fair comparison.

Table 3. Statistical analysis of energy consumption

System configuration	MEC (kWh)	SD (kWh)	ER (%)	p-value
Conventional PLC	1000	42.6	-	-
PLC + IoT Monitoring	850	35.2	15	0.021
Proposed Adaptive PLC	750	28.4	25	0.003

where:

MEC = Mean Energy Consumption (kWh); SD = Standard Deviation (kWh); ER = Energy Reduction (%).

3.2. PLC Scan Time Performance

Figure 5 compares the PLC scan-time performance of the three control architectures. The proposed adaptive PLC reduced the average scan time from 75.2 ms (conventional PLC) to 29.8 ms, corresponding to a 60.4% reduction.

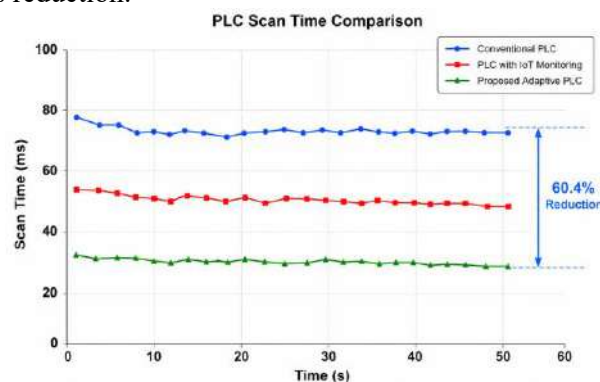


Figure 5. PLC scan time performance

This improvement results from adaptive scan-time optimization, which dynamically adjusts the PLC execution cycle according to real-time process variability, reducing computational load while maintaining rapid controller response [15], [17]. Statistical analysis (Table 4) confirmed a significant reduction in scan time ($p < 0.05$), demonstrating improved controller responsiveness with lower computational overhead.

Table 4. Statistical analysis of PLC scan time

System configuration	MST (ms)	SD (ms)	I (%)	p-value
Conventional PLC	75.2	4.8	-	-
PLC + IoT Monitoring	50.7	3.2	32.6	0.009
Proposed Adaptive PLC	29.8	2.1	60.4	0.001

where:

MST = Mean Scan Time (ms); I = Improvement (%).

The statistical analysis confirms that the proposed adaptive PLC significantly reduced scan time ($p < 0.05$), demonstrating improved controller responsiveness with lower computational overhead.

3.3. Predictive Maintenance Accuracy

The predictive maintenance subsystem used temperature, pressure, flow rate, vibration, and current measurements. The dataset contained two classes: 34,272 normal observations (85%) and 6,048 fault observations (15%), and was divided into 80% training and 20% independent testing data. The Random Forest achieved 95.0% accuracy, 94.8% precision, 95.2% recall, and a 95.0% F1-score on the independent test set, indicating reliable binary fault classification [8], [9], [21].

3.4. Network Communication Efficiency

Figure 6 compares the communication latency of the conventional architecture and the proposed IoT gateway. The proposed method reduced the average latency from 100.3 ms to 80.1 ms (20.1%, $p = 0.007$) through local data aggregation and optimized ESP32-based routing. The results demonstrate improved Industrial IoT communication efficiency and are consistent with previous studies [3], [11].

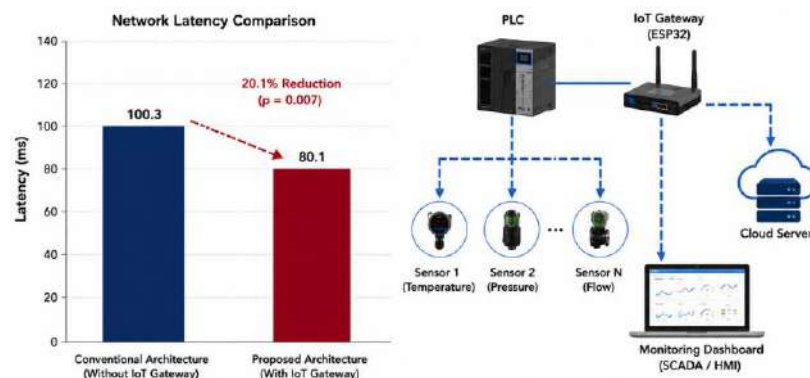


Figure 6. Network communication efficiency

3.5. Digital Twin Validation

The Digital Twin was validated by comparing estimated electrical power consumption with synchronized physical-system measurements in the original kW scale. It achieved RMSE = 0.82 kW, MAE = 0.64 kW, and $R^2 = 0.97$, indicating close agreement within the laboratory operating range. Unlike primarily visualization- or simulation-based studies [5], [9], [22], the framework links Digital Twin feedback with adaptive PLC scan-time optimization and predictive maintenance; however, industrial-scale validation is still required.

4. CONCLUSION

This study experimentally validated a unified PLC–SCADA framework integrating adaptive scan-time optimization, IoT monitoring, Random Forest-based predictive maintenance, and Digital Twin feedback. The architecture improved energy efficiency, scan time, communication latency, and fault-classification performance relative to the conventional PLC configuration. Its principal contribution is closed-loop integration of adaptive control, predictive intelligence, and Digital Twin synchronization. Because validation was limited to a laboratory pumping platform, future work should examine industrial deployment, multi-PLC coordination, cybersecurity, and AI-based optimization.

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Low-Cost AIS Vessel Tracking System for Real-Time Web Visualization Using Software Defined Radio and Leaflet.js

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Tracking; Web-Based Monitoring

ABSTRACT

A low-cost edge-based Automatic Identification System (AIS) monitoring platform was developed for real-time vessel surveillance, integrating AIS signal acquisition, decoding, data management, and geospatial visualization within a unified web-based architecture. The proposed platform was implemented using commercially available hardware components with a total hardware cost of approximately USD 189, providing a cost-effective alternative for real-time AIS monitoring. The system employs RTL-SDR for signal reception and a lightweight C-based processing pipeline incorporating GMSK demodulation, NRZI decoding, and CRC16 validation. Experimental deployment at Tanjung Perak Port under dense maritime traffic conditions demonstrated continuous end-to-end operation, achieving an average throughput of 3.71 messages per second and an end-to-end latency of 0–2 seconds. Decoded AIS records were stored in MariaDB and visualized through a Leaflet.js-based interface supporting real-time vessel tracking, historical trajectory reconstruction, and traffic analytics. Existing AIS studies commonly address signal reception, decoding, and visualization as separate processing stages. In contrast, the proposed platform consolidates the complete processing chain from radio-frequency AIS acquisition to web-based maritime information delivery within a single edge-computing environment. The results demonstrate the feasibility of employing resource-constrained edge devices for continuous AIS processing and provide an integrated framework for real-time maritime monitoring without reliance on high-performance computing infrastructure.



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1. INTRODUCTION

The increasing density and operational complexity of maritime traffic have made reliable real-time vessel monitoring an essential component of maritime safety and surveillance systems [1, 2]. This requirement is particularly critical in Indonesia, an archipelagic nation with extensive territorial waters and strategic positioning along major international shipping routes, resulting in continuous high-volume vessel traffic [3]. To ensure safety of life at sea, navigational efficiency, and environmental protection, the International Maritime Organization (IMO) mandates the use of the Automatic Identification System

(AIS) under Chapter V of the SOLAS Convention [4, 5]. AIS is required for vessels above specific tonnage thresholds and operates over VHF maritime channels at 161.975 MHz and 162.025 MHz [6], continuously broadcasting vessel identity, position, speed, heading, and navigational status for collision avoidance and maritime domain awareness [7, 9].

Despite its established role, conventional AIS monitoring infrastructures remain limited by deployment cost and computational requirements, which restrict the scalability of distributed surveillance systems in resource-constrained environments. Recent adoption of Software Defined Radio (SDR), particularly RTL-SDR, has reduced acquisition cost while enabling reception across a wide frequency range including AIS channels [10,11]. However, existing studies typically address AIS subsystems in isolation: signal reception and tracking improvements using RTL-SDR-based setups [12], GIS-based visualization and traffic analysis from preprocessed AIS data [13], and standalone demodulation and decoding pipelines implemented using GNU Radio frameworks [14]. These approaches do not provide a continuous transformation pathway from raw AIS RF signals to operational maritime information, particularly when deployed on resource-constrained edge platforms.

The primary contribution of this work is a complete AIS edge-computing architecture that unifies RF signal acquisition, GMSK demodulation, NRZI decoding, CRC16 validation, database structuring, trajectory reconstruction, maritime metric computation, and web-based geospatial visualization into a single continuous processing pipeline on low-cost hardware. The system is implemented using RTL-SDR for AIS capture, Raspberry Pi for edge processing, MariaDB for data storage, and Leaflet.js for spatial visualization. The processing chain enables continuous transformation of raw AIS signals into decoded message streams through sequential processing stages. Experimental results under dense maritime traffic conditions demonstrate sustained message throughput and bounded end-to-end latency from RF reception to database insertion and map rendering.

2. RESEARCH METHOD

The proposed AIS monitoring platform was implemented to perform signal acquisition, message decoding, data management, and web-based vessel visualization within a unified processing framework. The overall system design and operational workflow are illustrated in Figure 1 and Figure 2.

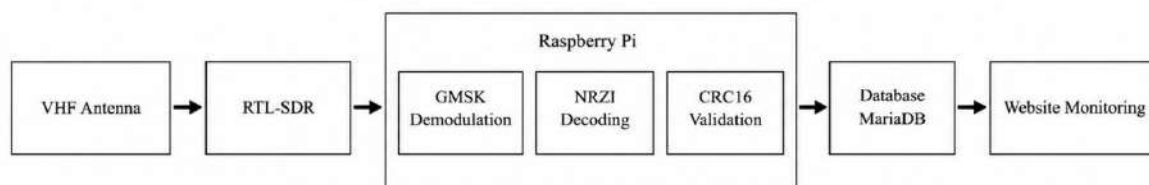


Figure 1. AIS monitoring system block diagram

Figure 1 outlines the principal functional components of the proposed platform and their interactions within the end-to-end AIS processing chain. AIS signals received through the VHF antenna are captured by the RTL-SDR receiver and forwarded to the Raspberry Pi, where message decoding and validation are performed before the resulting vessel information is stored and delivered to the web-based monitoring interface.

2.1. System Design

The system was configured to receive AIS transmissions over the maritime VHF channels at 161.975 MHz and 162.025 MHz. As shown in Figure 1, the architecture comprises a VHF antenna, an RTL-SDR receiver, a Raspberry Pi processing unit, a MariaDB database, and a Leaflet.js-based visualization interface.

AIS signals captured by the VHF antenna are digitized by the RTL-SDR and subsequently processed by the Raspberry Pi for message decoding, data management, and visualization. The hardware and software specifications employed in the implementation are summarized in Table 1.

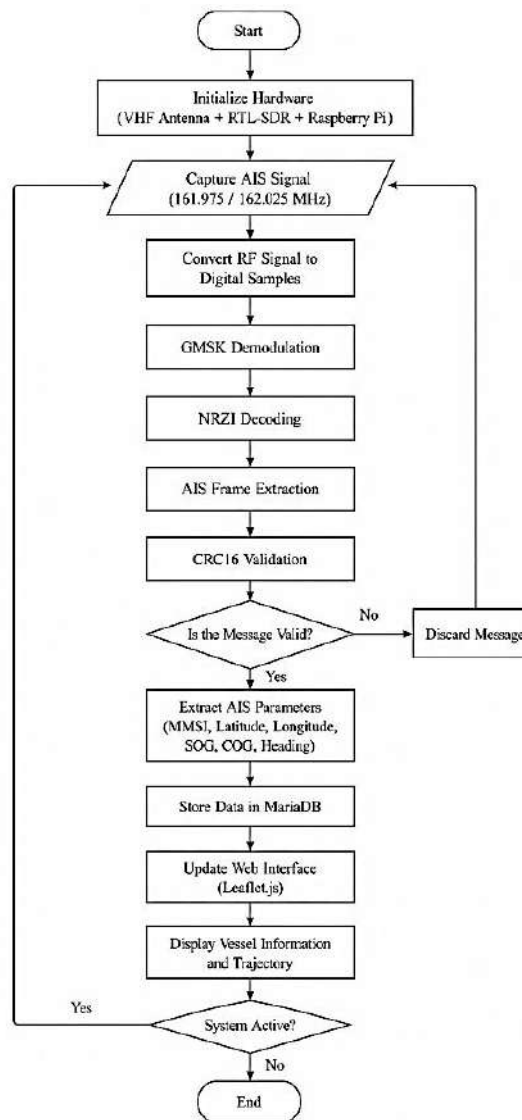


Figure 2. System workflow

2.2. Procedure and AIS Data Acquisition

As illustrated in Figure 2, the system workflow begins with AIS signal reception through the VHF antenna and RTL-SDR, followed by the conversion of radio signals into digital data for processing on Raspberry Pi using an AIS decoding algorithm developed in the C programming language.

The decoding process includes GMSK demodulation, NRZI decoding, and data verification using CRC16 to ensure the validity of the received information. Subsequently, the validated AIS data are extracted to obtain vessel parameters and stored in the database.

Table 1. Hardware and software configuration

Component	Specification
Processing Unit	Raspberry Pi 3 Model B+
Operating System	Raspberry Pi OS (32-bit)
SDR Receiver	RTL-SDR V4
AIS Frequencies	161.975 MHz, 162.025 MHz
Sampling Rate	300 kHz
Receiver Gain	80 dB
Database	MariaDB
Visualization Library	Leaflet.js

To substantiate the low-cost positioning of the proposed platform, the itemized hardware cost of the implemented system is presented in Table 2.

Table 2. Bill of materials and total hardware cost

Component	Unit Cost (USD)
RTL-SDR V4	50.28
Raspberry Pi 3 Model B+	55.08
VHF Antenna	67.04
MicroSD Card 32 GB	8.38
USB Cable	1.40
Coaxial Cable RG58	6.70
Total	188.88

The total hardware cost of the proposed system is approximately USD 189, substantially lower than commercial AIS receiver and base station systems, which typically range from USD 500 to over USD 10,000 depending on channel capacity and connectivity features [15]. This cost differential substantiates the low-cost positioning of the proposed platform relative to existing commercial alternatives.

2.3. Database Integration and Web-Based Visualization

Decoded AIS records are automatically stored in MariaDB, which serves as a centralized repository for both real-time and historical vessel information. The database is integrated with the web application to enable continuous access to vessel data and support subsequent analytical functions.

Geospatial visualization is implemented using Leaflet.js through an interactive map interface. Leaflet.js was selected for its lightweight architecture and efficient handling of dynamic geospatial data [16]. Vessel locations are rendered as dynamically updated markers, each containing key navigational attributes, including MMSI, geographical coordinates, speed, heading, and navigational status. This integration enables continuous spatial representation of vessel activity while facilitating intuitive observation of maritime traffic conditions through a web-based environment.

2.4. Experimental Setup and Evaluation Metrics

Field observations were conducted in the vicinity of Tanjung Perak Port, Surabaya, a maritime corridor characterized by intensive vessel activity and persistent AIS transmissions. AIS data were collected continuously over a 60-minute observation period. During the experiment, AIS signals received by the RTL-SDR receiver were processed by the Raspberry Pi, stored in the MariaDB database, and subsequently delivered to the web-based visualization platform.

System performance was evaluated using three operational metrics, message throughput, end-to-end latency, and processing stability. Message throughput refers to the number of valid AIS messages successfully decoded and processed within each observation interval. The average message throughput was calculated using equation (1):

$$\text{Throughput} = \frac{N_{msg}}{T} \quad (1)$$

where:

N_{msg} denotes the total number of valid AIS messages processed during the observation period (messages), and T represents the corresponding observation time (s).

End-to-end latency represents the elapsed time between AIS signal reception and the availability of vessel information on the web interface. Processing stability was assessed through the continuity of AIS decoding, database synchronization, and visualization updates throughout the observation period.

Collectively, these metrics were employed to quantify the performance of the complete processing chain and to assess the capability of the proposed architecture to sustain continuous AIS acquisition, decoding, data management, and visualization within a unified operational environment.

3. RESULTS AND DISCUSSION

The implemented AIS monitoring platform establishes an integrated processing environment that combines AIS signal acquisition, message decoding, data management, and vessel visualization. The hardware implementation of the AIS receiver system is presented in Figure 3.



Figure 3. Hardware implementation of the AIS receiver system

The decoded output displayed on the Raspberry Pi terminal, as shown in Figure 4, confirms consistent extraction of vessel-related information. The results indicate that signal reception stability is influenced by the combined configuration of the RTL-SDR and VHF antenna optimized for AIS frequencies. In addition, the use of a C-based decoding algorithm reduces computational overhead, allowing the system to remain responsive on resource-constrained hardware. The CRC16 mechanism also plays a crucial role in improving data reliability by filtering invalid AIS packets.

3.1. Web-Based Vessel Data Visualization

Decoded AIS records were successfully stored in the MariaDB database in real time, as illustrated in Figure 5. The stored information includes MMSI, geographical coordinates, vessel speed, heading, and navigational status, providing the data foundation required for real-time visualization and historical trajectory analysis.

A comparison between the timestamps observed in Figure 4 and Figure 5 indicates that decoded AIS records became available in the database within approximately 0–2 seconds after successful decoding, demonstrating timely propagation of information across the processing chain.

```
[REKAP] 1 menit ke-1 = 213 data diterima
Ter kirim: MMSI 525000011 | waktu 2026-05-25 20:54:03
Ter kirim: MMSI 525023138 | waktu 2026-05-25 20:54:04
Ter kirim: MMSI 525114133 | waktu 2026-05-25 20:54:04
Ter kirim: MMSI 525201479 | waktu 2026-05-25 20:54:04
Ter kirim: MMSI 525016550 | waktu 2026-05-25 20:54:05
Ter kirim: MMSI 525801170 | waktu 2026-05-25 20:54:05
Ter kirim: MMSI 525901286 | waktu 2026-05-25 20:54:06
Ter kirim: MMSI 525007390 | waktu 2026-05-25 20:54:06
Ter kirim: MMSI 525020261 | waktu 2026-05-25 20:54:07
```

Figure 4. AIS decoded output on Raspberry Pi terminal

id	mmsi	latitude	longitude	speed	course	waktu
214	525000011	-7.217932	112.721722	0	111	2026-05-25 20:54:03
215	525023138	-7.187277	112.725833	0	0	2026-05-25 20:54:04
216	525114133	-7.194522	112.74243	0.1	360	2026-05-25 20:54:04
217	525201479	-7.188257	112.724585	0	34.3	2026-05-25 20:54:04
218	525016550	-7.204395	112.724708	0.1	273	2026-05-25 20:54:05
219	525801170	-7.20305	112.722633	0.1	148	2026-05-25 20:54:05
220	525901286	-7.17372	112.685027	0	311.4	2026-05-25 20:54:06
221	525007390	-7.20584	112.725213	0	266.1	2026-05-25 20:54:06
222	525020261	-7.18048	112.670385	0	0	2026-05-25 20:54:07

Figure 5. AIS data storage in MariaDB database

The stored AIS records were subsequently visualized through a Leaflet.js-based web interface, as shown in Figure 6. Vessel locations are represented as dynamic markers positioned according to their

geographical coordinates. Marker interaction provides access to vessel-specific information, including MMSI, speed, heading, country of origin, and navigational status, as illustrated in Figure 7.

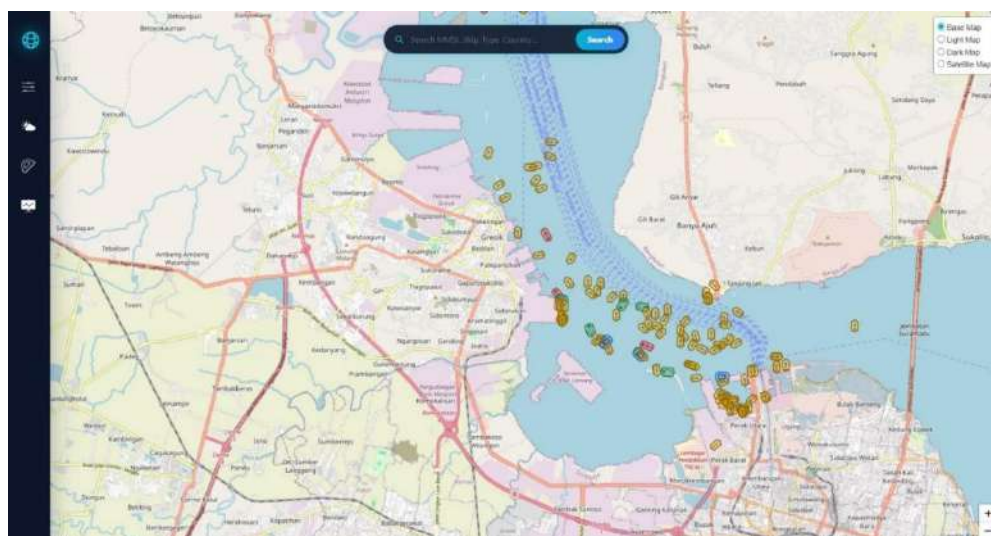


Figure 6. Web-based AIS vessel monitoring interface

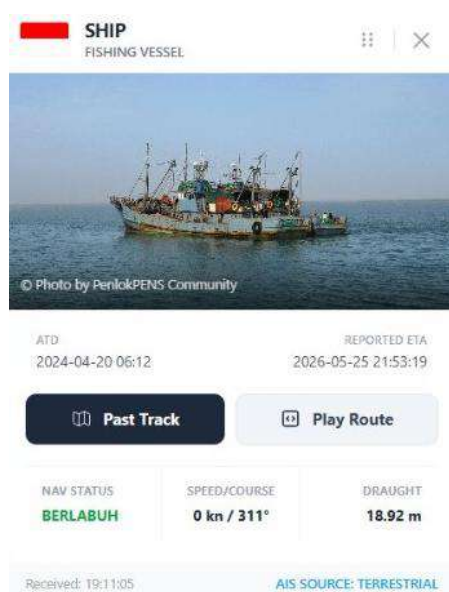


Figure 7. Vessel detailed information view

From an interpretative perspective, spatial visualization significantly enhances data interpretability compared to text-based representations, as it enables users to directly observe vessel distribution and movement patterns within a geographic context without additional interpretation steps. The system also integrates a vessel trajectory tracking feature that enables historical movement analysis. This feature provides temporal analysis of vessel trajectories over a specified time interval, as shown in Figure 8. Such capability can be utilized for maritime surveillance, traffic density analysis, and maritime incident investigation.

To enhance situational awareness, the system also provides maritime traffic statistics through an interactive dashboard, as shown in Figure 9. The dashboard aggregates AIS records stored in the database and presents vessel distributions according to vessel type, navigational status, and country of origin. During the observation period, a total of 114 vessels were identified, consisting of 98 anchored vessels and 16 sailing vessels. These results demonstrate the capability of the platform to consolidate AIS data into operationally interpretable maritime information within a single interface.



Figure 8. Vessel trajectory tracking feature

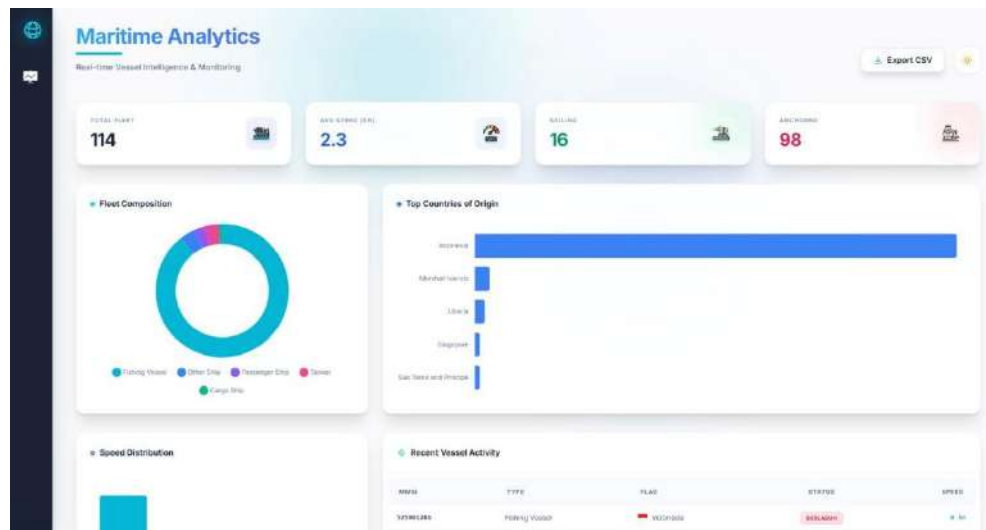


Figure 9. System dashboard and statistical visualization

3.2. System Performance Evaluation

System performance was evaluated over a 60-minute observation period using message throughput, end-to-end latency, and processing stability as evaluation metrics. Message throughput statistics are presented in Table 3.

As shown in Table 3, message counts ranged from 996 to 1,295 across the twelve 5-minute intervals, with an average of 1,113 valid messages processed per interval and a cumulative total of 13,357 messages. Based on (1), the corresponding average throughput was approximately 3.71 messages s^{-1} . To quantify the dispersion of message counts across observation intervals, the standard deviation (SD) and coefficient of variation (CV) were calculated using equations (2) and (3):

$$SD = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n - 1}} \quad (2)$$

$$CV = \frac{SD}{\bar{x}} \times 100\% \quad (3)$$

where:

x_i denotes the message count in interval i , $\bar{x}$ denotes the mean message count (messages), and n is the total number of observation intervals ($n = 12$).

The calculated SD and CV were 96.12 messages and 8.64%, respectively, indicating limited temporal variability and demonstrating that the proposed AIS receiver maintained consistent message acquisition and stable throughput throughout the 60-minute observation period despite natural fluctuations in maritime traffic density.

Table 3. AIS data received at tanjung perak

Interval Time	Number of Data Received
20:53 – 20:58	1,295
20:59 – 21:03	1,045
21:04 – 21:08	1,029
21:09 – 21:13	1,055
21:14 – 21:18	1,036
21:19 – 21:23	1,040
21:24 – 21:28	1,117
21:29 – 21:33	1,159
21:34 – 21:38	1,238
21:39 – 21:43	1,215
21:44 – 21:48	1,132
21:49 – 21:53	996
Total	13,357
Average	1,113

End-to-end latency was estimated from the timestamp differences between decoded AIS messages generated at the Raspberry Pi processing stage and the corresponding database insertion records. A comparison of the timestamps shown in Figures 4 and 5, together with uninterrupted updates on the web interface, confirms continuous temporal propagation throughout the acquisition, decoding, storage, and visualization pipeline. The observed end-to-end latency ranged from 0 to 2 seconds, demonstrating the capability of the proposed edge-based architecture to support near real-time maritime monitoring.

3.3. Discussion

The results indicate that the integration of RTL-SDR-based AIS reception with web-based visualization enables a cohesive maritime monitoring workflow within a single edge-computing environment. Beyond AIS data reception, the implemented platform combines signal acquisition, message decoding, data management, trajectory reconstruction, and geospatial visualization to support near real-time observation of vessel movements.

Table 4 summarizes the comparison between the proposed system and previous AIS monitoring studies. As shown, the main contribution of this work is not merely the implementation of AIS reception, but the integration of signal acquisition, decoding, database management, and web-based visualization into a unified edge-computing framework. In addition, the proposed platform extends conventional AIS monitoring by providing historical trajectory analysis and statistical dashboard visualization within a single system.

The integration of Leaflet.js further enhances the practicality of the proposed platform by providing a lightweight and interactive visualization interface suitable for resource-constrained edge devices such as the Raspberry Pi. Beyond real-time vessel positioning, the platform supports historical trajectory analysis and statistical dashboard visualization, extending the functionality of conventional AIS monitoring systems. These capabilities enable the proposed platform to provide not only real-time vessel tracking but also comprehensive maritime situational awareness within a unified web-based environment.

Table 4. Comparison with previous studies

Previous Studies	Object	Method	Throughput (msg/s)	Latency	Hardware Cost
[9]	AIS signal reception, decoding, and web-based visualization	VHF antenna + AIS receiver + LabVIEW + Leaflet.js	NR	NR	NR
[12]	AIS signal reception and monitoring	Yagi antenna + RTL-SDR + Low Noise Amplifier + SDR-Sharp + AISMon + OpenCPN	NR	NR	NR
[13]	Ship movement tracking using AIS data	VHF antenna + AIS receiver + Quantum GIS	NR	NR	NR
Proposed System	AIS signal reception and monitoring	VHF antenna + RTL-SDR + Raspberry Pi + C-based AIS decoding + MariaDB + Leaflet.js	3.71	0–2 s	USD 189

4. CONCLUSION

This study presented an AIS-based vessel monitoring platform that integrates signal acquisition, message decoding, data management, and web-based geospatial visualization within a unified edge-computing architecture. Field observations conducted under dense maritime traffic conditions showed that the system processed a total of 13,357 valid AIS messages during a 60-minute observation period, corresponding to an average throughput of 3.71 messages per second. The measured end-to-end latency of approximately 0–2 seconds indicates that vessel information can be delivered to the monitoring interface with minimal delay. The integration of RTL-SDR-based reception, Raspberry Pi-based processing, MariaDB data management, and Leaflet.js visualization establishes a continuous processing chain from AIS radio transmissions to operational vessel information. In addition to real-time vessel tracking, the platform supports historical trajectory reconstruction and maritime traffic analytics within a single operational environment. With a total hardware cost of approximately USD 189, substantially lower than commercial AIS receiver and base station systems, the proposed platform demonstrates that reliable real-time maritime monitoring can be achieved using low-cost edge-computing hardware, highlighting its feasibility for large-scale deployment in resource-constrained environments.

A limitation of the proposed system is that situational awareness is constrained to vessels transmitting valid AIS messages, as the monitoring process relies exclusively on AIS-derived information. Consequently, non-AIS targets, stationary maritime objects, coastal infrastructure, and vessels with inactive AIS transponders cannot be detected or visualized by the platform. Future work may therefore explore the integration of complementary sensing technologies, such as marine radar, camera-based monitoring, or multi-source data fusion, to provide a more comprehensive representation of the maritime environment.

Acknowledgments

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Design and Implementation of an IoT-Based Web Server System for Real-Time Vital Signs Monitoring

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ABSTRACT

The goal of this project is to develop and put into use a web server-based vital signs monitoring system for tracking health conditions in real time. The device is designed to enable medical personnel to remotely monitor blood pressure, body temperature, oxygen saturation (SpO₂), and heart rate. The system architecture integrates Internet of Things (IoT) physiological sensors, a microcontroller for data gathering, and a web server for data storage and visualization. Authorized users can view sensor data on a web-based dashboard after it is wirelessly delivered to the server. Requirements study, system design, implementation, and testing were all part of the prototype process used to create the system. Sensor accuracy, data transfer stability, and web interface responsiveness were assessed by system testing. The average measurement error for heart rate was 2.57%, with an accuracy of 97.43%; for oxygen saturation (SpO₂), it was 1.37%, with an accuracy of 98.63%; and for body temperature, it was 2.04%, with an accuracy of 97.96%, according to the test findings. The installation results show that the system is capable of low-latency, real-time monitoring and early notifications when critical metrics exceed normal limits.



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1. INTRODUCTION

Significant advancements in remote vital-signs monitoring systems have been fueled by the increased focus on an individual's physical health [1-3]. Heart rate [4], oxygen saturation (SpO₂) [5-9], body temperature [10-12], and blood pressure [13-14] are examples of vital signs, essential physiological indicators used to evaluate a person's health [15-18]. These measures have typically been monitored in a clinical context, which can restrict ongoing observation and postpone the early identification of serious problems. As a result, there is increasing demand for reliable, real-time monitoring systems that enable healthcare delivery outside traditional hospital settings.

The integration of biomedical sensors [19] with networked systems for real-time health data collection [20-21] has been enabled by recent advancements in the Internet of Things (IoT). Through automated data collection, transmission, and analysis via networked devices, IoT-based healthcare systems provide ongoing monitoring [22]. These technologies, when paired with web server technology,

enable remote visualization and retrieval of health data via web-based dashboards [23], increasing accessibility for medical professionals and boosting decision-making effectiveness [24].

Despite these advancements, there are still several challenges in developing IoT-based vital signs monitoring systems, including reliability in real-world scenarios, data transmission latency, sensor accuracy, and system scalability. Sensor devices, communication protocols, and user interfaces appropriate for clinical applications are not fully integrated into many existing systems, which are still restricted to prototype-scale implementations. To get around these limitations, this study suggests developing and implementing an IoT-based web server system for real-time vital signs monitoring. The proposed system aims to enable remote healthcare services, improve early detection capabilities, and provide accurate, stable, and real-time visualization of physiological data. By increasing monitoring effectiveness and facilitating prompt clinical treatments, the suggested strategy is anticipated to progress smart healthcare systems.

2. RESEARCH METHOD

This research uses a research and development approach with a design-and-implementation model, focusing on the design, development, implementation, and testing of an IoT-based vital signs monitoring system integrated with a web server. This approach is used because the research aims not only to produce a prototype device but also to evaluate system performance based on sensor reading accuracy and the system's ability to perform real-time monitoring. The research stages include identifying system requirements, designing hardware and software, testing performance, collecting and analyzing data, and evaluating system feasibility.

2.1. Block Diagram

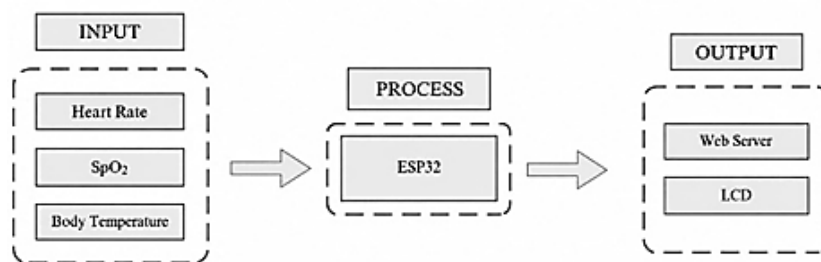


Figure 1. Block diagram of the vital signs monitoring

The three primary parts of a physiological health monitoring system input, processing, and output units are depicted in Figure 1. The input unit displays the physiological data of the patient as measured by the MAX30100 sensor (heart rate and SpO₂) and the MLX90614 sensor (body temperature). An ESP32 microcontroller is used in the processing unit to process the data collected from the sensors. At this point, an ESP32-CAM is used to acquire, validate, and process data before sending it over the internet to the output system. The output device then uses a web server, an LCD, and a buzzer to show the data processing findings. A monitoring dashboard is used by the web server function to show data in real time.

2.2. Schematic Circuit Diagram

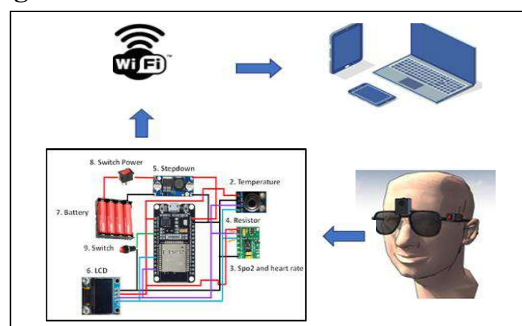


Figure 2. Schematic diagram of the vital signs monitoring system

Figure 2 shows a schematic of a vital signs monitoring circuit that is integrated with a web server. First, sensors installed on the device (part of the ESP32 circuit) are used to read body conditions such as heart rate, temperature and blood pressure. Next, the data is sent via a Wi-Fi connection to the internet. From the internet, data is forwarded to user devices such as laptops, computers or smartphones. On the user's side, the data is displayed on a monitoring display so that health conditions can be monitored in real time. Meanwhile, the image of a human head wearing glasses on the right side depicts a doctor recording patient or user data, with medical personnel monitoring the patient's condition.

2.3. Operating Principle of the Device

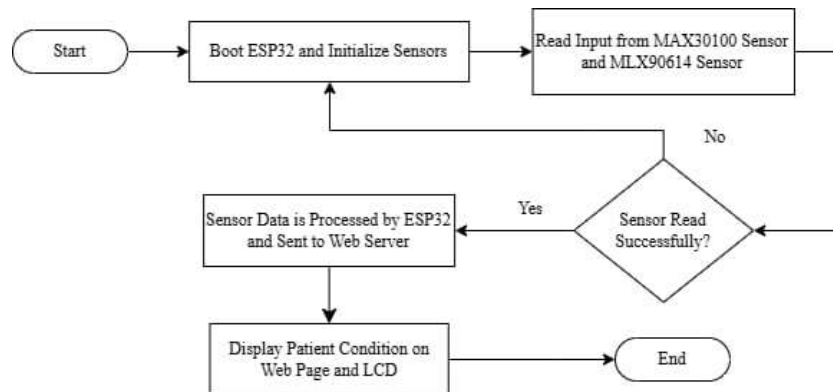


Figure 3. Flowchart of the working principle of the vital signs monitoring device

A flowchart illustrating the working concept of the vital signs monitoring device is shown in Figure 3. The ESP32 microcontroller boots up and initialises all of the system's embedded sensors to start the procedure. The ESP32 starts reading data from the MAX30100 and MLX90614 sensors once the initialisation process is complete. The system then performs validation to ensure the sensor data is accurately read. If the sensor reading fails, the system will return to the initialisation stage and repeat the reading until reliable sensor data is acquired. Nevertheless, the ESP32 handles the measurement data, including translating sensor readings and computing the required health parameter estimates, assuming all sensors have been correctly read.

After data processing is complete, the measurement results are transmitted via Wi-Fi to a web server for real-time display on a webpage for remote monitoring. As the device's local interface, the data is simultaneously shown on the LCD. To ensure the system is prepared to read and transmit data for the upcoming monitoring cycle repeatedly, this operation is performed continuously.

3. RESULTS AND DISCUSSION

3.1. Physical Form of the Device

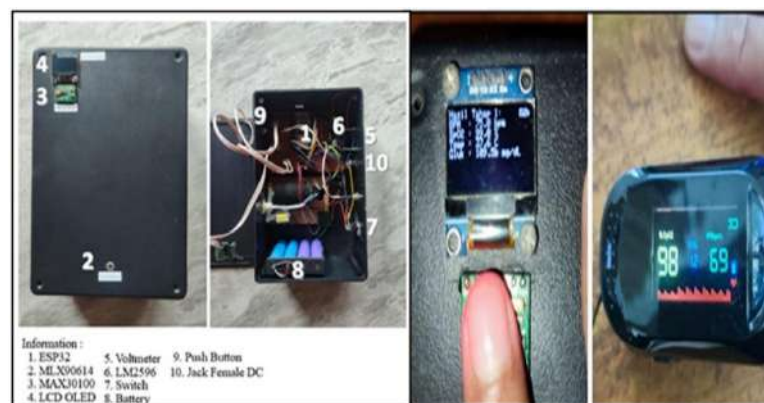


Figure 4. Design results of the vital signs monitoring system

Figure 4 shows the physical form of the vital signs monitoring system device developed in this study. The device is designed in a box shape, containing the main components: an ESP32, a DC pump, a solenoid valve, a Li-Ion battery, and a step-down module as a voltage regulator. On top of the device are an LCD screen for local display, a MAX30100 sensor for heart rate and SpO₂ measurements, and an MLX90614 sensor for body temperature measurements. Meanwhile, on the right side of the device, there is a three-mode switch (battery, off, and adapter), a push button for system reset, and a voltmeter for monitoring the input voltage. On the left side of the device, there is an air duct connected to the blood pressure cuff and a push button used for menu selection during the measurement process.

3.2. Heart Rate Testing

Table 1. Testing of the MAX30100 sensor for heart rate measurement

Id_Number	Age	Heart Rate (BPM)		Error (%)
		MAX30100	Pulse Oximeter	
001	55	79.40	75	5.87
002	67	73.10	75	2.53
003	59	92	90	1.33
004	75	86.4	85	1.65
005	60	73.7	75	1.73
006	73	68.70	71	3.24
007	67	73.3	75	2.27
008	56	83.60	86	2.79
009	55	67.20	66	1.82
010	57	98.10	96	2.19
Average				2.57

The heart rate measurement performance evaluation of the MAX30100 sensor compared to a pulse oximeter, a common medical device, is shown in Table 1. Ten respondents aged 55-75 participated in testing to evaluate the reliability of the IoT-based real-time vital signs monitoring system in practical use cases. The measurement findings demonstrate that, with only minor variations across all test samples, the heart rate readings derived from the MAX30100 sensor show a significant correlation with the pulse oximeter reference value. Respondent 001 had the largest mistake value (5.87%), while respondent 003 had the lowest error value (1.33%). The system's susceptibility to external influences, such as sensor-skin contact, motion artefacts, and individual physiological fluctuations, is indicated by variability in error across responses.

Overall, the system achieved 97.43% accuracy with an average error of 2.57%. This figure shows that the MAX30100 sensor operates in the high-accuracy range and can be used in an IoT-based real-time vital-sign monitoring system. These results also show that integrating the sensor with a web server and microcontroller maintains measurement consistency in multi-subject testing scenarios, which may facilitate its use in telemedicine and remote health monitoring systems.

3.3. Oxygen Saturation Testing

The results of oxygen saturation (SpO₂) testing with the MAX30100 sensor and a reference instrument, a pulse oximeter, are displayed in Table 2. Ten participants aged 55-75 were tested to determine how well the sensor measured blood oxygen levels. According to the test results, responders 001, 004, and 009 showed an error value of 0%, meaning that the sensor readings matched the reference equipment. Respondent 008 had the greatest error value (4.30%), with a MAX30100 reading of 89% and a pulse oximeter reading of 93%. Several variables, including the location of the finger on the sensor, the stability of the skin-sensor contact, hand movement during the measurement, and the state of the respondents' peripheral blood circulation, can affect measurement findings. Overall, the system accuracy was 98.63% with an average error of 1.37% in SpO₂ measurements. These findings show that the

MAX30100 sensor is appropriate for use in an IoT-based web server system for Real-Time Vital Signs Monitoring and performs well in measuring oxygen saturation.

Table 2. Testing of the MAX30100 sensor for oxygen saturation measurement

Id_Number	Age	Oxygen Saturation (%)		Error (%)
		MAX30100	Pulse Oximeter	
001	55	98	98	0
002	67	99	97	2.06
003	59	94	92	2.17
004	75	98	98	0
005	60	99	98	1.02
006	73	91	90	1.11
007	67	99	97	2.06
008	56	89	93	4.3
009	55	99	99	0
010	57	98	99	1.01
Average				1.37

3.4. Body Temperature Testing

Table 3. Testing of the MLX90614 sensor for body temperature measurement

Id_Number	Age	Temperature (C°)		Error (%)
		MAX30100	Pulse Oximeter	
001	55	35,9	35,6	0,84
002	67	35,7	34,8	2,59
003	59	38,8	38,4	1,04
004	75	33,6	34,1	1,47
005	60	33,9	33,8	0,3
006	73	37,1	38,7	4,13
007	67	36,4	36,1	0,83
008	56	34,5	34,2	0,88
009	55	36,9	34,7	6,34
010	57	34,2	34,9	2,01
Average				2.04

The body temperature test results for 10 respondents aged 55-75 are shown in Table 3. To assess measurement accuracy, the system readings were compared with those of a reference device to calculate the error (%). The body temperature measurements from the system were mostly in line with those from the reference device, as shown in the table. Respondent 005 had the lowest error, at 0.30%, with a system reading of 33.9°C and a reference device of 33.8°C. With a system measurement result of 36.9°C and a reference device reading of 34.7°C, Respondent 009 had the largest error, 6.34%. The device measured body temperature with an average total error of 2.04%, yielding an accuracy of 97.96%. This chart demonstrates that the device has reasonably good temperature measurement capabilities and can monitor vital signs in real-time.

Several factors, such as sensor position, distance from the body surface, ambient temperature, respondent movement, and the stability of the data-reading process, can influence differences in measurement values. Overall, test results indicate that the system can provide relatively stable body temperature readings that are close to those of the comparison device.

3.5. Web Server Testing

Web server testing was conducted to ensure the system could automatically receive, store, and display patient examination data sent from ESP32-based devices. This testing included user authentication, patient data storage, sensor data transmission, and visualization of examination results on a web page.



Figure 5. Web server interface for vital signs monitoring

The admin login page and the patient examination results page are the two primary sections of the web-based vital signs monitoring system depicted in Figure 5. The administrator or other authorised users use the system login page. The entry point for tracking and managing patient health data is this page. Before gaining access to the vital signs monitoring system, users must input their login and password.

The "Patient Examination Details" page displays real-time patient examination data. The displayed data include examination time, patient name, age, gender, and vital parameters such as heart rate, oxygen saturation (SpO₂), and body temperature. Each measurement result is displayed in a table for easy reading and analysis. Additionally, an information note explains that the color or value of the examination result can serve as an indicator of the patient's overall health. This helps medical personnel monitor patient conditions more quickly and efficiently.

4. CONCLUSION

This study successfully designed and implemented an IoT-based web server system for real-time vital signs monitoring. The system integrates an ESP32 microcontroller, MAX30100 sensor, MLX90614 sensor, LCD, buzzer, Wi-Fi communication, and a web-based dashboard to acquire, process, transmit, store, and display physiological data in real time. The experimental results show that the proposed system achieved good measurement performance, with heart rate accuracy of 97.43% and an average error of 2.57%, SpO₂ accuracy of 98.63% and an average error of 1.37%, and body temperature accuracy of 97.96% and an average error of 2.04%. These results indicate that the developed device can provide relatively accurate and stable measurements compared with reference instruments. The web server testing also confirmed that patient examination data could be transmitted and displayed through the monitoring interface, enabling remote access to vital sign information. Therefore, the proposed system is feasible as a supporting tool for real-time patient monitoring and telemedicine applications. However, further development is recommended to improve measurement stability under movement conditions, expand clinical validation with more respondents, and enhance data security and system scalability for broader healthcare implementation.

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Voltage–Frequency Stability of a 300W Portable Cross-Flow Pico-Hydropower System under Low-Flow Conditions

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ABSTRACT

Pico-hydropower systems are widely recognized as a reliable solution for rural electrification; however, their performance is highly sensitive to hydraulic and load variations, particularly under low-flow conditions. This study presents an experimental investigation of voltage–frequency stability in a 300 W portable cross-flow pico-hydropower system. The system consists of a simple weir intake, a variable-diameter PVC penstock, a cross-flow turbine, and a directly coupled single-phase AC generator without a governing mechanism. Experimental tests were conducted by applying six resistive load levels ranging from 0 to 100 W to evaluate the output voltage, frequency, generator rotational speed, overall system efficiency, and voltage regulation. The results show a significant frequency drop from 77 Hz at no-load to 57 Hz at full-load, corresponding to a deviation of approximately 35%. The system also exhibits a low overall efficiency of 15.21% and a voltage regulation of 36.6%, indicating poor energy conversion and unstable voltage performance. These findings reveal that the absence of a speed control mechanism and turbine–generator mismatch significantly affect system stability. The study concludes that load variation alone is insufficient to maintain stable operation, highlighting the need for advanced control strategies such as ELC to improve the voltage and frequency stability.



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1. INTRODUCTION

The increasing global demand for sustainable energy has significantly accelerated the development of decentralized power generation systems, particularly for rural and off-grid applications [1], [2]. Among the various available technologies, pico-hydropower systems are widely recognized for their reliability, primarily due to their ability to provide continuous and predictable energy output, in contrast to intermittent renewable sources such as solar and wind energy. Cross-flow turbines are extensively employed in pico-hydropower systems owing to their simple construction, cost-effectiveness, and suitability for operation under low-head conditions [2], [6]. Previous studies have demonstrated that cross-flow turbines exhibit relatively stable performance under varying flow conditions and continue to attract considerable research attention in pico-hydropower applications due to their robustness, operational flexibility, and adaptability [1], [6], [10]. However, standalone pico-hydropower systems face significant challenges in maintaining voltage and frequency stability under variable load conditions.

In isolated or weak electrical systems, load disturbances may lead to significant voltage and frequency deviations, thereby reducing power quality and system reliability [3]–[5]. These issues become more critical in systems without control mechanisms such as governors or electronic load controllers (ELC), which are commonly employed to maintain voltage and frequency stability in standalone pico-hydropower systems [8].

Although several studies have reported electrical output characteristics of pico-hydro systems [1], [2], recent reviews indicate that quantitative investigations of voltage regulation, frequency deviation, and the interaction between mechanical and electrical parameters remain limited, particularly for portable pico-hydropower systems [9], [10]. This study experimentally investigates the voltage–frequency behavior of a 300 W portable cross-flow pico-hydropower system operating under low-flow conditions and variable electrical loads. The experimental evaluation includes voltage regulation, frequency deviation, generator rotational speed, and the mechanical–electrical coupling to provide a comprehensive assessment of the system stability under standalone operating conditions. Unlike previous studies, which primarily focused on turbine hydraulic performance or electrical output characteristics separately, this work integrates the analysis of electrical and mechanical response parameters in a portable direct-coupled turbine–generator system under actual field conditions. The findings are expected to provide valuable experimental data for the development of effective voltage and frequency control strategies, particularly through the implementation of ELC, in portable standalone pico-hydropower systems.

2. RESEARCH METHOD

2.1. System Configuration

The experimental setup consists of a portable pico-hydropower system utilizing a cross-flow turbine coupled to a 300 W single-phase AC generator. The main components of the system include a water intake and flow channel, penstock pipeline, cross-flow turbine runner, mechanical shaft coupling, AC generator (300 W), voltage regulator (post-generator), and a resistive load bank based on a lamp loading system. The overall configuration of the system is illustrated in Figure 1, which presents the main components in three sections: (a) water intake, (b) penstock pipeline, and (c) turbine–generator assembly. The water intake system, shown in Figure 1(a), employs a simple weir structure designed to collect water from a natural spring source, which provides a relatively continuous flow throughout the year. The weir has a cross-sectional area of approximately 0.256 m², allowing sufficient water accumulation before entering the conveyance system. This configuration is selected due to its simplicity, low construction cost, and suitability for rural and off-grid applications.

The penstock pipeline, as depicted in Figure 1(b), is constructed using PVC pipes with a gradually decreasing diameter to enhance the hydraulic pressure at the turbine inlet. The pipe diameters are reduced from 6 inches to 4 inches and finally to 3 inches at the nozzle end. The total length of the penstock is 23.83 m. This design aims to minimize hydraulic losses while increasing flow velocity at the turbine entrance. The system operates under an effective head of 2.95 m, with a measured flow rate of 0.02705 m³/s at the outlet.

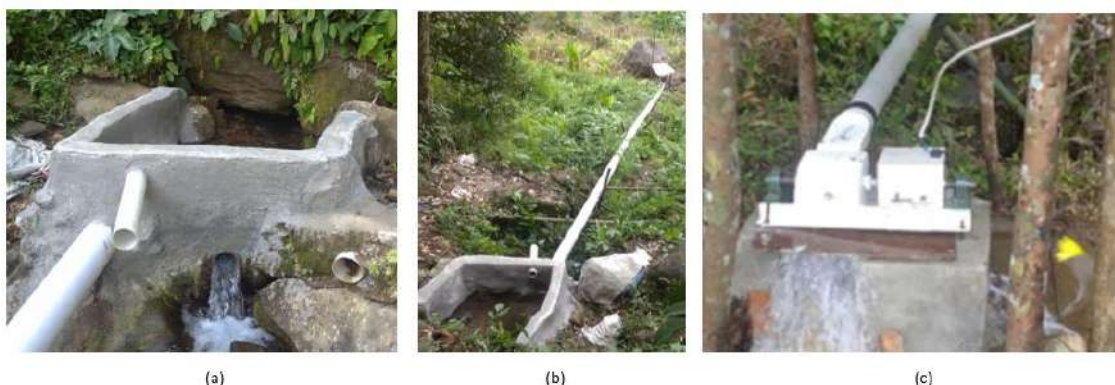


Figure 1. Experimental setup of the portable pico-hydropower system: (a) weir structure, (b) penstock pipeline, and (c) turbine–generator assembly

The turbine-generator assembly shown in Figure 1(c) adopts a direct-coupled single-shaft configuration, in which the cross-flow turbine and the single-phase AC generator are mounted coaxially on the same shaft without intermediate transmission components such as belts or gearboxes. This arrangement minimizes mechanical transmission losses, improves rotational power transfer, and provides a compact structure suitable for portable applications. The complete assembly is supported by a detachable steel-frame structure, allowing convenient transportation, installation, and maintenance in remote locations. The detailed mechanical and electrical specifications of the prototype are summarized in Table 1.

Table 1. Geometrical and electrical specifications of Pico-Hydropower

Item	Specification
Nozzle Inclination	45°
Inlet Nozzle Diameter	3 in
Turbine	
Runner Diameter	10 cm
Shaft Diameter	5 cm
Runner Width	12.5 cm
Number of Runner Blades	14
Generator Rated Power	300 W

The experimental pico-hydropower was installed at the Bukit Aur Durian Plantation, Limau Manis Village, Pauh District, Padang City, West Sumatra, Indonesia. The geographical location of the experimental site is shown in Figure 2. The site is located approximately 4.1 km from Politeknik Negeri Padang and 33 km from Minangkabau International Airport, with an average travel time of approximately 12 min by motorcycle from the campus. Geographically, the installation site is located at 0°55'08.22" S, 100°28'53.12" E (-0.918949, 100.481296) at an elevation of 419 m above mean sea level. The site was selected because it is supplied by a perennial spring capable of providing a continuous water flow suitable for evaluating the performance of the portable pico-hydropower system under actual field conditions.



Figure 2. Geographic location of the portable pico-hydropower experimental site in Bukit Aur Durian Plantation, Limau Manis, Pauh District, Padang City, West Sumatra, Indonesia
(Source: Google Maps, accessed July 2026)

2.2. Experimental Parameters

The key parameters used in this study are based on actual measured and calculated values: Water flow rate: $Q=0.02705 \text{ m}^3/\text{s}$, Effective head: $H=2.95\text{m}$, Gravitational acceleration: $g=9.81\text{m}/\text{s}^2$, Water density: $\rho=1000 \text{ kg}/\text{m}^3$. The theoretical hydraulic power is calculated using:

$$P_{hyd} = \rho g Q H \quad (1)$$

In this equation, P_{hyd} represents the hydraulic power available in the system (W), while ρ , g , Q , and H correspond to the water density (kg/m^3), gravitational acceleration (m/s^2), volumetric flow rate (m^3/s), and effective head (m), respectively. This equation represents the maximum available power from the water source prior to any conversion losses in the turbine and generator system [13], [21].

2.3. Measurement and Instrumentation

To ensure consistency with the reported results, several key parameters were measured during the experiment. The output voltage (V) was measured and used for voltage regulation analysis, while the output current (I) was recorded for electrical power calculation. The output frequency (Hz) was monitored to evaluate frequency stability, and the rotational speed (rpm) was measured to analyze the mechanical performance of the system.

The measurements were carried out using standard electrical instruments, including a digital multimeter for voltage measurement, a clamp meter for current measurement, a frequency meter for frequency monitoring, and a tachometer for rotational speed measurement. These instruments are commonly used in experimental analysis of small-scale power systems [19].

According to the manufacturer's specifications, the Everwell MT87 provides an AC voltage measurement range of 200/750 V with an accuracy of $\pm(1.0\% + 5 \text{ digits})$ and an AC current measurement range of 20 A with an accuracy of $\pm(2.5\% + 10 \text{ digits})$. Prior to the experiments, all measuring instruments were inspected for proper operation, and their readings were verified against known reference values following the manufacturer's recommended procedures to minimize measurement errors. These specifications and verification procedures were considered throughout the experimental campaign to improve the reliability of the acquired data.

2.4. Experimental Procedure

The experimental procedure is illustrated in Figure 3. Prior to each test, the portable pico-hydropower system was operated under no-load conditions until steady-state operation was achieved. During the experiments, the hydraulic input parameters, including the effective head and water flow rate, were maintained as constant as possible to ensure consistent operating conditions [13], [18]. The electrical load was increased sequentially in 20 W intervals, from 0 W to 100 W, resulting in six loading conditions (0, 20, 40, 60, 80, and 100 W). At each load level, the system was allowed to stabilize before measurements were taken to minimize transient effects associated with sudden load changes. Once steady-state conditions were reached, the output voltage, current, frequency, and generator rotational speed were recorded [19]. Each loading condition was tested three times, and the average values were used for subsequent analysis to improve the repeatability and reliability of the experimental results. The entire experimental campaign was conducted over seven consecutive days under nearly constant hydraulic conditions so that the observed variations in electrical performance were primarily attributed to changes in the applied electrical load rather than fluctuations in the available water resource [24].

2.5. Performance Analysis

1. Electrical Power Output

The electrical output power is calculated using:

$$P_{out} = V \times I \quad (2)$$

In this equation, P_{out} represents the electrical output power, whereas V and I denote the terminal voltage and load current, respectively. This formulation is commonly used for electrical power calculation in AC systems [19].

2. System Efficiency

The efficiency of the pico hydro system is determined by:

$$\eta_{sys} = \frac{P_{out}}{P_{hyd}} \times 100\% \quad (3)$$

Where η_{sys} represents the system efficiency (%), P_{out} is the electrical output power and P_{hyd} is the theoretical hydraulic power available from the water source (W). his efficiency definition is widely used in small hydropower system analysis [13], [21].

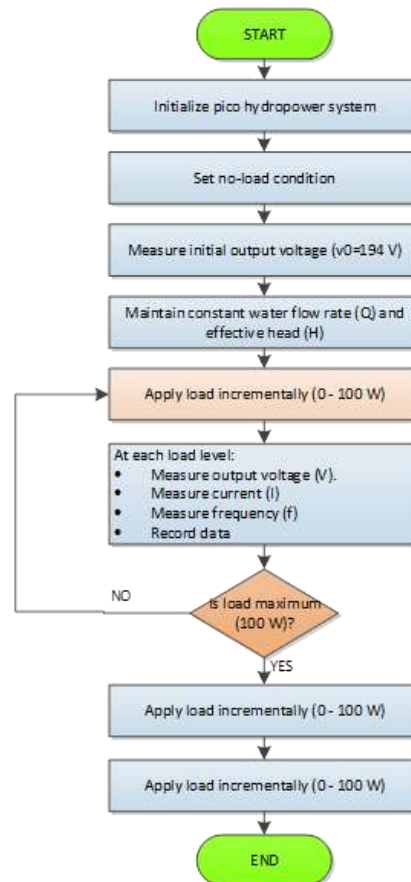


Figure 3. Flowchart of the experimental procedure

3. Voltage Regulation

Voltage regulation is evaluated to determine system stability:

$$VR = \frac{V_{no-load} - V_{full-load}}{V_{full-load}} \times 100\% \quad (4)$$

Where VR represents the voltage regulation (%), $V_{no-load}$ is the output voltage at no-load condition, and $V_{full-load}$ is the output voltage at full-load condition. Voltage regulation is a key indicator of power quality in electrical systems [11], [16].

4. Frequency Stability

Frequency deviation is evaluated to assess generator performance under varying load conditions and is calculated as:

$$FD = \frac{f_{no-load} - f_{full-load}}{f_{full-load}} \times 100\% \quad (5)$$

In this equation, FD represents the percentage frequency deviation, whereas $f_{no-load}$ and $f_{full-load}$ correspond to the system frequencies under no-load and full-load conditions, respectively. Frequency stability plays a crucial role in ensuring the reliability and operational continuity of standalone power systems [16], [22]. Moreover, the relationship between rotational speed and output frequency is systematically analyzed to evaluate the electromechanical coupling behavior of the system. This relationship follows the fundamental generator equation:

$$f = \frac{P \times N}{120} \quad (6)$$

where f represents the electrical frequency (Hz), while P and N denote the number of poles and the rotational speed (rpm), respectively [19].

3. RESULTS AND DISCUSSION

3.1. Hydraulic and Generator Power

Based on the experimental data, the generator power output (P_{out}) was recorded at 119 W against a hydraulic power potential P_{hyd} of 782,31 W, resulting in an overall system efficiency η_{sys} of approximately 15.21%. The calculated overall efficiency is considerably lower than that reported for well-designed small hydropower systems, where overall efficiencies typically range from approximately 50% to 70% under favorable operating conditions [13], [20]. This substantial performance degradation can be attributed to severe mechanical friction within the rotating assembly, a pronounced rotational speed (rpm) mismatch between the cross-flow turbine and the generator, or an overestimation of the theoretical hydraulic power relative to the actual operational capacity of the turbine.

3.2. Voltage Characteristics and Regulation

The experimental results show that the output voltage decreases significantly with increasing load, from 194 V at no-load to 142 V at full-load (100 W). The voltage characteristics under varying load conditions are presented in Figure 4. This substantial voltage reduction demonstrates the limited capability of pico-hydropower to maintain a stable output voltage under increasing load demand.

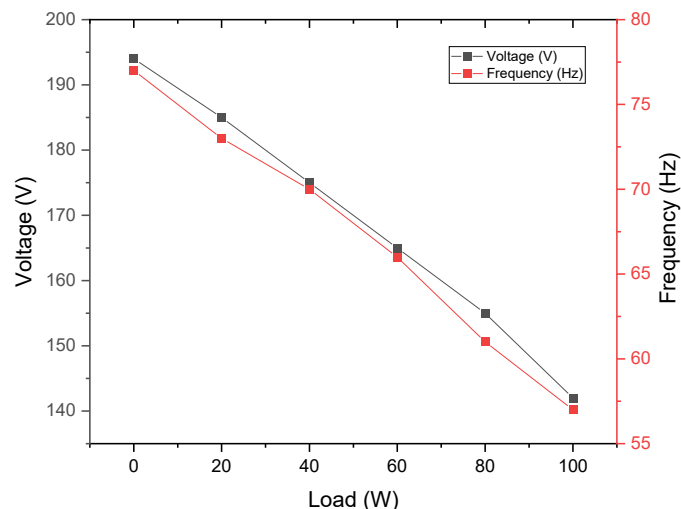


Figure 4. Voltage and frequency characteristics under varying load conditions

According to IEC 60038, the nominal low-voltage supply for 50 Hz systems is 230 V. Considering the commonly accepted operating tolerance of $\pm 10\%$, the acceptable operating voltage range is approximately 207–253 V [12]. In the present study, the measured no-load voltage of 194 V was already below the minimum recommended operating limit by approximately 6.3%. As the electrical load increased, the output voltage further decreased to 142 V, corresponding to a deviation of approximately 31.4% below the minimum acceptable voltage. These results indicate that the prototype operated under undervoltage conditions throughout the entire experimental range and was unable to satisfy the standard voltage requirements even before loading was applied.

This behavior is further reflected by the calculated voltage regulation of the prototype, which was 36.6%. This value is considerably higher than the recommended voltage variation of $\pm 5\text{--}10\%$ for small-scale power systems [11], [12], confirming that the prototype exhibits poor voltage regulation and limited voltage stability under varying load conditions.

The observed voltage degradation is primarily attributed to the reduction in generator rotational speed caused by the increasing mechanical load imposed on the turbine. In direct-coupled pico-hydropower systems without an active governing mechanism, the generated voltage is strongly dependent on turbine speed and generator excitation characteristics [13]. Consequently, the reduction in turbine speed directly lowers the generator terminal voltage as the electrical load increases.

A more pronounced voltage drop was observed when the load exceeded 80 W, indicating that the turbine-generator set approached its operating limit. Under these conditions, the available hydraulic power was insufficient to sustain the required generator speed, resulting in inadequate electromagnetic energy conversion and a rapid decline in output voltage [15]. Similar voltage instability has been reported in previous studies on cross-flow pico-hydropower systems, where the absence of an ELC prevented the generator from maintaining a stable voltage under varying load conditions [14]. Therefore, the present results confirm that the implementation of an appropriate voltage and frequency control strategy, such as an ELC, is essential to improve the electrical performance and operational stability of standalone portable pico-hydropower systems.

3.3. Frequency Stability Analysis

The frequency response of the system shows a substantial deviation from nominal conditions. At no-load conditions, the measured frequency is 77 Hz, which decreases significantly to 57 Hz under full-load conditions. Based on Equation (5), this variation corresponds to a frequency deviation of approximately 35%, indicating poor frequency stability of the system. The frequency characteristics under varying load conditions are presented in Figure 4.

According to IEC 60038, the nominal supply frequency for low-voltage power systems in Indonesia is 50 Hz [12]. Under normal operating conditions, the system frequency is expected to remain within a narrow tolerance, typically ranging from $\pm 1\%$ to $\pm 5\%$ of the nominal value according to IEEE and IEC recommendations [11], [22]. Compared with the nominal frequency, the measured no-load frequency of 77 Hz was approximately 54% higher than the standard value, indicating that the turbine-generator assembly operated under a severe overspeed condition. Even at full-load operation, the measured frequency remained at 57 Hz, which is approximately 14% above the nominal frequency. These measured frequencies exceed the allowable deviation recommended by IEEE and IEC standards, confirming that the prototype does not satisfy the frequency quality requirements for standalone AC power generation [11], [22].

The experimental data further show that the generator rotational speed decreased from 1695 rpm to 1450 rpm, resulting in a corresponding reduction in output frequency from 77 Hz to 57 Hz. This observation confirms the direct relationship between generator rotational speed and electrical frequency in AC generators [19]. Because the turbine and generator were directly coupled through a single shaft, any variation in turbine speed was immediately reflected in the generator output frequency. The excessively high no-load frequency indicates that the turbine operated beyond the rotational speed required to produce the nominal 50 Hz output. This behavior suggests a mismatch between the available hydraulic power, turbine rotational speed, and generator characteristics, which is commonly observed in standalone pico-hydropower systems operating without an active speed regulation mechanism [17].

Although the output frequency decreased as the electrical load increased, it remained above the nominal 50 Hz throughout the entire experiment. Consequently, the prototype exhibited persistent over-frequency operation rather than stable frequency regulation, indicating that the generated electrical power was unsuitable for direct connection to conventional AC loads [11], [16]. From a practical perspective, the inability to maintain the nominal frequency may adversely affect the operation of conventional electrical loads, particularly induction motors, transformers, and frequency-sensitive electronic equipment [11], [16], [19]. Since the synchronous speed of AC machines is directly proportional to the supply frequency, frequency deviations directly influence motor operating speed, torque characteristics, and overall efficiency [19]. Furthermore, prolonged operation under abnormal frequency conditions may increase thermal stress, reduce equipment efficiency, and shorten equipment service life [11], [16].

The observed results demonstrate that the prototype lacks an effective mechanism for regulating turbine speed under varying load conditions. Without a governing mechanism or an ELC, the turbine speed cannot be maintained at the level required to produce a stable 50 Hz output frequency [18]. Therefore, the implementation of an active speed-control strategy, such as an ELC or governor system, is essential for maintaining generator frequency within the acceptable operating limits and improving the operational reliability of standalone portable pico-hydropower systems.

3.4. Mechanical Performance and Speed Behavior

The rotational speed of the generator decreases progressively with increasing load, declining from 1695 rpm under no-load conditions to 1450 rpm at full-load. This behavior is consistent with theoretical expectations, as higher electrical loads impose greater mechanical torque on the turbine, resulting in a reduction in rotational speed. However, it is observed that the rate of frequency reduction is more pronounced than the decrease in rotational speed, indicating the presence of additional system losses. These losses can be attributed to several factors, including mechanical friction within the rotating components, generator slip, and electrical losses in the stator windings. Figure 5 depicts the relationship between generator rotational speed and load variation, highlighting this nonlinear behavior. Such losses are commonly reported in small-scale generation systems and tend to become more significant in low-power applications [19]. Furthermore, the absence of a speed governing mechanism exacerbates this issue, as the turbine is unable to maintain a constant rotational speed under varying load conditions, leading to further instability in system performance [20].

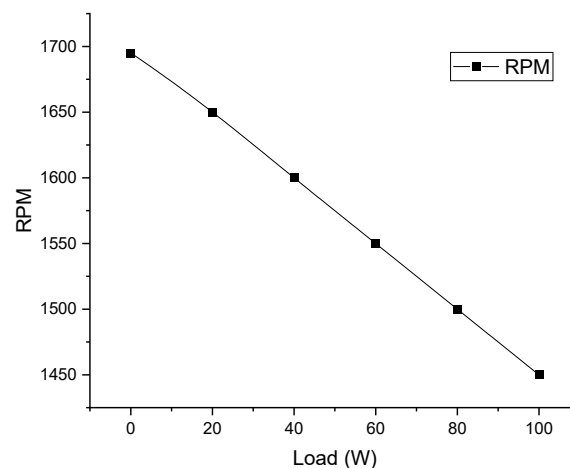


Figure 5. Rotational speed characteristics under varying load conditions

3.5. Discussion and Comparison with Previous Studies

The results of this study are in close agreement with prior research on pico-hydropower systems, which consistently emphasize the challenges associated with maintaining voltage and frequency stability in the absence of advanced control mechanisms. Recent studies [7], [8], [22], [23] report that small-scale pico-hydropower systems without electronic load controllers often experience voltage drops exceeding 20% and significant frequency deviations under variable load conditions. Similarly, [17] emphasizes that direct coupling between turbine and generator leads to poor dynamic response under load variations. The strong correlation between rotational speed, voltage, and frequency observed in this study confirms the dominant influence of electromechanical coupling in uncontrolled pico-hydropower systems. Compared to these studies, the present system exhibits even higher voltage regulation (36.6%) and frequency deviation (77–57 Hz), indicating that portable configurations are more vulnerable to instability due to their simplified design and lack of control mechanisms.

3.6. Implications for System Improvement

The findings clearly indicate that the current system configuration is not suitable for providing a stable electrical supply without the implementation of additional control mechanisms. To enhance system performance, several improvement strategies can be considered. These include the integration of an ELC to stabilize frequency, the use of an inverter-based system for both voltage and frequency regulation, the implementation of a mechanical or electronic governor to control turbine speed, and the optimization of turbine-generator matching to ensure efficient energy transfer. These approaches have been widely reported to significantly improve the stability and overall performance of pico-hydropower systems [16], [20], [22].

4. CONCLUSION

The experimental results demonstrate that the 300 W portable pico-hydropower system exhibits significant voltage and frequency instability under varying load conditions. The output voltage decreases from 194 V to 142 V, corresponding to a voltage regulation of 36.6%, while the frequency decreases from 77 Hz to 57 Hz as the electrical load increases. In addition, the generator rotational speed decreases proportionally with increasing load, confirming a strong coupling between the mechanical input and electrical output of the direct-drive system. The overall system efficiency obtained in this study is 15,21%, indicating considerable potential for performance improvement. The observed instability is primarily attributed to the absence of an active governing mechanism for maintaining constant generator speed under dynamic loading conditions. Therefore, the implementation of an ELC or other power electronic control strategies is essential to improve voltage and frequency stability in standalone pico-hydropower systems. Future work will focus on the design, implementation, and experimental validation of an ELC-based control system to evaluate its effectiveness in enhancing voltage regulation, frequency stability, and overall system performance under dynamic load conditions.

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Performance Comparison of RTL-SDR and HackRF as ADS-B Signal Receivers at 1090 MHz

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ABSTRACT

The development of Software Defined Radio technology enables flexible reception and analysis of communication signals using software-based devices. One of its applications is the Automatic Dependent Surveillance-Broadcast (ADS-B) system, which operates at a frequency of 1090 MHz to digitally transmit flight information. This compare the performance of RTL-SDR and HackRF in receiving ADS-B signals at 1090 MHz. The research was conducted using an experimental method by testing both SDR devices under the same testing conditions and configurations. Signal reception was performed using SDR software and ADS-B decoding software to obtain flight data that could be successfully received and decoded. The test results were used to evaluate the capability of each device to receive and display ADS-B data at 1090 MHz. Based on the experimental results, both devices were capable of receiving ADS-B signals at 1090 MHz but exhibited different performance characteristics. These differences were influenced by device capabilities, receiver configurations, and environmental conditions during signal reception. RTL-SDR offers advantages in terms of cost and ease of use, while HackRF provides greater device flexibility for signal configuration and testing. The results indicate that both devices can be utilized as ADS-B signal receivers, with device selection depending on the specific requirements and intended application. Expected to serve as a reference for the use of SDR devices in receiving and monitoring ADS-B signals at 1090 MHz.



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1. INTRODUCTION

As an archipelagic nation, Indonesia relies heavily on air transportation as the backbone of national connectivity and economic mobilization. Consequently, establishing a robust aviation safety and airspace monitoring system is a fundamental prerequisite. Within this framework, the Automatic Dependent Surveillance-Broadcast (ADS-B) system plays a critical role by periodically transmitting aircraft information—such as identification, flight position, altitude, speed, and other flight-related data—at a frequency of 1090 MHz, enabling ground-based receivers to monitor aircraft movements.[1].

Given the importance of ADS-B data for aircraft monitoring, accessible and reliable signal receivers are highly required for independent research and secondary monitoring systems. However, industrial-grade receivers are often constrained by high procurement costs and rigid hardware designs. To overcome these limitations, Software-Defined Radio (SDR) technology offers a flexible and cost-effective alternative by enabling radio-frequency signals to be received and processed through software-based algorithms rather than relying solely on dedicated hardware.[2].

In the SDR ecosystem, the RTL-SDR and HackRF One are two popular platforms capable of capturing aviation communications in the VHF band. Despite their foundational similarity, they differ sharply in hardware specifications and market segmentation; the RTL-SDR is a low-end, highly economical device, whereas the HackRF One is a premium instrument offering a broader frequency range and superior hardware stability[3].

This hardware divergence creates variations in the Signal-to-Noise Ratio and signal stability, which directly influence packet decoding success and bit error rates. Therefore, a comparative evaluation is necessary to address the aspect of cost-effectiveness (value for money). This research aims to evaluate whether the low-cost RTL-SDR provides sufficient reliability for precise ACARS decoding or if the higher investment in a HackRF One correlates with a necessary improvement in data quality. Ultimately, these findings are expected to provide technical recommendations for developing independent, affordable air traffic monitoring networks to support national transportation safety[4].

2. RESEARCH METHOD

This research uses an experimental method to evaluate and compare the performance of RTL-SDR and HackRF One in receiving and decoding Automatic Dependent Surveillance-Broadcast (ADS-B) signals at a frequency of 1090 MHz. The experimental procedure was designed to ensure that both SDR devices were tested under comparable conditions, including the same target frequency, antenna, software environment, and observation conditions. The research consists of several stages, including hardware preparation, receiver configuration, signal reception, ADS-B data decoding, data collection, and comparative analysis.[5].

The following image below shows the design of the RTL-SDR and HackRF One performance comparison on the ACARAS signal receiver.



Figure 1. RTL-SDR and HackRF one test system suite

2.1. Experimental Approach

This phase involves configuring, testing, and evaluating various system commands and software environments across multiple platforms to optimize both RTL-SDR and HackRF One setups.

2.2. Literature Review

A comprehensive analysis of academic literature, textbooks, and relevant online technical resources is conducted to build a solid theoretical framework and support the empirical analysis.

2.3. Technical Consultation

Continuous academic and technical guidance is maintained through structured discussions with primary advisors and laboratory technicians to refine the experimental parameters and resolve technical constraints.

3. RESULTS AND DISCUSSION

This section presents the experimental results of the performance comparison between the RTL-SDR Blog V3 and HackRF One in receiving and decoding Automatic Dependent Surveillance-Broadcast (ADS-B) signals at a frequency of 1090 MHz. The evaluation was conducted under comparable testing conditions to identify differences in the reception and decoding capabilities of both SDR devices. The analysis focuses on quantitative and qualitative measurements obtained during the experiments, including the number of successfully decoded ADS-B packets, decoding success rate, signal-to-noise ratio (SNR), reception range, and reception stability. The experimental results were collected through repeated observations using both SDR devices. For each trial, the received ADS-B data were recorded and the relevant measurement parameters were documented. The results from the repeated tests were then calculated using descriptive statistical methods, including the mean and standard deviation. This approach provides a more objective comparison of the performance characteristics of RTL-SDR and HackRF One.[6]

3.1. Overview of Testing and System Environment

A comparative experiment evaluating the digital signal processing performance between the RTL-SDR Blog V3 and HackRF One Software Defined Radio (SDR) devices was conducted throughout June 2026 in the airspace of Palembang City. The primary objective of this test was to evaluate the reliability, reception sensitivity, and data pulse extraction capabilities of Automatic Dependent Surveillance-Broadcast (ADS-B) signals at a center frequency of 1,090 MHz.

To ensure data validity against the effects of radio propagation environments, mapping was performed across 6 distinct geographical scenarios:

1. Location I (SMB II International Airport): Optimal Line-of-Sight (LOS) conditions directly facing the runway area with a straight-line air distance of ≤ 2 km.
2. Location II (Ogan Street, Bukit Lama): A representation of a densely populated urban environment located ± 11.5 km from the airport, characterized by high physical obstructions (Non-Line-of-Sight / NLOS).
3. Location III (Semi-Outdoor Urban Cafe Area): A public urban environment located $\pm 6-8$ km from the airport, featuring high electromagnetic interference complexity and structural metallic barriers.
4. Location IV (Jasdam II Sriwijaya Field): A wide open urban area located $\pm 7-9$ km from the airport, providing an unobstructed vertical sky view.
5. Location V (Talang Keramat Area, Banyuasin): A suburban area located $\pm 5-7$ km from the airport with low building density to test the lower threshold sensitivity of the receivers.
6. Location VI & VII (Cross-Station / Interleaved Scenario): Simultaneous testing where the RTL-SDR was positioned at the SMB II Airport area (short-range, LOS), while the HackRF One was deployed in an urban area (Jasdam II Sriwijaya or an outdoor cafe) to evaluate long-range performance and noise resilience.

Data logging sessions were executed periodically with a consistent duration of 2 hours per session under partly cloudy weather conditions (temperatures ranging from 28°C to 34°C). Signal conditioning, radio frequency (RF) spectrum visualization, and decoding processes were centrally integrated using the open-source software platform SDRAngel (Version 7.26.1 for RTL-SDR and Version 7.25.1 for HackRF One) running on a Windows 11 architecture.[7]

3.2. DSP Architecture and Data Processing Flow

The mechanism for converting high-frequency analog electromagnetic waves into structured digital flight data within the SDRAngel software involves several functional interconnected stages described as follows:

1. Raw Data Sample Acquisition Stage (Input Stage): The dipole antenna captures ADS-B radio wave emissions at 1,090 MHz. The SDR hardware acts as the front-end, digitizing the analog signals into binary raw data samples structured as In-phase and Quadrature (I/Q) signal matrices, which are then transmitted via the USB Bus interface to the host computer.
2. Signal Conditioning and Gain Control Stage (Gain Conditioning Stage):

- 1) On the RTL-SDR Blog V3, amplification is managed through a single RF Gain optimization up to a maximum value of 40.2 dB.
- 2) On the HackRF One, a multi-stage gain management system is applied, separating the functions of the Low Noise Amplifier (LNA) at 40 dB and the Variable Gain Amplifier (VGA) at 32 dB. This multi-stage conditioning is crucial for elevating the original pulse amplitude above the environmental noise floor while preventing clipping at the Analog-to-Digital Converter (ADC).
3. Frequency Locking and Sampling Stage (Tuning & Sampling Stage): A digital local oscillator module locks the center frequency precisely at 1,090 MHz with a uniform sample rate of 2,000,000 S/s (2 MSPS) to isolate the aircraft transponder emission spectrum from adjacent channel interference.
4. Parallel Processing Branching Stage (Dual-Processing Stage): The binary sample stream is simultaneously distributed into two channels:
 - 1) Spectral Analysis Pathway: Utilizes the Fast Fourier Transform (FFT) algorithm to transform data from the time domain to the frequency domain, generating spectrograms and waterfall displays.
 - 2) Demodulation Pathway: The signal streams into the ADS-B Demodulator Engine to detect the distinctive preamble structure of Pulse Position Modulation (PPM) pulses.
5. Binary Extraction and Information Output Stage (Decoding & Output Stage): The Digital Bit Decoder module translates the binary pulse arrays that pass the error correction algorithm validation into two visual output formats:
 - 1) Textual Log Output: A data table containing real-time flight parameters such as ICAO ID, airline Callsign, and Squawk codes.
 - 2) Spatial Geographical Output: The extraction of coordinate (latitude/longitude), speed, and altitude parameters to dynamically plot the aircraft over the OpenStreetMap digital map module.

3.3. Exploratory Experimental Results: RTL-SDR Analysis

1. Chronological Data Log History

Testing with the RTL-SDR demonstrated a high level of sensitivity at the 1.090 GHz operating frequency. Based on the spectrum visualization and data panels, the RTL-SDR dongle successfully identified and decoded binary messages continuously from afternoon into the evening. At 18:55:04 WIB, the ground station locked onto the movement of a Batik Air flight with Callsign BTK7058 (ICAO ID: 8a093c) over the Talang Kelapa airspace with an altitude status marked as Surface. By 19:00:53 WIB, the signal significantly strengthened to a level of -40.4 dB as the aircraft initiated its take-off phase, climbing to an altitude of 230 feet. Long-range tracking capabilities were further demonstrated at 19:42:47 WIB, when the device successfully captured signals from an aircraft with ICAO code 885170 cruising at a stable altitude of 36,000 feet. [8]

2. Evaluation of Signal Quantity and Sensitivity

To validate the reliability of signal capture by the RTL-SDR, raw data samples from the system log files were extracted into Table 1:

Table 1. Sample log of flight signals captured by RTL-SDR

Time (WIB)	Payload Data Code (Hexadecimal)	Correlation Value (dB)	Object Description
18:36:45	8d8a0a6599091dabb00860b3e07d	27.8976	Pre-Testing Phase
20:05:15	8f8a063539f880448d47a029a274	36.0519	Highly Strong Signal (Peak)
20:07:45	8f8a037839e9b0442b478323c240	21.1289	Citilink CTV986

Analysis of the data quantity indicates that the logging intervals for the RTL-SDR maintain a very high density. For instance, at 20:05:15 WIB, the system recorded a burst where 3 data

packets were successfully decoded simultaneously within the exact same second. This phenomenon serves as empirical evidence that the RTL-SDR possesses a denser packet success rate compared to the HackRF One, whose data captures appeared more temporally sparse.

Despite the RTL-SDR being a low-cost, 8-bit ADC-based device, the optimization of the R828D tuner chip specifically for the 1,090 GHz frequency allowed it to maintain a very healthy average correlation value above 16.0 dB, peaking at 36.0519 dB. This stable correlation metric confirms minimal front-end interference within the RTL-SDR receiver section.

3.4. Comparative Performance Analysis Across Geographical Locations

To dissect the influence of hardware architecture and environmental characteristics on signal processing parameters, the comparative results across various testing sites are summarized and analyzed below.

1. Performance Analysis in Short-Range and LOS Conditions (Location I: SMB II Airport)

During testing at the perimeter of the SMB II International Airport under optimal LOS conditions (≤ 2 km), both devices operated highly efficiently due to the low attenuation of the airspace path. A comparison of the real-time performance parameters for both devices is presented in Table 2.

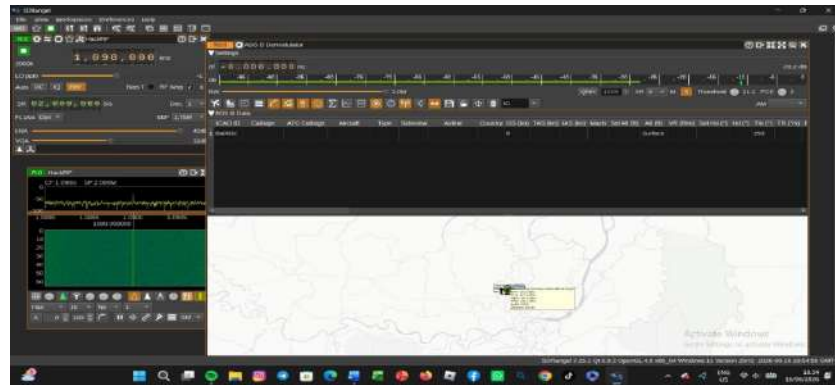


Figure2. Location I (SMB II International Airport)

The image above displays the SDRangel interface, a Software Defined Radio, software used to receive, monitor, and analyze radio signals in real time. The display shows the SDR operating at approximately 1090 MHz (1090 MHz), the ADS-B (Automatic Dependent Surveillance–Broadcast) communication frequency used by aircraft to transmit identity, position, altitude, and speed information. Successfully received data is displayed as a list of aircraft information in the center, while the aircraft's position is visualized on a map at the bottom. Furthermore, the signal spectrum and waterfall on the left side indicate the signal conditions received by the antenna, allowing users to monitor the quality of signal reception in real time. This display indicates that the SDR system is successfully receiving and decoding ADS-B signals from aircraft within the reception area.

The absence of physical obstructions at this location benefited the RTL-SDR Blog V3; its tuner architecture locked onto data parameters securely without encountering missing bits. Conversely, the HackRF One distinguished itself through the flexibility of its signal conditioning, utilizing internal LNA and VGA amplification architectures to effectively suppress the noise floor, which produced a darker and cleaner graphical visualization on the waterfall display.[9]

Table 2. Comparative performance of devices at location I (SMB II International Airport)

Condition & Performance Parameters	Device I: RTL-SDR Blog V3	Device II: HackRF One
Real Testing Time (System)	June 16, 2026, at 19:55:24 GMT+7	June 16, 2026, at 19:54:56 GMT+7
Line-of-Sight & Distance	Optimal Line-of-Sight (LOS), ≤ 2 km	Optimal Line-of-Sight (LOS), ≤ 2 km
Spectrum Graph Characteristics	Sharp frequency spikes at the center frequency; relatively stable noise floor.	Cleaner signal spikes; lower noise floor suppression achieved via multi-stage gain.
Signal-to-Noise Ratio (SNR)	Ranging between 20 dB and 25 dB	Consistently superior above 28 dB
Textual Log Decoding Results	Excellent: Successfully decoded ICAO ID 8a03ab with full Citilink Callsign (CTV988).	Good: Successfully captured the unique transponder code with ICAO ID 8a093c in the data table.
Geographical Map Visualization	Plots aircraft positions with circular Coverage Map indications.	Precisely plots the ground station pin over the airport info coordinates.

2. Performance Analysis in Urban Environments and NLOS Conditions (Locations II, III, and IV)

When the ground station was relocated to urban areas dense with structural barriers and high electromagnetic interference (such as Ogan Street at ± 11.5 km and the Semi-Outdoor Cafe terrace at $\pm 6-8$ km), signal degradation occurred due to multipath fading from buildings.

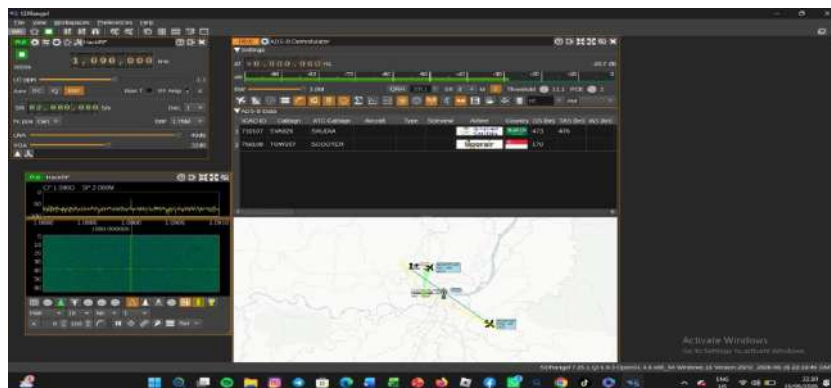


Figure 3. Location II Ogan Street

The image shows the interface of the SDRangel application (version 7.25.1), a Software Defined Radio (SDR) software being used to track aircraft flights in real time using HackRF hardware. The radio frequency is set to 1,090,000 kHz (1,090 MHz), which is the global standard frequency for ADS-B (Automatic Dependent Surveillance-Broadcast) receiver flight transponder signals. In the lower left corner, there is a spectrum analyzer visualization and a waterfall display showing a graph of the active radio signals coming from the HackRF device.

In the main panel on the right, the ADS-B Demodulator module is processing captured flight data. The data table displays two detected airlines: Saudia (SVA826) with the country code Saudi Arabia and Tigerair/Scotair (TRW207) with the country code Singapore, along with their flight speed information (GS/TAS). This spatial information is then mapped directly onto the map window at the bottom, which shows a visualization of the position and movement path of the two aircraft geographically relative to the receiving station.

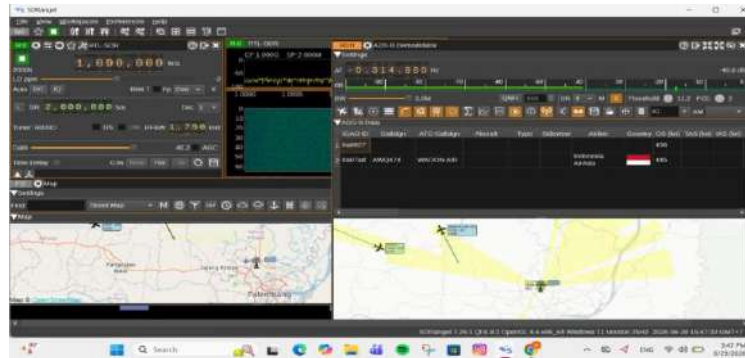


Figure 4. Location III Urban Cafe

This image shows the SDRangel software interface used to receive ADS-B signals for real-time flight tracking of aircraft. In the upper left, the radio frequency is set to 1,090,000 kHz (1,090 MHz) using an RTL-SDR hardware dongle with an R828D tuner. The incoming signal is processed by the ADS-B Demodulator module in the right panel, which successfully detects flight information such as the Indonesian AirAsia flight (AWQ474 / WAGON AIR) and its speed. This aircraft position information is then visualized geographically on the map panel at the bottom, which displays radar tracking in the area around Palembang.

Table 3.Real-time data comparison in Obstructed Urban Environments (Location II & Location III)

Performance Parameters	Location II (Ogan St. - NLOS Urban ± 11.5 km)	Location III (Urban Cafe - Obstructed Semi-Outdoor)
Architecture & Gain Config	RTL-SDR: R828D Tuner, Gain 40.2 dB HackRF One: LNA 40 dB, VGA 32 dB	RTL-SDR: R828D Tuner, Gain 40.2 dB HackRF One: LNA 40 dB, VGA 32 dB
Spectrum Characteristics	RTL-SDR: Noise floor -80 to -95 dB with urban ripples. HackRF One: Noise floor tightly suppressed at -95 dB.	RTL-SDR: Noise floor rose to -50 to -60 dB due to iron grille reflections. HackRF One: Constant spectrum fluctuation at -28.9 dB.
Text Decoding (RTL-SDR)	Excellent: Successfully tracked international airline Singapore Airlines (SINGAPORE 965) & Squawk 2373/2413.	Excellent: Fully decoded the binary data of a foreign private jet VistaJet (VJT543) from Canada.
Text Decoding (HackRF One)	Limited: Text log table was empty during sampling, but binary interconnection was stable at -28.9 dB.	Limited: Decoder required a longer pulse integration time; log and map were blank during sampling intervals.
Spatial Map Visualization	RTL-SDR: Yellow coverage map distribution widely crossed flight paths. HackRF One: Thin coverage sector pointing north-east.	RTL-SDR: Coverage map expanded into a radial fan pattern due to cafe wall obstructions. HackRF One: Map grid was empty without active plotting.

In urban NLOS testing environments (Table 3), the RTL-SDR Blog V3 consistently demonstrated superior resilience regarding temporal textual log decoding success. The internal filtering capabilities of the R828D tuner proved robust in isolating ADS-B PPM pulses from multipath fading caused by surrounding buildings and iron grille structures at the cafe area. This resilience was highlighted by the successful data recording of long-range international flights such as Singapore Airlines and VistaJet.

Conversely, the HackRF One features a highly sensitive wideband circuit architecture. In urban zones with elevated electrical interference, this high sensitivity caused the noise floor to lift fluctuationally within the application. Although the demodulator module's connection indicators displayed constant connectivity at an amplitude power level of -28.9 dB, the HackRF One's text decoding algorithms required cleaner pulse integration periods to isolate information bits from surrounding noise, resulting in frequent textual log and map rendering lag (blanks) during sampling intervals.

Meanwhile, at Location IV (Jasdam II Sriwijaya Field), which presented minimal vertical obstructions (an open sky view) despite being $\pm 7\text{--}9$ km away from the airport, shadowing effects were minimized. In this area, the RTL-SDR successfully locked ICAO ID 8a0515 onto the log table with a wide radial coverage map graphic. The HackRF One also showed optimal performance at the Jasdam field, suppressing the lower noise floor down to a deep -95 dB level thanks to its multi-stage LNA and VGA gain management, ensuring a constant incoming data stream without triggering ADC system clipping.[10]

3. Performance Analysis in Suburban Environments (Location V: Talang Keramat)

The suburban fringe area of Talang Keramat, located $\pm 5\text{--}7$ km away, is characterized by low building density. This condition offers a mechanical advantage for radio wave propagation due to the minimal presence of tall vertical obstructions.

- 1) RTL-SDR Blog V3 displayed a highly stable performance efficiency, where its circuit architecture preserved the data integrity of ADS-B pulses, successfully locking the unique binary transponder data of ICAO ID 8a0515 in real-time and forming a sharp, yellow radial coverage map plot over the Palembang airspace.
- 2) HackRF One reinforced its excellence in RF spectrum isolation clarity in outdoor environments. Configured with an LNA of 40 dB and a VGA of 32 dB, the device suppressed the system noise floor to -95 dB, allowing waveform shapes on the SDRAngel spectrogram menu to appear highly contrasted and completely free of erratic noise spikes.[11]

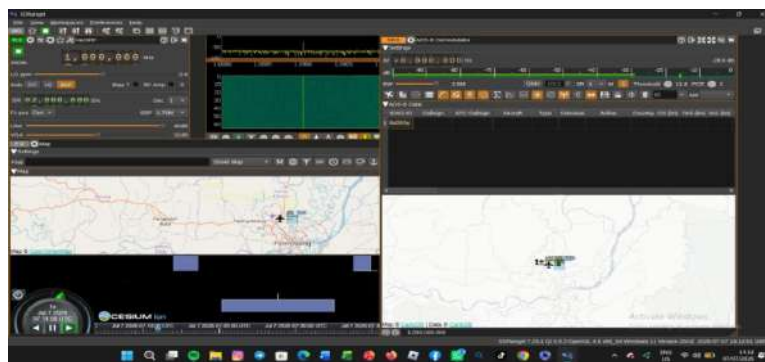


Figure 5. Location III Talang Keramat

This image shows the SDRAngel software interface used to receive ADS-B signals for real-time flight tracking of aircraft. In the upper left, the radio frequency is set to 1,090,000 kHz (1,090 MHz) using an RTL-SDR hardware dongle with an R828D tuner. The incoming signal is processed by the ADS-B Demodulator module in the right panel, which successfully detects flight information such as the Indonesian AirAsia flight (AWQ474 / WAGON AIR) and its speed. This aircraft position information is then visualized geographically on the map panel at the bottom, which displays radar tracking in the area around Palembang.

4. Cross-Station and Cross-Device Scenario Evaluation (Locations VI & VII)

A specialized cross-testing scenario was conducted to compare performance at extreme limits: an RTL-SDR positioned directly at the SMB II Airport area (short-range, ideal LOS) was paired simultaneously against a HackRF One located in a remote urban/cafe zone (long-range, full NLOS interference).

The results of this interleaved scenario emphasized the physical limitations inherent to each hardware architecture:

- 1) Short-Range / Close-Distance LOS Conditions: The RTL2832U chipset-based circuit architecture of the RTL-SDR operated at its maximum capacity and proved highly cost-effective. Strong aircraft signal emissions during approach or take-off phases were extracted instantaneously without data bit loss, yielding flawless textual logs for domestic flights (such as Citilink CTV988) along with their respective airline logos.

- 2) Long-Range / Distant NLOS Conditions: The HackRF One demonstrated its capabilities as a mid-range radio transceiver platform. Even when challenged by distances up to ± 9.5 km and dense urban infrastructure or vegetation blockages, the optimization of its three internal amplification stages successfully lifted weak, severely attenuated signals from far below standard sensitivity thresholds. Consequently, the spatial coordinate positions of aircraft (such as ICAO 8a0604) were plotted continuously across the digital map grid without severe data discontinuity.

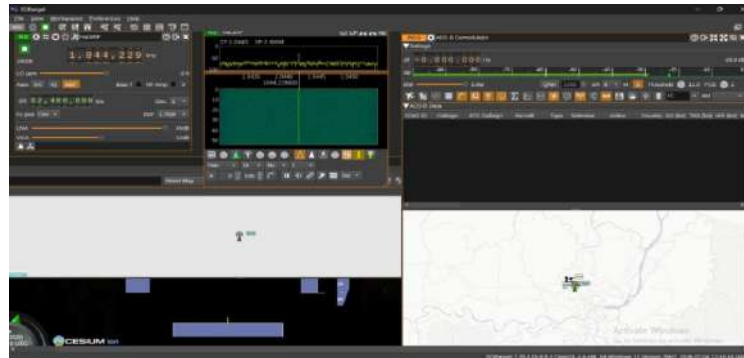


Figure 6. Location VI Jasdarn II Sriwijaya

This image shows the SDRangel application interface connected to the HackRF hardware, but in a different configuration than before, as the radio frequency is now set to 1,044.229 kHz (1.044 GHz). Because the frequency used deviates from the standard 1,090 MHz, the ADS-B Demodulator panel on the right is not detecting any flight data (the table is blank). Consequently, the map visualization at the bottom is also blank with no active airline tracking, leaving only the spectrum analyzer graph and the waterfall display at the top center monitoring the frequency spectrum.

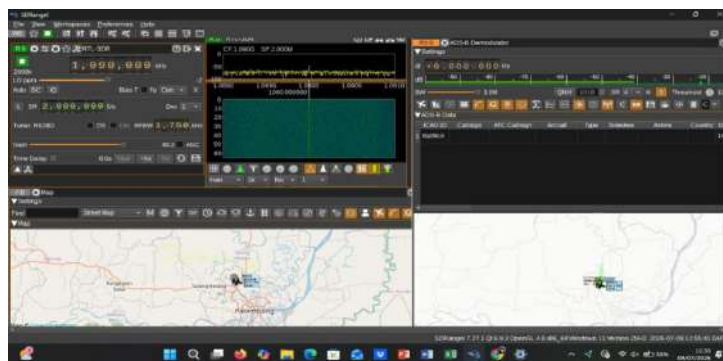


Figure 7. Location VII

This image shows the SDRangel application interface connected to the HackRF hardware, but in a different configuration than before, as the radio frequency is now set to 1,044.229 kHz (1.044 GHz). Because the frequency used deviates from the standard 1,090 MHz, the ADS-B Demodulator panel on the right is not detecting any flight data (the table is blank). Consequently, the map visualization at the bottom is also blank with no active airline tracking, leaving only the spectrum analyzer graph and the waterfall display at the top center monitoring the frequency spectrum.

4. CONCLUSION

This research compared the performance of RTL-SDR Blog V3 and HackRF One in receiving Automatic Dependent Surveillance-Broadcast (ADS-B) signals at 1090 MHz. The experimental results show that RTL-SDR Blog V3 demonstrated superior performance in rapidly receiving and displaying aircraft information, including Callsign, Squawk, and aircraft type. It also generated a more continuous and dense coverage map visualization, particularly in urban environments affected by

multipath fading. HackRF One demonstrated greater flexibility in signal conditioning through its multi-stage gain architecture using the Low Noise Amplifier and Variable Gain Amplifier. The device achieved a system noise floor of approximately -95 dB, resulting in cleaner and sharper spectrum waveforms and waterfall visualizations with fewer spurious noise spikes. This characteristic also supports long-range aircraft signal monitoring in open environments.

Overall, both SDR devices are capable of receiving ADS-B signals at 1090 MHz, but each provides different advantages. RTL-SDR Blog V3 is more suitable for stable and cost-effective ADS-B monitoring, while HackRF One is more suitable for applications requiring greater flexibility in signal conditioning and spectrum analysis. Therefore, the selection of the SDR device should be based on the specific requirements and intended application.

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Design and Performance Evaluation of a Hybrid Photovoltaic System Integrated with Battery Storage and Utility Grid for Residential Applications

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ABSTRACT

The increasing demand for residential electricity requires a reliable and sustainable energy supply. However, photovoltaic (PV) systems are highly dependent on solar irradiance, resulting in fluctuating power generation. This study designs and evaluates a prototype hybrid PV system integrating a 160 Wp solar panel, a 12 V 100 Ah battery, a 1000 W hybrid inverter, and the utility grid (PLN). Performance was evaluated based on voltage, current, power, and irradiance. The results show that an average irradiance of 560.7 W/m² produced 15.91 V, 1.77 A, and 28.03 W, with a maximum power of 45.49 W at 754.9 W/m². The system maintained stable output voltage while current and power increased with irradiance, and it reliably supplied a daily load of 320 Wh using solar energy as the primary source, batteries for storage, and the grid as backup. These results demonstrate that the proposed hybrid PV system improves the reliability of residential electricity supply.



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1. INTRODUCTION

Electrical energy is essential for household activities, and demand continues to increase with population growth and technological development [1]. However, electricity generation is still dominated by fossil fuels, which have limited availability and contribute to environmental pollution. Therefore, renewable energy sources, particularly solar energy, have become an important alternative. Indonesia has strong potential for solar energy utilization due to its high solar irradiance throughout the year, making Solar Power Plants (PLTS) a promising solution for residential electricity supply [3], [4].

However, the independent implementation of solar power plants still faces several obstacles, particularly related to dependence on weather conditions [5]. In addition, high initial investment costs and limited daily energy production remain major challenges [1]. With PLN integration, electricity supply can be maintained when the power from solar panels and batteries is insufficient. Furthermore, the use of a hybrid system is more economical because it does not require a large battery capacity like an off-grid system. This system is also known to increase system reliability and flexibility in meeting electricity needs [6].

Previous studies have shown that hybrid photovoltaic (PV) systems can improve the reliability of electricity supply and reduce dependence on conventional energy sources. However, most existing

research focuses on simulation-based analysis or large-scale implementations, with limited experimental validation of residential-scale hybrid PV prototypes under actual operating conditions. Therefore, this study aims to design, develop, and experimentally evaluate a residential-scale hybrid PV system integrated with a battery, a hybrid inverter, and the utility grid (PLN). The system performance is assessed based on solar irradiance, voltage, current, and power characteristics to evaluate its operational reliability and effectiveness in providing a continuous electricity supply. The findings are expected to provide practical insights into the implementation of residential hybrid PV systems and support the broader adoption of renewable energy in line with national energy development policies [2].

2. RESEARCH METHOD

The research method is used in designing a prototype hybrid solar power plant (PLTS) system with the PLN. The research method is structured systematically according to the stages shown in Figure 1.

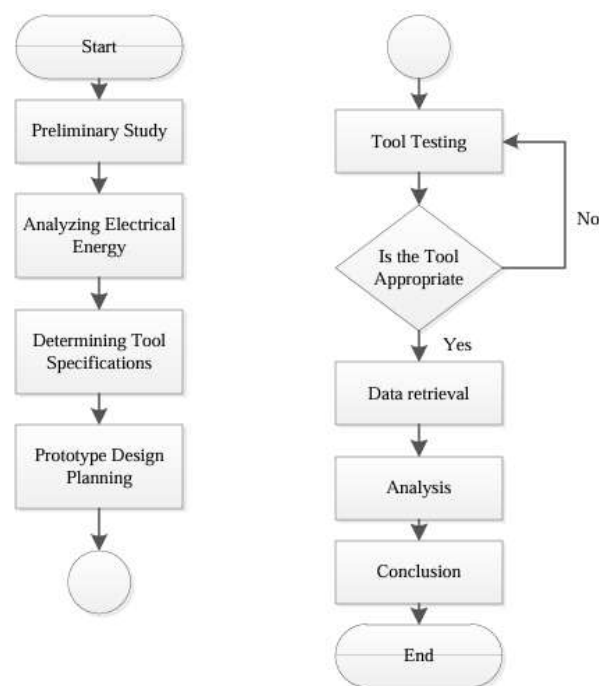


Figure 1. Research flowchart of the hybrid PLTS prototype system

Based on Figure 1, the research began with a preliminary study and analysis of the electrical energy requirements to determine the system capacity. The main components, including the solar panels, battery, and inverter, were then selected, followed by the design and implementation of the hybrid PV prototype. System performance was evaluated by measuring voltage, current, and power under actual operating conditions. Finally, the collected data were analyzed to assess the overall system performance, and conclusions were drawn based on the experimental results.

2.1. Planning

A hybrid solar power plant (PV) system integrated with the utility grid (PLN) was designed to meet residential electricity demand by utilizing solar panels as the primary energy source, batteries for energy storage, and the utility grid as a backup to ensure a continuous power supply. As shown in Figure 2, the system configuration was developed by first analyzing the household electrical load to determine the daily energy consumption (kWh/day), which served as the basis for sizing the solar panels and battery according to the calculated energy demand. [7].



Figure 2. Prototype Components of the Hybrid Solar Power System

The research methodology included energy demand analysis, component selection, prototype implementation, and system testing. Household energy consumption was analyzed to determine the capacities of the PV panels, battery, and hybrid inverter. The prototype was tested at Universitas Trisakti, Jakarta Barat, Indonesia, on December 17–19, 2025, from 10:00 AM to 2:00 PM at 20-minute intervals. System performance was evaluated based on solar irradiance, voltage, current, power output, and load supply capability. Figure 3 illustrates the proposed hybrid PV system, where the solar panels and battery are connected to a hybrid inverter that supplies power to household loads. The inverter is also connected to the PLN grid as a backup source [10].

The system prioritizes energy from the PV panels, followed by the battery, and finally the utility grid when required. The household load used for system sizing is presented in Table 1.



Figure 3. Configuration of the proposed hybrid solar power system

Table 1. Loads

No	Load	Unit	Watt	Time	Watt/hour	Info
1	Lamp	3	3 W	10 h	90 Wh	Room
2	Fan	1	25 W	4 h	100 Wh	Bedroom
3	Electric Socket	1	65 W	2 h	130 Wh	HP, Laptop
Total			99 W		320 Wh	

Figure 4 shows that household electricity consumption is predominantly at night, so a hybrid solar PV system with PLN (State Electricity Company) needs to be supported by adequate battery capacity to meet the load demand when solar energy is not available [11].

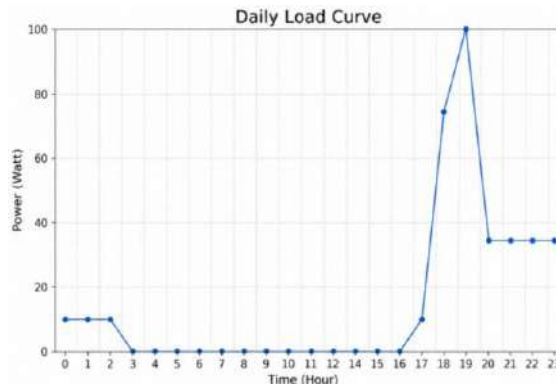


Figure 4. Daily Loads Curve

Therefore, the total daily energy requirement is:

$$E_{total} (Wh) = 320 Wh$$

Before implementation, calculations are made regarding the required component capacity. The calculations are as follows:

1. Solar Panel Capacity Calculation

The solar panels must be capable of producing 320 Wh of energy per day. Assuming an average of 4 hours of effective sunlight per day, the calculation based on equation 1 for the panel capacity is [12]:

$$P_{panel} (Wp) = \frac{E_{daily}}{T_{sun}} = \frac{320 Wh}{4 \text{ hours}} = 80 Wp \quad (1)$$

Considering system losses, including cable losses, inverter efficiency, and a safety factor for variations in solar irradiance, two 80 Wp solar panels were selected for the prototype. This configuration provides additional capacity to improve energy generation reliability and support battery charging under non-optimal irradiation conditions.

2. Solar Charge Controller Capacity Calculation

The SCC is used to regulate the current and voltage from the panel to the battery. The SCC capacity is determined based on equation 2 and the output of the solar panel [12]:

$$SCC(A) = \frac{P_{panel}}{V_{system}} = \frac{80 Wp}{12 V} = 6.6 A \quad (2)$$

Use an SCC with a minimum current of 10A.

3. Inverter Capacity Calculation

An inverter is used to convert the 12 V DC battery output into 220 V AC for household loads. Although the maximum simultaneous load is 99 W, a 1000 W Pure Sine Wave inverter was selected to accommodate efficiency losses, inductive load starting currents, and future system expansion, ensuring reliable system operation.

4. Battery Capacity Calculation

Batteries are used to store energy from solar panels and supply the load when there is no sunlight. Battery capacity can be calculated using equation 3 as follows [12]:

$$Capacity(Ah) = \frac{E_{total}}{V_{system}} = \frac{320 Wh}{12 V} = 6.6 A \quad (3)$$

A 12 V 100 Ah VRLA battery was selected, providing a theoretical storage capacity of approximately 1200 Wh. However, the actual usable energy is lower due to the battery DoD, inverter efficiency, and safe operating limits. Therefore, the selected battery capacity is sufficient for the designed load while maintaining battery reliability.

2.2. Testing

To evaluate the hybrid PV system performance, tests were conducted on the solar panel, battery, hybrid inverter, and household load. Solar irradiance was measured using a solar power meter, while

voltage and current were measured using a digital multimeter. The PV module was tested under outdoor conditions, and the load used was based on the household load listed in Table 1.

Solar Panel Output Testing, this test is conducted to ensure that the solar panels are capable of producing DC voltage and current according to specifications [7]. Measurements are taken during daylight hours with optimal sunlight intensity using a digital multimeter. The parameters observed include the panel's voltage (V), current (A), and power output (W).

Inverter Performance Testing, inverter testing aims to evaluate the power conversion from direct current (DC) to alternating current (AC), as well as the automatic switching function between solar panels, batteries, and the electricity grid. Testing is carried out by monitoring the AC output voltage (220V), frequency stability (50Hz), and inverter response when the main power source (panel) is unavailable.

Household Load Supply Testing, this test was conducted by connecting household electrical loads directly to the system. The loads included LED lights, televisions, and mini fans. The goal was to ensure the system could supply the loads stably, without voltage disruptions or sudden power outages. Observed parameters included voltage stability and the system's ability to maintain energy supply within the inverter's capacity.

2.3. Component List

Component selection is based on system requirements and their functions for use in designing a hybrid solar power system with PLN. The specifications of each component are based on the calculations used as the basis for system design, as shown in Table 2.

Table 2. Specifications component

No	Component	Unit	Specification	Function
1	Solar Panel	2	80Wp, 16V	Source from PLTS
2	Battery VRLA	1	12V, 100Ah	Saving Energy
3	Inverter Hybrid	1	1000W, 12VDC to 220VAC	DC to AC for Loads

3. RESULTS AND DISCUSSION

This section presents the implementation of the hybrid PV system with PLN, including the experimental results and performance analysis. The system performance was evaluated based on PV panel and inverter testing through measured voltage, current, power, and irradiance data. The analysis includes comparisons of daily performance variations, the effect of irradiance on power output, and the system capability in supplying the load.

3.1. Design Result

Based on the design, the system developed is a hybrid solar power system that combines energy sources from solar panels, batteries, and the PLN grid with a hybrid inverter, as shown in Figure 5.



Figure 5. Design of the hybrid solar power system

Based on Figure 5, this hybrid solar power system has met the criteria for testing. All major

components have been properly integrated, including the solar panels, hybrid inverter, battery, PLN power source, and load. The configuration and interconnections between components in the hybrid solar power system with PLN implemented in this study can be seen in Figure 6.

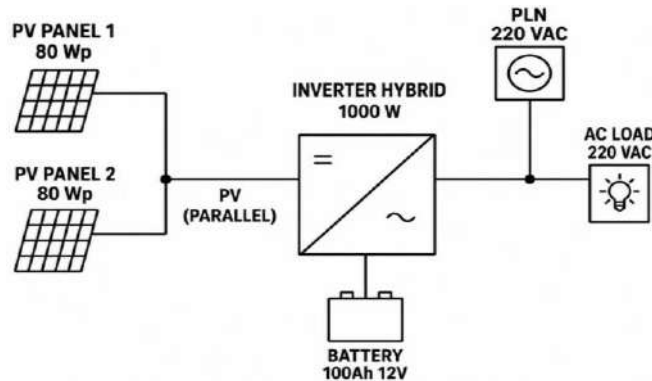


Figure 6. Single-Line diagram of the proposed hybrid solar power system

Therefore, this system is ready for performance testing, which includes testing the solar panel output, testing the performance of the hybrid inverter, and evaluating the system's ability to supply the load under various operating conditions.

3.2. Test Result

1. Solar Panel Output Testing

The solar panel output was measured over three days. Test results are presented in Table 3.

Table 3. Output solar panel first day

Time	W/m^2	V	A	W
10.00	285.4	15.91	0.65	10.34
10.20	334.3	16.18	0.72	11.65
10.40	294.6	16.19	0.62	10.04
11.00	423.9	16.41	1.12	18.38
11.20	620.8	16.18	1.26	20.39
11.40	637.7	16.36	1.62	26.50
12.00	721.5	15.96	2.85	45.49
12.20	754.9	14.82	2.56	37.94
12.40	702.3	14.91	2.67	39.81
13.00	668.4	16.87	2.45	41.33
13.20	615.7	15.91	2.51	39.93
13.40	642.1	15.62	2.41	37.64
14.00	587.4	15.53	1.61	25.00
Average	560.7	15.91	1.77	28.03

Based on Tables 3 and 4, the PV panel performance was strongly influenced by solar irradiance and weather conditions. On the first day, a maximum irradiance of $754.9 W/m^2$ produced a stable voltage of 14.82–16.87 V (average 15.91 V), with a maximum current of 2.85 A, maximum power of 45.49 W, and average outputs of 1.77 A and 28.03 W. On the second day, cloudy weather and light drizzle reduced the maximum irradiance to $435.2 W/m^2$, resulting in a stable voltage of 12.43–16.42 V (average 14.59 V), a maximum current of 1.92 A, maximum power of 29.03 W, and average outputs of 0.93 A and 13.66 W. These results indicate that higher irradiance increases the PV panel current and power output, while the output voltage remains relatively stable.

Table 4. Output solar panel second day

Time	W/m^2	V	A	W
10.00	200.8	12.43	0.91	11.31
10.20	218.8	14.31	1.02	14.60
10.40	210.4	12.93	0.42	5.43
11.00	227.3	15.26	0.67	10.22
11.20	243.9	13.84	0.48	6.64
11.40	252.2	15.29	0.82	12.54
12.00	278.5	16.42	0.92	15.11
12.20	313.2	15.01	1.12	16.81
12.40	348.8	15.69	1.85	29.03
13.00	392.2	14.04	1.92	26.96
13.20	435.2	15.47	0.82	12.69
13.40	243.8	15.49	0.64	9.91
14.00	182.6	13.53	0.47	6.36
Average	272.9	14.59	0.93	13.66

The third-day results show that irradiance gradually increased to a maximum of 624.2 W/m^2 at 1:20 PM before decreasing. The solar panel output voltage remained relatively stable between 14.82–16.36 V, with an average of 15.68 V. The output current reached a maximum of 2.39 A at 1:00 PM, while the output power ranged from 5.04 W to 36.95 W. These results indicate that higher irradiance increases the solar panel output current and power, whereas the voltage remains relatively stable. The third-day results are presented in Table 5.

Table 5. Output solar panel third day

Time	W/m^2	V	A	W
10.00	218.3	15.91	0.66	10.50
10.20	235.8	16.19	0.91	14.73
10.40	252.2	16.18	0.89	14.40
11.00	269.6	16.36	0.91	14.89
11.20	295.4	15.96	1.32	21.07
11.40	330.9	15.25	1.01	15.40
12.00	408.9	14.82	0.34	5.04
12.20	443.6	14.91	1.67	24.90
12.40	478.3	15.68	1.93	30.26
13.00	538.3	15.46	2.39	36.95
13.20	624.2	15.62	1.68	26.24
13.40	606.5	15.95	1.20	19.14
14.00	496.6	15.53	1.14	17.70
Average	397.8	15.68	1.23	19.33

Overall, the average irradiance value of 397.8 W/m^2 resulted in an average voltage of 15.68 V, an average current of 1.23 A, and an average power of 19.33 W. These results it can be concluded that irradiance remains the dominant factor influencing the current and power output of the solar panel, while the voltage remained relatively stable in response to changes in solar radiation intensity.

2. Hybrid Inverter Output Testing

In this testing phase, the hybrid inverter is connected to a battery, with the inverter's input power coming from the battery's output. The test results can be seen in Table 6.

Table 6. Output Hybrid Inverter

Time	V	A	W
19.00	209.5	0.14	29.33
19.20	209.7	0.17	35.65
19.40	209.4	0.19	39.79
20.00	209.8	0.31	65.04
20.20	209.6	0.27	56.59
20.40	209.9	0.34	71.37
21.00	210.1	0.41	86.14
21.20	210.2	0.43	90.39
21.40	210.1	0.36	75.64
22.00	210.3	0.38	79.91
22.20	210.2	0.31	65.16
22.40	210.4	0.26	54.70
23.00	210.1	0.22	46.22
Average	209.95	0.29	61.23

3.3. Analysis of Results

This section presents the results of testing conducted using manual measurements from 10:00 AM to 2:00 PM WIB, with data collected every 20 minutes for three days.

1. Solar Panel Voltage Output Analysis

In this analysis, researchers tested the solar panel's output voltage. The test results are in Figure 7.

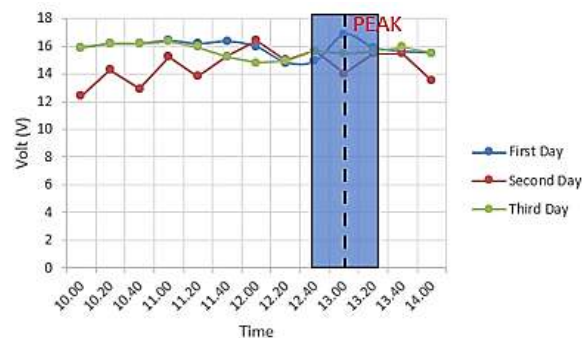


Figure 7. Comparison of solar panel output voltage during peak hours

2. Solar Panel Current Output Analysis

In this section, we analyze the solar panel output current to determine the amount of current generated by the system. The results of the analysis are presented in Figure 8. Figure 8 shows that the output current varied more significantly than the voltage. On the first day, the current reached a maximum of approximately 2.8 A at around 12:00 PM before decreasing. On the second day, the peak current was lower, at approximately 2.0 A, due to cloudy weather and drizzle. On the third day, the current increased to approximately 2.4 A at around 1:00 PM.

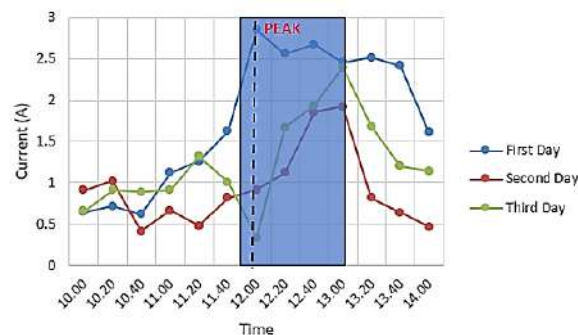


Figure 8. Comparison of solar panel output current during peak hours

These results indicate that the solar panel output current is strongly influenced by solar irradiance and weather conditions.

3. Solar Panel Power Output Analysis

This analysis discusses the solar panel output power to determine the amount of power generated by the system. The results of the analysis are as follows.

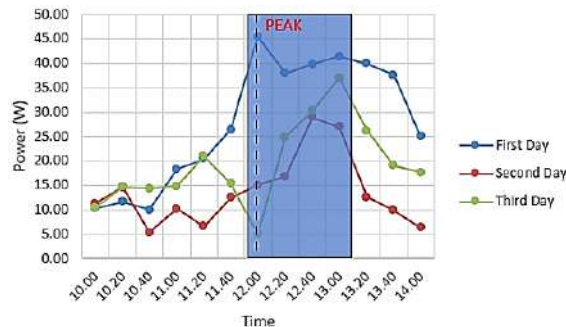


Figure 9. Comparison of solar panel output power during peak hours

Figure 9 shows that the output power follows the same trend as the output current. On the first day, the output power gradually increased and reached the highest value of approximately 45 W at around 12:00 PM before decreasing in the afternoon. On the second day, the maximum power was lower, at approximately 29 W, due to reduced irradiance caused by cloud cover and light rainfall. On the third day, the output power reached approximately 37 W at around 1:00 PM, which was higher than the second day but lower than the first day. These results indicate that the solar panel output power is strongly influenced by variations in solar irradiance.

4. Irradiance and Output Power

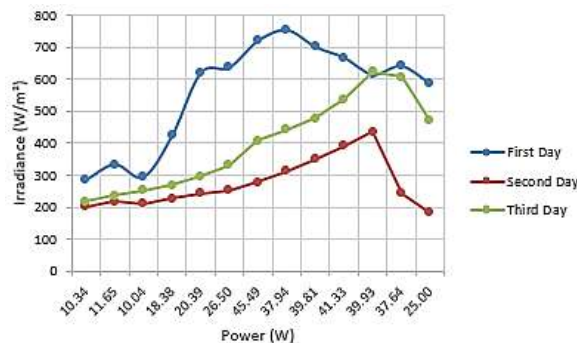


Figure 10. Relationship between irradiance and output power

Overall, the results show that current and power are strongly affected by solar radiation, while voltage remains relatively stable. Variations across the three test days indicate that weather conditions, especially cloud cover and sky clarity, significantly influence solar panel performance.

5. Inverter Output Analysis

The test results showed that the hybrid inverter maintained a stable output voltage of 209.4–210.4 V with an average of 209.95 V despite load variations. The output current increased from 0.14–0.19 A with three lamps to a maximum of 0.43 A when additional charging loads were connected. These results indicate that the inverter was able to maintain voltage stability and provide reliable power for household loads.

6. Battery Charging Time

To calculate the time to fully charge the battery, use equation 3 [12]:

$$\begin{aligned} \text{Battery Power} &= 1200\text{Wh} \\ \text{Apparent solar panel power (Highest)} &= 80\text{ Wp} \end{aligned}$$

$$\text{Battery Charging Time} = \frac{1200 \text{ Wh}}{80 \text{ Wp}} = 15 \text{ Hours}$$

In this calculation, the apparent solar panel power is obtained from measurements over three days. To fully charge the battery, with a 12V 100Ah battery capacity that can power the load for four days, the charging time is 15 hours.

7. Operational Efficiency of the PV Module During Field Testing

Efficiency data is calculated using test results from the first day, when conditions were relatively bright and slightly cloudy. Therefore, to find this value, the solar panel area is first measured using equation 4 [11]:

$$A = p \times l = 0.998 \times 0.664 = 0.66 \text{ m}^2 \times 2 (\text{Panels}) = 1.32 \text{ m}^2 \quad (4)$$

Therefore, to determine P_{in} (watts), use equation 5 as follows [11]:

$$P_{in} = G \times A = 560.7 \times 1.32 = 740.1 \text{ W} \quad (5)$$

Therefore, to determine P_{out} (watts), use equation 6 as follows [11]:

$$P_{out} = V \times I = 15.91 \text{ V} \times 1.77 \text{ A} = 28.2 \text{ W} \quad (6)$$

Therefore, the efficiency of the solar power plant can be calculated based on equation 7 as follows [11]:

$$\eta = \frac{P_{out}}{P_{in}} \times 100\% = \frac{28.2}{740.1} \times 100\% = 3.8\% \quad (7)$$

Based on the measured irradiance, panel area, and output power, the operational efficiency of the PV module was calculated at 3.8%. This value is lower than the typical rated efficiency of commercial PV modules (18–24%) because it represents real outdoor operating conditions. The reduced efficiency was mainly affected by lower irradiance, module temperature, fixed panel orientation, and electrical losses in the system.

8. Overall Analysis

This section analyzes the hybrid PV system based on experimental results. The solar panel supplies the load and charges the battery during the day, while PLN provides backup power when needed. The hybrid inverter manages the energy sources to maintain continuous operation in Table 7.

Table 7. Performance specifications of system components

Component	Parameter	Spec	Result
Solar Panel	V	16 V	15.91 V
	A	5 A	2.85 A
	W	80 W	45.49 W
Hybrid Inverter	V	220 V	210.4 V
	A	40 A	0.43 A
	W	1000 W	90.39 W
	F	50 Hz	50 Hz

Based on Table 7, the hybrid solar PV system demonstrated satisfactory performance in supplying the load, although some parameters did not reach the planned targets. The solar panel voltage of 15.91 V was close to the target of 16 V, while the current and power outputs of 2.85 A and 45.49 W were lower due to variations in weather conditions, solar irradiance, and the angle of sunlight during testing.

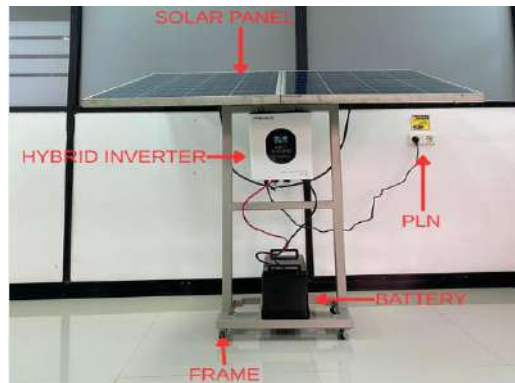


Figure 11. Prototype of the proposed hybrid solar power system

Figure 11 demonstrates that the hybrid PV system effectively stored solar energy during the day and supplied power at night with PLN as backup. The inverter maintained a stable 210.4 V, 50 Hz output and supplied 320 Wh of daily energy, showing potential for residential use.

4. CONCLUSION

This study successfully developed a hybrid PV system prototype consisting of a 160 Wp solar panel, 12 V 100 Ah battery, 1000 W hybrid inverter, and PLN backup. The system supplied a 320 Wh daily load, with solar energy as the primary source and battery storage for energy management. The results show that PV performance is affected by solar irradiance, while the inverter provides stable AC output and automatic source switching. Future work should focus on optimizing panel orientation, MPPT performance, and long-term system evaluation.

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Implementation of On-Device Convolutional Neural Network Inference for Indoor Occupancy Detection on the ESP32-S3

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ABSTRACT

Indoor occupancy detection is a key enabling technology for energy-efficient smart building management, as heating, ventilation, air conditioning, and lighting systems waste significant energy when conditioned spaces are unoccupied. This paper implements a compact Convolutional Neural Network (CNN) trained on the UCI Occupancy Detection Dataset and deployed entirely on the ESP32-S3 microcontroller using TensorFlow Lite Micro with INT8 post-training quantization, eliminating any cloud dependency. Models are trained under a leakage-controlled protocol on the designated training file, selected on the first test file, and evaluated on the held-out second test file; the INT8 quantizer is calibrated from an evenly spaced spread of training windows to avoid class bias. Twelve configurations spanning four filter capacities, $(F_1, F_2) \in \{(4,8), (8,16), (16,32), (32,64)\}$, and three temporal window lengths, $W \in \{15, 30, 60\}$ minutes, are quantized, flashed, and measured on the device for tensor arena, flash footprint, inference latency, and held-out F1. All twelve configurations execute successfully: the best compact model, CNN(8,16) at a fifteen-minute window, reaches a held-out F1 of 0.959 using 4.2 KB of tensor arena and 1.24 ms per inference, with more than 320 KB of heap remaining free; the tensor arena across the full grid stays between 2.6 and 30 KB; and INT8 quantization changes F1 by at most ± 0.021 relative to the floating-point baseline. These results demonstrate that on-device CNN occupancy detection is practical on a low-cost microcontroller, that a compact two-block architecture is sufficient to reach near-optimal accuracy, and that the full pipeline from leak-free training through representative INT8 calibration to on-device measurement is reproducible.



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1. INTRODUCTION

Smart buildings are among the most productive applications of the Internet of Things (IoT) paradigm because the energy savings they enable are large and the sensing infrastructure they require is genuinely low-cost. Heating, ventilation, air conditioning, and lighting together account for a substantial fraction of commercial building energy consumption, and much of that energy is wasted on spaces that no one is using [1],[2]. Occupancy-driven control addresses this problem directly: instead of running systems on fixed schedules, a building management system responds to actual demand. Candanedo and

Feldheim [1] showed that ambient measurements of temperature, humidity, CO₂, and light are sufficient for reliable binary occupancy classification, and that result remains the foundation for much of the subsequent work in this area.

The challenge in this field has shifted from whether ML-based occupancy detection can work to where inference should happen. Most published solutions route classification to a server or cloud backend, treating the edge microcontroller as a data relay. This design is functional in well-controlled deployments, but it introduces latency that scales with network conditions, a dependency on continuous connectivity that many installations cannot guarantee, and the transmission of environmental data that some operators prefer to keep local [3],[4],[5]. Camera-based systems offer higher spatial resolution and suit multi-occupant scenarios [6], but they carry substantial compute requirements and surveillance concerns that exclude them from many buildings [2]. Inference performed entirely on-chip eliminates each of these drawbacks.

Tiny Machine Learning (TinyML) provides this capability, and the field has matured rapidly with more capable microcontrollers and improved compression techniques [7],[8]. Post-training INT8 quantization is the most practically important of these techniques: Ray [9] documents how it reduces memory footprint to a fraction of the floating-point original, and Elhanashi et al. [10] confirm that accuracy loss under a well-calibrated INT8 scheme is typically small across sensing tasks. Alajlan and Ibrahim [11] survey TinyML on ultra-low-power devices and show that environmental classification is well within current hardware limits, while Abadade et al. [12] identify occupancy sensing as one of the targets best aligned with TinyML. Sanchez-Iborra and Skarmeta [8] argue that such microcontrollers should be treated as autonomous decision nodes rather than data endpoints.

The ESP32-S3 is a strong candidate for this role. Its dual Xtensa LX7 cores include vector instructions suited to the multiply-accumulate operations that dominate convolution [13], it provides 512 KB of internal SRAM, and it runs TensorFlow Lite Micro, the embedded inference framework maintained for microcontroller-class devices [14]. The convergence of edge computing and artificial intelligence that Deng et al. [5] call edge intelligence frames why this matters at a system level. The MLPerf Tiny benchmark [15] standardizes INT8 TFLM inference at this scale, Osman et al. [16] benchmark TinyML frameworks across platforms, Rodriguez-Conde et al. [17] show that distributed DNN inference across IoT nodes is feasible, and Tsoukas et al. [18] identify on-device smart-environment sensing among the most promising near-term applications. Recent work has extended this to human sensing, including convolutional activity recognition on the ESP32-S3 from Wi-Fi channel state information [19].

This paper reports a complete, working implementation of CNN-based occupancy detection running entirely on the ESP32-S3 and documents the full pipeline from split-clean training to on-device measurement. The work makes three contributions. First, it provides a leakage-controlled, end-to-end pipeline: models are trained on the UCI training file, selected on the first test file, and evaluated on the second test file, with no window crossing a split boundary and the INT8 quantizer calibrated from a representative spread of training data. Second, quantized models deploy and execute on the ESP32-S3 under TensorFlow Lite Micro; measured tensor arena, flash footprint, inference latency, and accuracy are reported for each of twelve configurations. Third, it shows that a compact two-block CNN already reaches an F1 near 0.95 and that INT8 quantization is near-lossless, making a small network sufficient for practical deployment.

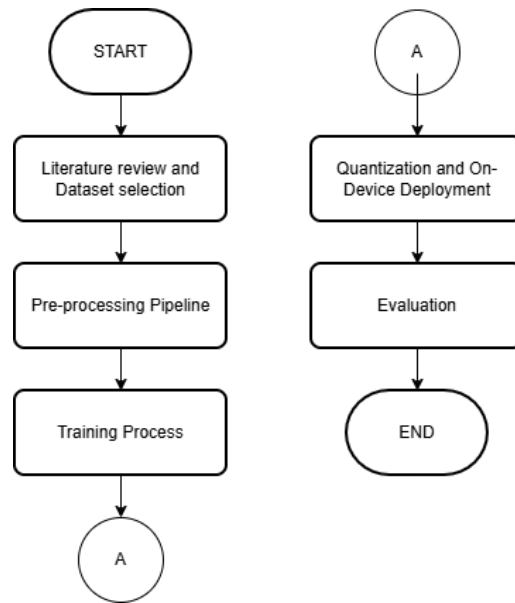


Figure 1. Research workflow

Table 1. Number of sliding windows generated per file at each window length

W (min)	Train windows	Validation windows	Test windows
15	8,128	2,650	9,737
30	8,113	2,635	9,722
60	8,083	2,605	9,692

2. RESEARCH METHOD

The research workflow adopted in this study is presented in Figure 1. The details of each stage in the research process are described in this section.

2.1. Dataset

This study uses the UCI Occupancy Detection Dataset [1], a public benchmark for binary room occupancy from ambient sensing. A single office room was instrumented for temperature, relative humidity, light intensity, CO₂ concentration, and humidity ratio, sampled once per minute, with ground truth from time-stamped photographs. The data is distributed as three separate files: a training file of 8,143 samples and two test files of 2,665 and 9,752 samples. This natural separation is used directly. Models are trained on the training file, hyperparameters are selected on the first test file, and all reported accuracy is measured on the second test file, which no model sees during training or selection. The datetime column is discarded because it carries information a deployed node could not use. Humidity ratio is retained, since Candanedo and Feldheim [1] showed it encodes a combined thermodynamic signal that aids classification. For on-device evaluation an evenly spaced subsample of windows from the held-out file was compiled into firmware as static C arrays, while the full file was used for the offline figures.

2.2. Preprocessing Pipeline

Five numerical features remain after the datetime column is removed. Each is scaled to the unit interval by min-max normalization whose minimum and maximum are computed on the training file alone and applied unchanged to both test files, so no test statistic leaks into preprocessing. A sliding window of length W is then formed with a step of one sample and reshaped to $(W, 5, 1)$ for a two-dimensional convolution, with the occupancy of the sample immediately following the window as its label. Three window lengths are studied, $W \in \{15, 30, 60\}$, corresponding to fifteen, thirty, and sixty minutes of history. Windows are built within each file independently, so none spans a split boundary. Because each window is labeled by the sample that follows it, the number of windows per file is its length minus W ; the resulting counts are listed in Table 1.

2.3. Model Architectures

The implementation uses a single compact CNN template and varies only its capacity. Each model takes the (W, 5, 1) window through a first convolutional block of F_1 filters of size 3×3 with same padding and ReLU activation, followed by 2×2 max pooling, then a second block of F_2 filters of the same size and activation. Global average pooling reduces the resulting feature map to a vector of length F_2 , which feeds a single sigmoid unit. The full data path is shown in Figure 2. Four capacities are implemented: (F_1 , F_2) of (4, 8), (8, 16), (16, 32), and (32, 64), corresponding to 345, 1,265, 4,833, and 18,881 parameters. Global average pooling is used in place of flattening so the classifier stays independent of window length [19]. Models were trained with Adam and binary cross-entropy for up to 100 epochs with early stopping on the validation file, restoring the weights of the lowest validation loss with a patience of fifteen epochs. Learning rate was tuned over {0.001, 0.010}, with the better of the two by validation F1 retained for each configuration.

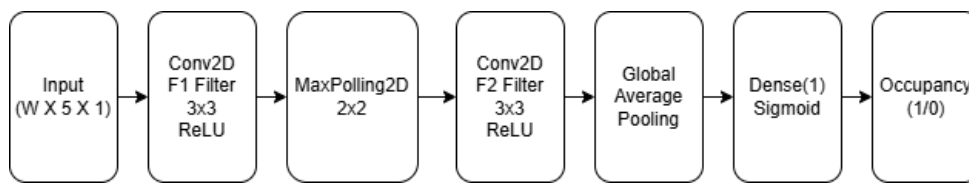


Figure 2. The two-block CNN used in all configurations.

2.4. Model Training

All training was performed offline on a host machine, and only the resulting quantized models were transferred to the device. The three dataset files were kept in their distributed roles throughout: the training file fitted the model weights, the first test file guided model selection, and the second test file was reserved for the final held-out measurement and never influenced any training decision. The min-max scaler was fitted on the training file alone, and its fixed minimum and maximum were applied to the validation and test files, so no statistic from the evaluation data entered the pipeline.

Each configuration was trained with the Adam optimizer against a binary cross-entropy loss, in mini-batches of thirty-two windows, for a maximum of one hundred epochs. Rather than train for a fixed length, the procedure monitored the loss on the validation file after every epoch and stopped early once it had not improved for fifteen consecutive epochs, restoring the weights from the epoch of lowest validation loss. This early-stopping rule served two purposes: it prevented the larger-capacity models from overfitting the training file, and it removed epoch count as a manual hyperparameter, since each configuration trained only as long as its own validation curve justified.

Two learning rates, 0.001 and 0.010, were tried for every configuration, and the one giving the higher validation F1 was retained. This was the only hyperparameter search performed; no tuning was carried out against the held-out test file. The same procedure was applied identically to all twelve capacity and window configurations, so that any difference in their reported accuracy reflects the model rather than a difference in how it was trained.

2.5. Quantization and On-Device Deployment

Each configuration was converted to an INT8 TFLite Micro model by post-training quantization under the TFLITE_BUILTINS_INT8 scheme [20]. The calibration set was two hundred windows drawn at even spacing across the entire training file rather than from its start, because the recording begins with a long unoccupied period and a contiguous early slice would expose the quantizer to a single class and collapse the model toward it. To check the quantization penalty, each integer model was also evaluated offline on the full held-out file using the same arithmetic the device applies. Quantized binaries were embedded as C arrays and flashed to the ESP32-S3 under ESP-IDF v5.5 and TensorFlow Lite Micro, one model per flash cycle, using a six-kernel resolver (Conv2D, MaxPool2D, Mean for the pooling stage, FullyConnected, Reshape, and Logistic); the Mean operator must be registered explicitly or inference fails at the first call. On the device, the tensor arena reported by the interpreter, the inference latency from `esp_timer_get_time()`, the free heap from `esp_get_free_heap_size()`, and the task stack high-water mark were recorded, and the device figures were gathered on an evenly spaced subsample of the held-out file and validated against the offline integer results.

Table 2. Implementation results measured on the ESP32-S3

Filters (F1,F2)	W	Params	Flash (B)	Arena (B)	Latency (μ s)	Held-out F1	Δ F1 (INT8)
4,8	15	345	3,832	2,660	680	0.953	+0.002
4,8	30	345	3,832	2,980	1,232	0.812	-0.001
4,8	60	345	3,832	3,700	2,303	0.895	+0.001
8,16	15	1,265	5,072	4,244	1,237	0.959	+0.000
8,16	30	1,265	5,072	4,884	2,314	0.920	+0.021
8,16	60	1,265	5,072	6,084	4,423	0.865	+0.002
16,32	15	4,833	9,288	7,428	2,376	0.943	+0.009
16,32	30	4,833	9,288	8,708	4,569	0.943	+0.002
16,32	60	4,833	9,288	11,108	8,862	0.868	+0.000
32,64	15	18,881	24,632	23,012	5,040	0.951	+0.005
32,64	30	18,881	24,632	25,572	9,606	0.936	+0.005
32,64	60	18,881	24,632	30,372	18,539	0.950	-0.006

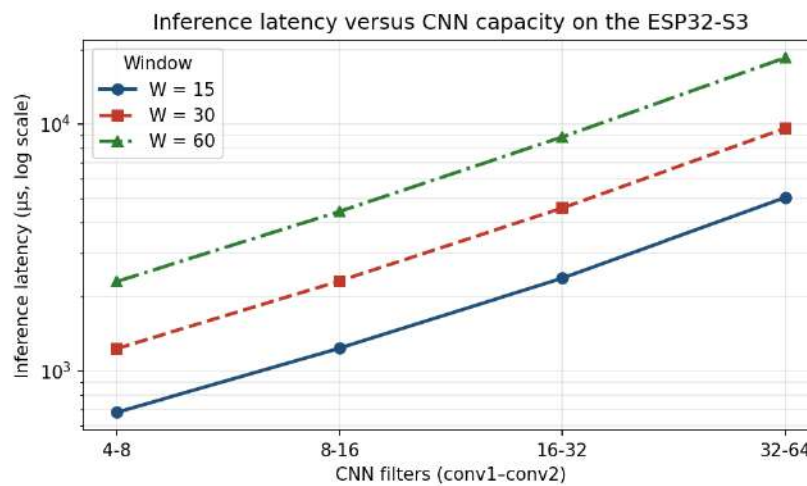


Figure 3. Measured on-device inference latency versus CNN filter capacity

3. RESULTS AND DISCUSSION

3.1. Implementation Results

All twelve configurations were successfully quantized, flashed, and executed on the ESP32-S3. Table 2 reports, for each configuration, the parameter count, flash footprint, on-device tensor arena, measured inference latency, held-out INT8 F1, and the float-to-INT8 F1 change. These measurements show that the leakage-controlled training pipeline produces deployable models and that TensorFlow Lite Micro executes all twelve configurations on the device without modification. The compact models reach a held-out F1 near 0.95, the tensor arena stays between 2,660 and 30,372 bytes across the full grid, and inference completes in 0.68 to 18.5 milliseconds. Every configuration allocated memory correctly and produced valid output.

3.2. Resource Usage on the Device

The models occupy a negligible share of the device's resources. The tensor arena ranges from 2,660 bytes for CNN(4,8) at W=15 to 30,372 bytes for CNN(32,64) at W=60, against the chip's 512 KB of internal SRAM; the largest configuration therefore consumes under six percent of available memory. More than 320 KB of heap remained free after model initialization in every case, and the worst-case task stack high-water mark was 1,608 bytes. This headroom is sufficient to simultaneously run a BLE stack, sensor drivers, FreeRTOS, and a modest application layer on the same chip. The tensor arena does not grow with window length for a given filter configuration: Global Average Pooling collapses the temporal dimension before the dense layer, so arena size is determined by filter count alone, not by W.

This property makes GAP-based CNNs substantially more memory-efficient than recurrent alternatives such as LSTM.

3.3. Inference Latency

Inference latency is reported for every configuration in Table 2 and plotted against filter capacity in Figure 3. It rises from 680 microseconds for CNN(4,8) at W=15 to 18,539 microseconds for CNN(32,64) at W=60, a span of approximately 27 $\times$. The increase is steep because convolutional layer cost scales with both filter count and input length, and the two factors compound: doubling the filter counts while quadrupling the window length raises the multiply-accumulate (MAC) count by roughly 8 $\times$ in the first convolutional block alone, before accounting for the second block. Despite this, even the heaviest model consumes only 0.031 percent of a sixty-second sensor interval. The ESP32-S3 can therefore perform occupancy inference continuously at the sensor's native cadence while leaving more than 99.97 percent of each cycle available for sensor polling, wireless communication, and other application tasks. Latency would become a binding design factor only at model sizes or sampling rates far beyond those evaluated here.

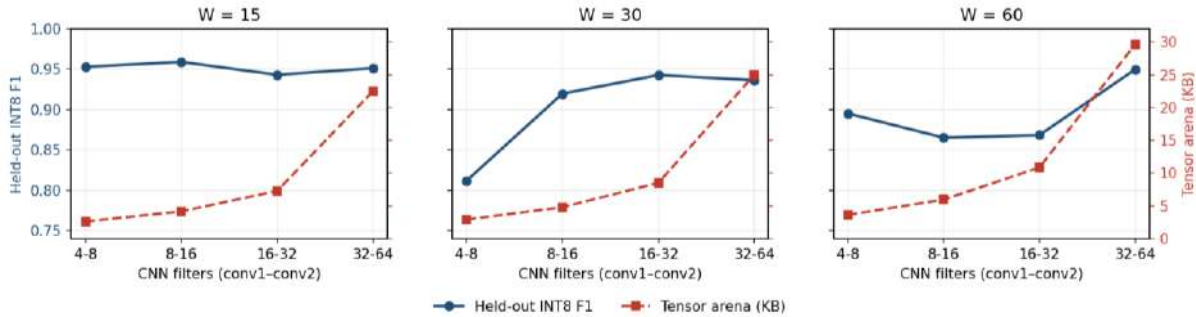


Figure 4. Held-out INT8 F1 (left axis) and on-device tensor arena (right axis) versus CNN filter size

Table 3. Held-out F1 across five random seeds for the two smallest capacities

Model	W	Mean F1	Std. dev.
CNN(4,8)	15	0.916	0.048
CNN(4,8)	30	0.914	0.034
CNN(4,8)	60	0.878	0.059
CNN(8,16)	15	0.933	0.059
CNN(8,16)	30	0.942	0.025
CNN(8,16)	60	0.886	0.013

3.4. Accuracy and the Effect of Window Size

The held-out INT8 F1 sits near 0.94 to 0.96 for the fifteen-minute window across all four filter configurations, and tends to decline at the sixty-minute window, while increasing model capacity does not raise accuracy. Figure 4 plots held-out F1 on the left axis and tensor arena on the right axis, and shows this flat accuracy profile against monotonically rising memory cost, which directly motivates the recommendation of the smallest sufficient model. Two observations are necessary to interpret the per-cell figures correctly.

First, the individual figures carry training variance. Retraining the two smallest filter configurations across five independent random seeds produced the mean F1 scores and standard deviations listed in Table 3. Standard deviations reach approximately 0.06 for CNN(4,8), and the single anomalous result in Table 2, CNN(4,8) at W=30 with F1=0.812, shifts to a mean of 0.914 across seeds. This indicates that the low value is within run-to-run noise rather than a stable effect of the window length. The seed study was restricted to the two smallest configurations because they are the deployment candidates of practical interest and because they exhibit the largest single-run spread; the larger-capacity models are more expensive to retrain and are not recommended given that their accuracy does not exceed the compact baseline, so a variance qualification on the small models is sufficient.

Second, the one pattern that survives training variance is a consistent, modest decline at the sixty-minute window relative to fifteen minutes. A plausible mechanism is the behavior of Global Average Pooling under long sequences: GAP averages activations across all W time steps, and at $W=60$ this averaging dilutes the short, recent transitions that most reliably signal a change in occupancy state. A longer window also yields fewer and more strongly auto-correlated training samples from a fixed-length recording, reducing effective training set diversity. Together these effects give the fifteen-minute window a consistent accuracy advantage. A controlled ablation that separates temporal dilution from reduced effective sample count would further clarify this mechanism and is a natural extension of the work.

3.5. INT8 Quantization

INT8 quantization is effectively lossless for this model class. Across all twelve configurations the held-out F1 changes by between -0.006 and $+0.021$ relative to the corresponding floating-point model evaluated with the same integer arithmetic the device applies. This near-lossless behavior arises because the convolutional filters here are small enough that the representational redundancy of a 32-filter bank averages out individual rounding errors, while the compact (4,8) configuration loses at most half a percent because each of its four filters must encode a more distinct pattern and is therefore more sensitive to per-weight rounding. The memory and latency reductions of INT8 inference therefore arrive at no meaningful accuracy cost, which is the key property that makes on-device deployment practical. This outcome is consistent with post-training quantization penalties reported for convolutional networks in the general literature [22],[23].

Table 4. Deployment ranking of the short-window ($W = 15$) configurations

Model ($W = 15$)	Held-out F1	Arena (B)	Latency (μ s)
CNN(4,8)	0.953	2,660	680
CNN(8,16)	0.959	4,244	1,237
CNN(16,32)	0.943	7,428	2,376
CNN(32,64)	0.951	23,012	5,040

Table 5. Confusion matrix of the recommended model.

	Predicted: Occupied	Predicted: Empty
Actual: Occupied	TP = 642	FN = 18
Actual: Empty	FP = 37	TN = 2303

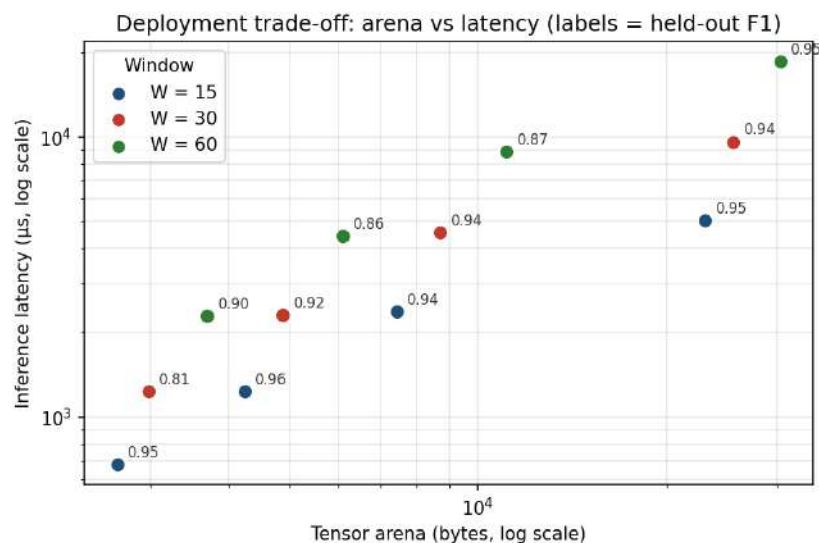


Figure 5. Tensor arena versus inference latency for all twelve configurations

3.6. Deployment Trade-offs and Recommendation

For deployment decisions, Table 4 ranks the four short-window ($W=15$) configurations by held-out F1 against their on-device arena and latency, and Figure 5 plots arena against latency for the full twelve-configuration grid with F1 annotated. CNN(4,8) and CNN(8,16) are statistically tied in accuracy at 0.953 and 0.959 respectively, so the choice between them depends on the relative importance of cost and recall margin. CNN(8,16) spends 4,244 bytes of arena and 1,237 microseconds to achieve a slightly higher recall, as the confusion matrix in Table 5 shows: on the 3,000-window device evaluation subsample it produces 37 false positives and 18 false negatives, giving a precision of 0.946 and a recall of 0.973. CNN(4,8) achieves nearly identical aggregate accuracy in 2,660 bytes and 680 microseconds. CNN(8,16) is the recommendation when a small recall margin matters and memory is available; CNN(4,8) is the recommendation when leaving the largest possible share of the chip free is the priority. The two larger configurations, CNN(16,32) and CNN(32,64), consume substantially more arena and latency without any accuracy benefit, making them suboptimal for this task under any cost constraint.

The latency figures become meaningful when set against the sensing cadence. With one sensor reading per minute, each inference has a sixty-second budget of sixty million microseconds. The recommended CNN(8,16) configuration consumes 1,237 microseconds of this budget, approximately 0.002 percent, leaving the processor idle for more than 99.99 percent of every cycle. Even the largest configuration, CNN(32,64) at $W=60$ with 18,539 microseconds, uses only 0.031 percent of the interval. A single node could therefore evaluate several models sequentially, maintain a BLE or Wi-Fi stack, poll multiple sensors, or run additional on-device analytics within each cycle without any timing conflict.

The memory picture supports the same conclusion. The recommended model requires 4,244 bytes of tensor arena, under one percent of the 512 KB of internal SRAM, and more than 320 KB of heap remained free after initialization in every configuration tested. These margins confirm that the ESP32-S3 can function as an autonomous sensing-and-decision node, rather than a data relay, with substantial capacity remaining for wireless communication stacks, sensor drivers, and application logic. The implementation therefore satisfies the design goal stated in the introduction: occupancy inference on the device is practical, the hardware is not the bottleneck, and the node can act locally without any cloud dependency.

4. CONCLUSION

This paper demonstrated a complete, working implementation of quantized CNN occupancy detection running entirely on the ESP32-S3, without any cloud dependency. All twelve configurations were trained under a leak-free protocol, quantized to INT8, deployed through TensorFlow Lite Micro, and executed on the device. The recommended configuration, CNN(8,16) at a fifteen-minute window, reaches a held-out F1 of 0.959 using 4.2 KB of tensor arena and 1.24 ms per inference, with over 320 KB of heap free, and INT8 quantization is essentially lossless. On-device CNN occupancy detection is therefore practical on a low-cost microcontroller, and a small network is sufficient. The time and memory it leaves unused, more than 99.99 percent of each sensing cycle and over 320 KB of heap, indicate that the chip can serve as an autonomous sensing-and-decision node rather than a data relay, with room for further on-device tasks.

The study has limits that point to the next steps. The benchmark is a single office room, so the accuracy obtained may not transfer directly to harder multi-room or noisier settings. Accuracy was measured on an evenly spaced subsample of the held-out file and validated against the full offline integer evaluation, and the smallest models were repeated across seeds while the others were trained once. Power and energy were not measured. Extending the implementation to live streaming sensors, to multi-occupant and multi-room occupancy [21], and to a measured energy budget under a full application workload would build on the working system demonstrated here.

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Adaptive Grasp Force Control for Robotic Gripper Based on Force Sensitive Resistor Sensor

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ABSTRACT

Robotics technology has been developed to support human tasks through robotic grippers that can control force on fragile surfaces. This research presents the design of an adaptive grasp force control system for two types of robotic grippers using FSR sensor and a PID control approach. This system was developed to adaptively regulate grip force when interacting with objects with varying surface characteristics. Experimental results showed that the FSR sensors provided feedback with an average error of 0.112 N. Implementation of PID control using the Ziegler–Nichols method successfully enabled the robotic gripper to achieve a desired force of 5 N. The gripper type A demonstrated the settling time of 1.75 seconds for glass cup, 2.25 seconds for plastic cup, and 3.25 seconds for paper cup. Meanwhile, gripper type B demonstrated a settling time of 2 seconds for glass cup, 2.75 seconds for plastic cup, and 3.75 seconds for paper cup. Although the response is slower, the gradual increase in force can reduce the risk of applying excessive force to soft object surfaces. A comparison between the two gripper designs highlights the importance of mechanical structure in influencing control performance.



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1. INTRODUCTION

Robotic technology has been increasingly developed to assist or replace human mobility and manipulation tasks through the use of robotic arms. One of the most important components of a robotic arm is the end effector, which directly interacts with the workpiece or target object. End effectors are also used in industrial [1]-[2] and medical [3]-[4] applications. Depending on the intended task, an end effector may take the form of a clamp, welding torch, paint gun, or gripper. Among these configurations, grippers are commonly used for object manipulation because they can grasp, hold, and transfer objects from one location to another. The gripper consists of rigid fingers that can open and close. In industrial applications, grippers are used to pick up and place manufactured items, such as food, beverage bottles, and machine components [5]. The actuation system of a gripper can be driven by an electric motor or pneumatic mechanism, which provides the force required to hold the object. Ideally, a gripper should

perform similarly to a human hand by applying sufficient force to securely hold an object while avoiding excessive force that may cause damage.

Although conventional grippers can effectively perform repetitive grasping tasks under controlled conditions, they may have difficulty handling objects with varying shapes and surface conditions [6]–[7]. In particular, insufficient force may cause the object to slip or fall, whereas excessive force may deform, dent, or break the object. Therefore, adaptive control methods can be employed to address this problem. For example, Proportional Integral Derivative (PID) control has been widely used in robotic systems because it can adjust the control response [8]–[11]. Such force regulation is relevant for grasping tasks involving objects with varying surface conditions.

In addition to the control strategy, the mechanical configuration of the gripper can influence its grasping capability. The gripper configuration is inspired by the structure of the human hand, which consists of fingers. For the purpose of grasping objects, most tasks utilize two- and three-finger grippers. During a grasping operation, the fingers may be actuated individually or simultaneously depending on the mechanical configuration. Syafeeza [12] demonstrated a gripper mechanism with multiple degrees of freedom (DOF) for grasping movements. To achieve flexible gripping movements, the gripper's fingers are designed to move together. Grippers with parallel finger configurations are designed with simple mechanisms and controls. Davar [13] developed and assembled a dual-jaw gripper for grasping tasks. This gripper consists of symmetrical parallel segments that move together to align and hold objects.

However, the mechanical of a gripper does not necessarily guarantee appropriate regulation of the force applied to the object. The design of a gripper, which is installed as an end effector for gripping tasks on objects with certain surfaces, requires additional devices such as sensors. Sensors placed on the gripper's fingers are crucial for assessing the surface condition of the object in direct contact with the gripper. One proposed method to control the gripper's force in object-grasping tasks is using force sensors. As explained in Payo [14], force control is required on the gripper when interacting with the target object, with a limit on the force applied to the object to prevent damage to its surface. An embedded force sensor device to detect the strength of the robotic hand's gripping force is integrated with a microcontroller. This method can benefit a robotic arm system with a gripper, because it reduces the risk of either dropping or damaging the grasped object.

A Force Sensitive Resistor (FSR) sensor is one type of sensor that can be used to detect applied force through changes in electrical resistance [15]. Differences in force on the sensor produce different resistance values. The FSR sensor is a simpler sensor for controlling gripping force by monitoring the detected force, similar to a human hand. The FSR sensor is placed at the fingertips of the gripper. Because of the difference in resistance values, this sensor can be used as a reference to adjust the grip strength. When the gripper contacts an object, the FSR sensor detects the resulting force and provides feedback to the controller. The measured response can then be used as a reference for adjusting the gripping action or limiting the applied force to a predefined threshold.

Although previous studies have investigated different gripper configurations and force-sensing approaches, the relationship between gripper design and adaptive gripping-force performance remains insufficiently explored. Existing studies have generally focused either on developing mechanical gripper mechanisms and on implementing force-control and sensing techniques, while comparative evaluation of different gripper configurations under the same force-feedback mechanism has received less attention. This study aims to design an adaptive grasping force control system for two robotic gripper designs to regulate the force applied during object grasping and compare their grasping performance and suitability for handling objects with different characteristics.

The main contributions of this research are twofold: (1) the development and implementation of an FSR sensor based adaptive grasping-force control method for regulating the force applied by a robotic gripper, and (2) a comparative experimental evaluation of two different gripper mechanism designs under the same force-feedback control framework when grasping objects with different surface and material characteristics.

2. RESEARCH METHOD

This research began with the design of an adaptive grasp force control system for the robotic gripper. It then continued with the design of the robot's gripper mechanics, followed by the development of a control algorithm to adaptively regulate the robot's grip force using an FSR sensor. Experiments were conducted to test the system's performance in stably grasping various objects.

2.1 Block Diagram of Robotic Gripper

This research began with the design of an adaptive grasp force control system for the robotic gripper, as shown in Figure 1. The proposed robotic gripper design is used as an end effector for grasping objects with a two-finger mechanism. The gripper has a simple structure with a parallel-finger arrangement, enabling it to handle objects of varying shapes and sizes within a specific range. The gripper is able to handle objects with shapes and sizes within a certain range. The actuator in the form of a servo motor is used to move the gripper fingers to open and close. In the implementation of the system for the task of grasping objects, the surface of the object being grasped has a variety of capabilities to withstand the force of the resistive forces. In the design, the sensor that detects the force when the gripper finger touches the object uses a force-sensitive resistor (FSR) sensor. A microcontroller is used to process the sensor data and execute the adaptive grasp force control algorithm. The control system determines when the gripper should stop closing based on the detected grasping force. In this study, the objects used for the grasping experiments were cups made of three different materials: glass, plastic, and paper.

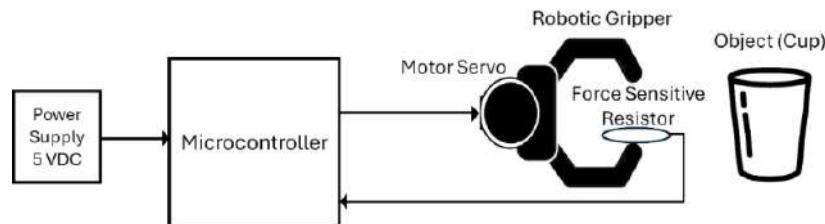


Figure 1. Block diagram robotic gripper

2.2 Robot Gripper Mechanism Design

The dimensions of the objects to be grasped were determined before the system was developed and used as a basis for designing the proposed robot gripper. Two distinct robot gripper mechanisms, namely a direct-driven mechanism (Type A) and a linkage-based mechanism (Type B), were developed to investigate the influence of mechanical configuration on grasping-force control performance under different object characteristics. The objects consisted of glass, plastic, and paper to evaluate the performance of the robot gripper. The reason for choosing these objects is because they have different surface sensitivities when the gripper's fingers touch the object's surface. The two proposed robot gripper mechanisms feature a two-finger structure that moves simultaneously during the opening and closing motions, as shown in Figure 2.

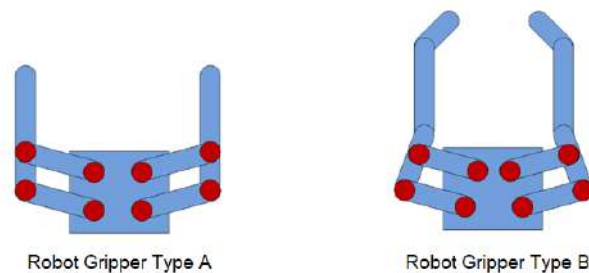


Figure 2. Robot gripper type A and type B

The design of a robotic hand from two two-finger gripper models connected in parallel for gripping cylindrical objects, such as glasses, with diameters ranging from 4 to 6 cm. The gripper structure material was fabricated from 4-mm-thick acrylic material. In the design of this two-finger gripper model,

has one degree of freedom (DOF) through an angular range of 45°. For type A gripper, the dimensions are 90mm x 48mm x 46mm with a gripper width of 45mm. For type B gripper, the gripper dimensions are 140mm x 50mm x 50mm with a width of 130mm. A servo motor was used as the actuator to drive the connecting and transmission mechanism to grasp and release the object. The hardware configurations of both two-finger grippers are shown in Figure 3.

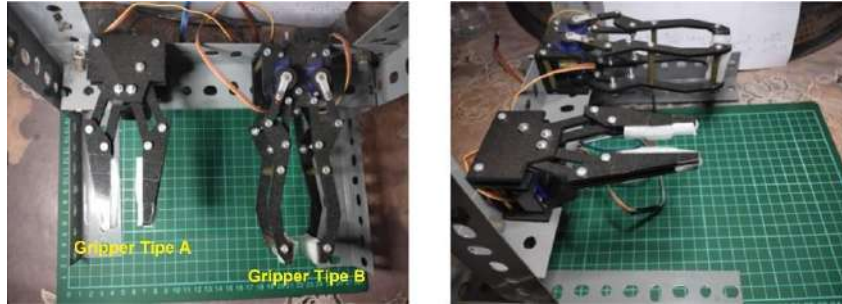


Figure 3. Two-finger gripper construction hardware

2.3 Force Sensor Calibration

The force sensor used for feedback is a force-sensitive resistor with of a 7.6 mm diameter polymer thick film, specifically the FSR-400. The FSR-400 has a force sensitivity range between 20 to 2000 grams (0.2 to 20 N). However, in this study, the applied force was limited to approximately 500 grams (4.91 N). The FSR-400 was installed on the gripper robot to measure the contact force between the object surface and the gripper fingertips. The sensor converts changes in resistance into voltage using a voltage-divider circuit. To acquire the sensor data, the FSR-400 was connected to a 1 kΩ resistor in the voltage-divider circuit. The output voltage was calculated using (1).

$$V_{out} = V_{in} \times \frac{R_1}{R_1 + R_{fsr}} \quad (1)$$

Where V_{in} is the supply voltage for the FSR sensor, which is 5 V. V_{out} is the output voltage of the voltage-divider circuit, calculated using a 10 kΩ resistor (R_1) and the resistance of the FSR sensor (R_{fsr}). The voltage value signal V_{out} is then used to initialize the microcontroller program on the Arduino Uno as shown in Figure 4.

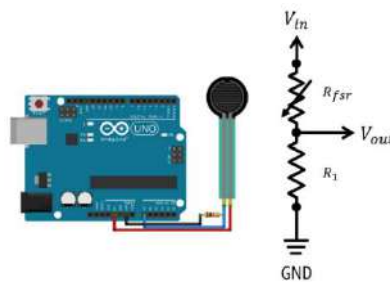


Figure 4. FSR sensor with Arduino UNO circuit diagram

The relationship between tension and load force required to grip an object is expressed in terms of force (N) using Equation (2). This process is performed during the calibration step which produces data presented in Table 1. Then the measured force values are then used to determine the set-point values in the program. Next, it is used to provide instructions to the hardware by controlling the servo motor on the robot's hand. In this context, m represents mass, which is measured in grams for force calibration and g is equals 9.81 m/s².

$$Force(N) = m \cdot g \quad (2)$$

Based on the force sensor calibration results presented in Table 1, it can be seen that at 0 grams, the sensor produces no voltage output from the voltage comparator circuit. In the range of 100-200 grams, the output voltage increases significantly, indicating that the sensor is highly responsive to changes in the applied force. However, in the range of 400-600 grams, the increase in output voltage becomes smaller, indicating that the sensor is approaching its saturation point. Therefore, to ensure reliable and

sensitive force measurement, the maximum force applied by the robotic gripper in this study was limited to 500 grams (4.91 N).

Table 1. Result of force sensor calibration

Object weight for force calibration (g)	Calculated force (N)	Voltage Output(V)
0	0.00	0.00
100	0.98	1.67
200	1.96	2.50
300	2.94	3.12
400	3.92	3.45
500	4.91	3.70
600	5.89	3.85

2.4 Gripper Robot System Programming

The robot gripper system is programmed to move and grip objects according to the setpoint value using PID control to stabilize the force. The system uses a microcontroller to control the movement of the servo motor with a PWM signal and reads the FSR sensor data. Figure 5 shows the flowchart of the programming design of the robot gripper system. When the FSR sensor reading reaches the setpoint value, the gripper stops moving and maintains its clamping position. By applying the FSR sensor as a force setpoint and using PID control, the robot gripper movement can be regulated to prevent excessive force and potential damage to the object's surface.

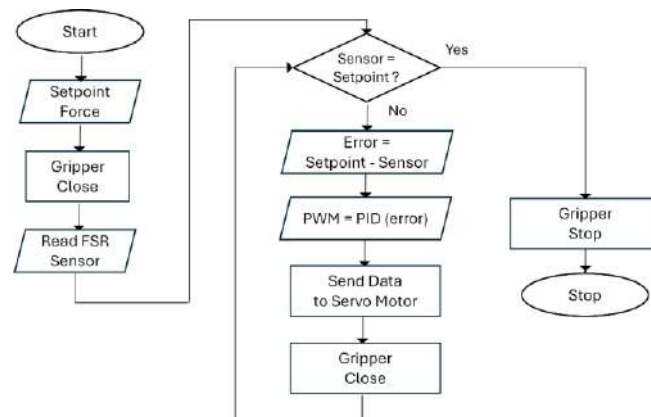


Figure 5. Flowchart of gripper robot system

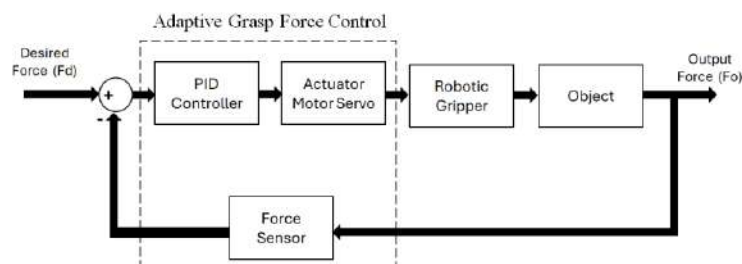


Figure 6. Block diagram of grasp force control

2.5 Grasp Force Control Design

Figure 6 shows a block diagram of grasp force control using Proportional-Integral-Derivative (PID) control applied to the robot's gripper via a servo motor. The purpose of controlling the servo motor during the gripping process is to achieve a stable gripping force when the gripper's fingers contact the object according to the desired force (F_d) setpoint. The output force (F_o) is measured by the FSR sensor, which provides feedback in the form of the measured force values.

During the design step of grasp force control, the PID controller is tuned using the Ziegler – Nichols method according to the tuning rules presented in Table 2. Determination of the PID controller parameters (K_p , K_i , and K_d) is based on an analysis of the unit step response characteristics of the regulated plant.

Table 2. Controller parameters for Ziegler-Nichols method

Controller	K_p	T_i	T_d
P	$0.5K_u$	-	-
PI	$0.45K_u$	$P_u/1.2$	-
PID	$0.6K_u$	$P_u/2$	$P_u/8$

In this method, to obtain K_u and P_u for continuous oscillation, a proportional control action is applied with $T_i = \infty$ and $T_d = 0$. Here, K_u is the gain when the system starts to exhibit sustained oscillation, and P_u is the oscillation period. The relationship between these parameters with K_i and K_d can use (3) and (4).

$$K_i = \frac{K_p}{T_i} \quad (3)$$

$$K_d = K_p \cdot T_d \quad (4)$$

In the experimental process, testing was conducted with a setpoint of 5 N. The first test was conducted on a Type A gripper. The resulting system yielded a K_u value of 5 and the P_u value is 3 seconds. Therefore the K_p , K_i , and K_d values were determined using calculations based on the Ziegler Nichols PID controller method. From the calculations and responses of the plant above, the obtained values of K_p is 3, K_i is 2 and K_d is 1.12.

The second test, conducted on a Type B gripper, also applied a gripping force setpoint of 5 N. The results yielded the K_u is 4 and the P_u is 2 seconds. The calculated K_p , K_i , and K_d values were 2.4, 2.4, and 0.6, respectively. These values were then entered into the microcontroller program.

2.6 Performance Evaluation of Robotic Grasping System on Various Objects

To evaluate the performance of the robotic grasping system on various objects, the test consisted of two parts: evaluating the gripping characteristics of the Type A gripper during gripping and testing the characteristics of the Type B gripper during gripping. To determine the grasp force control characteristics of the gripper system, the changes in the sensor force value changes as the gripper moved toward the closed position while grasping the object. The gripper stopped moving when the measured force reached the reference force threshold. Three types of objects were used: glass cups, plastic cups, and paper cups, as shown in Figure 7.



Figure 7. Glass cup, plastic cup, and paper cup objects

3. RESULTS AND DISCUSSION

To evaluate the performance of the proposed system, a series of experimental tests were conducted focusing on the accuracy of the force sensor and the effectiveness of PID based force control applied to the robot gripper. The evaluation was divided into FSR sensor accuracy testing, PID control performance testing of the Type A gripper and Type B gripper.

3.1. Testing the Accuracy of the FSR Sensor

To evaluate the accuracy of the force measurements obtained from the sensor, this test was conducted to determine the success of the system in obtaining the FSR sensor value when the sensor

touches and presses the object's surface. Comparison of the calculation results and response analysis using the force sensor against the reference pressure was carried out with different values. The results of the FSR sensor accuracy test are presented in Table 3.

Table 3. The accuracy of the FSR sensor force value

Testing	Weight Reference (g)	Force Reference (N)	Measurement Force (N)	Error (N)
1	300	2.94	2.80	0.14
			3.02	0.08
			2.90	0.04
2	400	3.92	4.05	0.13
			3.85	0.07
			3.95	0.03
3	500	4.91	5.10	0.19
			4.80	0.11
			4.95	0.04
4	600	5.89	6.20	0.31
			5.75	0.14
			5.95	0.06
Average error				0.112

The results show that the FSR sensor exhibited an average measurement error of 0.112 N, indicating a relatively good level of accuracy for force measurement. It is apparent that the error tends to increase at higher forces, especially in the 600 grams (5.89 N). This behavior can be attributed to the nonlinear characteristics of the FSR sensor and its sensitivity to changes in the applied force. Despite this limitation, the sensor provided a stable response over the tested force range and was considered suitable as a feedback system in the robot gripper force control system.

3.2. Testing the PID Control of the Gripper Type A

The force control performance of the Type A gripper was evaluated while gripping an object. This test was conducted to determine the response of the adaptive grasp force control implemented in the system. The control test applied a set point with a grip force of 5 N for commands to the microcontroller. The PID parameters used for the Type A gripper were ($K_p = 3$), ($K_i = 2$), and ($K_d = 1.125$). To determine the response when the gripper type A grips a glass cup, a plastic cup and a paper cup with the same setpoint. The force response of the Type A gripper when gripping the glass, plastic, and paper cups is presented in Figures 8, 9, and 10, respectively.

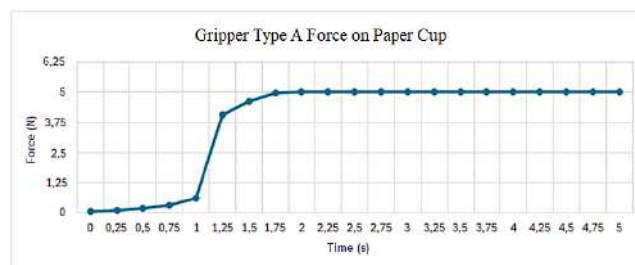


Figure 8. Response graph of gripper type A force on glass cup

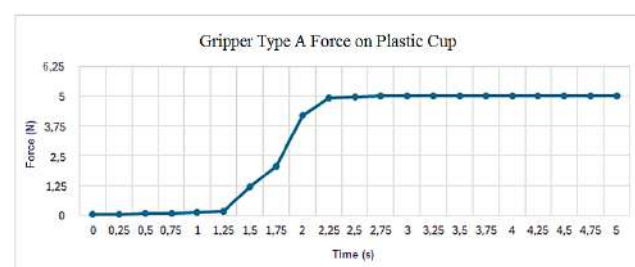


Figure 9. Response graph of gripper type A force on plastic cup

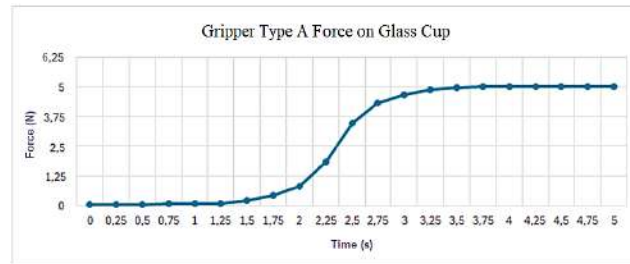


Figure 10. Response graph of gripper type A force on paper cup

Based on the force response graphs shown in Figures 8, 9, and 10, the Type A gripper was able to track the specified force setpoint, although the response characteristics varied depending on the object being gripped. In the glass cup test, the force response increased rapidly at approximately 1 second and reached the 5 N setpoint at 1.75 seconds, as the rigid surface of the glass cup allowed the applied gripping force to be transmitted effectively to the FSR sensor. In the plastic cup test, the system exhibited a slightly slower response, with a settling time of 2.25 seconds, due to the greater deformability of the plastic material, which affected the transmission of the gripping force to the sensor. Meanwhile, the paper cup produced the slowest response, with a settling time of 3.25 seconds, as its soft and easily deformable characteristics reduced the rate of force transmission to the sensor and consequently required more time for the controller to reach the specified force setpoint.

3.3. Testing the PID Control of the Gripper Type B

Testing the force response of Type B gripper was evaluated using the same three types of objects: a glass cup, a plastic cup, and a paper cup. The corresponding force responses are presented in Figures 11, 12, and 13, respectively. The PID parameters used for the Type B gripper were ($K_p = 2.4$), ($K_i = 2.4$), and ($K_d = 0.6$).

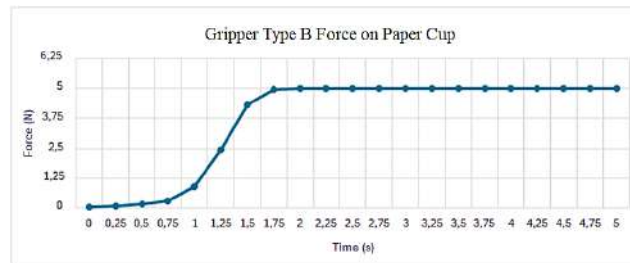


Figure 11. Response graph of gripper type B force on glass cup

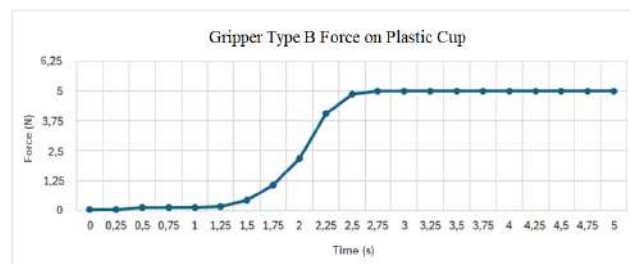


Figure 12. Response graph of gripper type B force on plastic cup

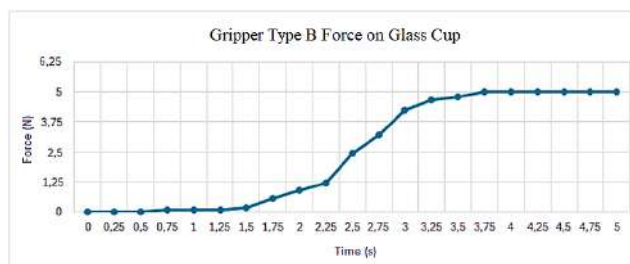


Figure 13. Response graph of gripper type B force on paper cup

Based on the force response graphs shown in Figures 11, 12, and 13, the Type B gripper was able to respond to changes in the applied force and approach the predetermined force setpoint. However, its response characteristics differed from those of the Type A gripper. In the glass cup test, the Type B gripper exhibited a relatively steady increase in gripping force and reached the desired force with a settling time of 2 seconds, although the response was slower than that of the Type A gripper. In the plastic cup test, the gripper showed a smoother response, with a settling time of 2.75 seconds. The paper cup produced the longest settling time of 3.75 seconds. Overall, the Type B gripper demonstrated a stable and relatively smooth force response across the three tested objects, and although it had longer settling times than the Type A gripper.

4. CONCLUSION

This research presents the design and implementation of an adaptive grasp force control system for a robotic gripper using a force-sensitive resistor (FSR) sensor and a PID control approach. The system was developed to enable the robotic hand to adaptively regulate its grip force when interacting with objects with varying surface characteristics. Experimental results showed that the FSR sensor provided force feedback with an average error of 0.112 N, indicating sufficient accuracy for gripping applications. The implementation of PID control tuned using the Ziegler–Nichols method successfully enabled the robotic gripper to achieve the desired force setpoint of 5 N. The Type A gripper demonstrated a faster response, with settling times of 1.75 seconds for a glass cup, 2.25 seconds for a plastic cup, and 3.25 seconds for a paper cup. The faster response observed with the glass cup was attributed to its rigid surface. However, the response became progressively slower when handling softer and more deformable materials, as deformation affected the transmission and detection of the applied force. In contrast, the Type B gripper exhibited longer settling times of 2.00 seconds for a glass cup, 2.75 seconds for a plastic cup, and 3.75 seconds for a paper cup. Overall, the proposed adaptive grasp force control system demonstrated its ability to regulate gripping force according to different object characteristics while reducing the risk of excessive force application. The comparison between the two gripper designs also demonstrates that the mechanical structure of the gripper plays an important role in determining force control performance and gripping behavior.

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Comparing Deep Learning and Ensemble Models for Photovoltaic Power Forecasting

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ABSTRACT

Precise forecasting of photovoltaic (PV) power is crucial for maintaining grid stability and effectively incorporating solar energy. This study compares four forecasting models, LSTM, GRU, Random Forest, and XGBoost, using three years of real operational data (2023–2025) from the DKASC solar database. Fourteen input features were constructed from irradiance measurements, meteorological variables, rainfall, wind direction, and cyclical time features. A sliding window of 36 time steps captured temporal dependencies, while the dataset was chronologically split into training, validation, and testing subsets. Model performance was assessed using R^2 , RMSE, MAE, and MAPE. Results show LSTM achieved the highest accuracy with R^2 of 0.9647 and RMSE of 88.40 W, whereas XGBoost obtained the lowest MAPE of 19.18%. SHAP analysis and an ablation study were conducted to identify influential features and evaluate their contributions to forecasting performance. SHAP analysis identified global horizontal radiation, global tilted radiation, and cyclical temporal features, particularly `day_cos` and `hour_cos`, as the most influential predictors, while wind speed and daily rainfall showed limited impact. The findings demonstrate that deep learning models can provide reliable PV power forecasts when combined with informative feature engineering and appropriate temporal window selection.



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1. INTRODUCTION

The world's transition to renewable energy sources is accelerated due to environmental concerns and the depletion of fossil fuels, has established solar photovoltaic (PV) systems as the foundation of contemporary sustainable energy infrastructure [1][2][3]. However, the intrinsic fluctuations and sporadic nature of solar radiation—influenced by meteorological factors such as cloud cover, temperature, humidity, and wind—provide serious obstacles to energy dispatch optimization and grid stability, and the reliable integration of PV power into existing electricity networks [4][5][6]. Accurate short-term PV power output predictions is therefore not merely beneficial but essential for balancing supply and demand, lowering the cost of operations, and enhancing the resilience of power systems [7]. This necessity has motivated extensive research into various forecasting approaches. However, a clear understanding of which models and input features are most effective under real-world conditions remains an open question.

Data-driven methods, especially machine learning (ML) and deep learning (DL) models, have gained popularity in recent years, have demonstrated remarkable success in capturing the complex, nonlinear, and time-dependent patterns of solar power generation [8][9]. Among these, recurrent neural network architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are widely recognized for their ability to model temporal dependencies over extended sequences [10]. At the same time, ensemble methods like Random Forest (RF) and Extreme Gradient Boosting (XGBoost) offer robust predictive performance by leveraging multiple decision trees, often with lower computational overhead [11][12]. Despite the proliferation of hybrid and optimized models in the literature—many of which incorporate metaheuristic algorithms, signal decomposition, or external optimization routines [13]—and the increasing recognition that such complex pipelines often lack generalizability [14], there remains a notable gap in fair, direct comparisons of these four fundamental models under strictly identical conditions. Moreover, comprehensive interpretability analyses (e.g., SHAP) and feature ablation studies are seldom reported alongside such comparative evaluations.

To address these gaps, this study presents a systematic and rigorous comparative analysis of LSTM, GRU, Random Forest, and XGBoost for 3-hour-ahead PV power forecasting using real-world operational data. The main contributions of this work are:

- Utilization of three consecutive years (2023–2025) of 5-minute resolution data from the DKASC solar database, with a clear temporal split (2023 training, 2024 validation, 2025 testing) and three independent runs per model to ensure statistical robustness.
- A comprehensive feature engineering process that results in 14 input variables, including multiple irradiance components, meteorological parameters, wind direction (converted to sine/cosine), daily rainfall, and cyclical time features (hour and day of the year).
- Application of a 36-step sliding window (equivalent to 3 hours) to capture short-term temporal dependencies.
- A fair, non-optimized comparison of the four models under identical preprocessing and hyperparameter settings.
- SHAP (SHapley Additive exPlanations) analysis and an ablation study to interpret model predictions and quantify the contribution of each feature group.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 describes the dataset, preprocessing steps, and the methodological framework. Section 4 presents and discusses the results, including model performance, feature importance, ablation study, and SHAP analysis. The work is finally concluded in Section 5, which also suggests future research areas.

1.2. Related Works

A hybrid FHOGRLSTM model optimized with the Fire Hawk algorithm achieved R^2 values above 0.996 for both polycrystalline and monocrystalline PV arrays [15]. Several machine learning models, including Random Forest and XGBoost, were evaluated across forecast horizons from 0.5 to 24 hours, with Random Forest giving the best average R^2 of 0.89 [16]. A comparison of BiLSTM, LSTM, and XGBoost for solar energy forecasting showed that BiLSTM slightly outperformed LSTM with a test RMSE of 0.1186 versus 0.1187, while XGBoost exhibited strong training fit but weaker generalization [17]. A decomposition-based hybrid model combining EEMD, LSTM, XGBoost, and the Snake Optimizer achieved R^2 values around 0.996 after signal decomposition [18].

An MLPLSTMGA hybrid model for both electrical consumption and PV generation forecasting reported near-perfect R^2 values (0.9999) after genetic algorithm optimization [13]. A direct comparison between LSTM and GRU for solar power forecasting found that GRU outperformed LSTM, achieving a lower MAE (1.618 vs. 1.964) and a higher R^2 (0.9836 vs. 0.9733) [19]. A novel interval forecasting approach combining LSTM, XGBoost, kernel density estimation (KDE), and differential evolution achieved significantly narrower prediction intervals (PINAW of 0.122 at 95% confidence level) [20]. In the context of energy communities, Random Forest achieved the lowest RMSE (5.35 Wh), while GRU excelled in short-term irradiance forecasting [21]. A comparative review highlighted that LSTM offers superior accuracy but higher computational complexity, whereas Random Forest and XGBoost provide

a better balance [22]. Despite these advances, most existing works either rely heavily on metaheuristic optimisation, signal decomposition, or focus on a single model type. In contrast, the present study provides a direct comparison under identical preprocessing, feature engineering (14 features), and temporal windowing (36 steps) using three years of real-world DKASC data, supported by SHAP explainability and ablation analysis.

2. RESEARCH METHOD

2.1. Dataset Description

The dataset comprises three consecutive years of operational data (2023–2025) obtained from the DKASC photovoltaic system, with 100_DKA_M1_A_Phase_Active_Power selected as the target variable. The recorded variables encompass solar irradiance and core meteorological parameters, with data split chronologically into training (2023), validation (2024), and testing (2025) subsets as detailed in Table 1.

Table 1. Summary of the dataset across the three years (after preprocessing)

Year	Split	Samples	Min Power (W)	Max Power (W)	Mean Power (W)	Std Power (W)
2023	Training	101,175	0.0	1674.9	344.9	488.6
2024	Validation	103,356	0.0	1674.3	331.8	471.4
2025	Testing	105,179	0.0	1641.2	337.5	471.5

Note: The number of samples is approximate (assuming 5-minute intervals for a full year: $365 \times 24 \times 12 = 105,120$). Max power = $1.6413 \text{ kW} = 1641.3 \text{ W}$; mean power = $0.3373 \text{ kW} = 337.3 \text{ W}$.

2.2. Data Preprocessing

Several preprocessing steps were applied before model development:

- **Missing values** were handled using linear interpolation followed by backward-fill and forward-fill. Any remaining missing values were replaced with zeros.
- **Invalid or negative power values** (due to sensor noise) were clipped to zero: $y = \max(y, 0)$. Similarly, negative radiation values were set to zero.
- **Wind direction** (measured in degrees) was transformed into sine and cosine components to preserve its cyclical nature: $\text{wind_dir_sin} = \sin(\theta \times \pi/180)$, $\text{wind_dir_cos} = \cos(\theta \times \pi/180)$.
- **Timestamp information** was converted into cyclical temporal features. Hour of day: $\text{hour_sin} = \sin(2\pi \times \text{hour}/24)$, $\text{hour_cos} = \cos(2\pi \times \text{hour}/24)$. Day of year: $\text{day_sin} = \sin(2\pi \times \text{day}/365)$, $\text{day_cos} = \cos(2\pi \times \text{day}/365)$.

Fourteen input variables made up the final feature set: temperature, relative humidity, wind speed, wind direction (sine and cosine), global horizontal radiation, diffuse horizontal radiation, global tilted radiation, diffuse tilted radiation, daily rainfall, hour sine, hour cosine, day sine, and day cosine. To guarantee numerical stability, all features were normalized to the range [0,1] using Min-Max scaling.

2.3. Time-Series Window Construction

To capture temporal dependencies in PV generation, a sliding-window approach was employed. A fixed window size of 36 consecutive observations (approximately 3 hours, given a 5-minute sampling interval) was used. For each prediction sample, the previous 36 time steps were provided as model input, while the power value at the next time step was used as the prediction target. Formally, the input sequence is $X_t = \{x_{t-35}, x_{t-34}, \dots, x_t\}$ and the corresponding target value is y_{t+1} . This strategy enables the models to learn temporal patterns and short-term dynamics in solar power production.

2.4. Prediction Models

Four machine learning and deep learning models were evaluated. All models were trained using the same training/validation/test split (2023/2024/2025) and were run three independent times with different random seeds to ensure statistical robustness.

1. Long Short-Term Memory (LSTM)

LSTM is a sophisticated recurrent neural network that uses gating methods to capture long-term relationships. The LSTM cell incorporates three multiplicative gates—the forget gate, input gate, and output gate—that regulate the flow of information by selectively retaining or discarding past states, thus mitigating the vanishing gradient problem commonly encountered in standard RNNs[24][25]. One LSTM layer with 64 hidden units, a 0.1 dropout rate, and a dense layer with linear activation make up the implemented architecture. Using mean squared error loss, the model was optimized using the Adam method (learning rate = 0.001). In order to reestablish the optimal weights, training was limited to 50 epochs with an early stopping patience of five periods depending on validation loss.

2. Gated Recurrent Unit (GRU)

A streamlined version of the LSTM, the GRU combines the input and forget gates into a single update gate. Specifically, the GRU employs an update gate that determines how much of the past information to carry forward, and a reset gate that controls the integration of new input with the previous hidden state. It often requires fewer parameters and can be computationally more efficient [26][27]. The GRU model followed the same configuration as the LSTM: one GRU layer with 64 hidden units, a dropout layer (0.1), a dense output layer (1 neuron), and the same optimizer, loss function, and early stopping settings.

3. Random Forest (RF)

Random Forest is an ensemble learning technique that creates many decision trees and averages their predictions. The algorithm constructs each tree using a bootstrap sample of the training data (bagging) and randomly selects a subset of features at each split, which decorrelates the individual trees and enhances generalization. It is robust to overfitting and can capture nonlinear relationships without requiring feature scaling [28][29]. The RF regressor was configured with 50 decision trees ($n_estimators = 50$), a maximum tree depth of 12 ($max_depth = 12$), and parallel processing enabled ($n_jobs = -1$).

4. Extreme Gradient Boosting (XGBoost)

XGBoost is a tree boosting technique that uses regularization to avoid overfitting and produces trees in a sequential fashion, each of which fixes the mistakes of its predecessor by focusing on the residuals of the previous trees. Unlike Random Forest, which builds trees independently, XGBoost employs a gradient-based optimization framework that minimizes a regularized objective function combining a loss term and penalty terms for model complexity (L1 and L2 regularization), which controls overfitting and enhances predictive performance [30][31]. The XGBoost model was configured with 500 boosting rounds, maximum tree depth of 8, learning rate of 0.03, subsample ratio of 0.8, column sampling ratio of 0.8, and objective function: `reg:squarederror`.

2.5. Model Evaluation

Each model was trained and assessed three times independently using distinct random seeds in order to guarantee outcome stability. The obtained metrics' mean $\pm$ standard deviation matches the stated data. Four commonly used regression measures were used to evaluate the model's performance: Mean Absolute Error (MAE), Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Samples with genuine power ≤ 0.01 W were not included in MAPE in order to prevent numerical instability (safe MAPE).

2.6. Feature Importance Analysis

The trained model's feature significance was derived using the built-in `feature_importances` attribute. Importance scores were aggregated across all 36 time lags to obtain a single importance value per original feature. This allowed the identification of the most influential variables affecting PV power prediction.

2.7. Ablation Study

To assess the contribution feature groups, an ablation study was carried out. Six experimental configurations were taken into account:

1. Full Features – all 14 variables.
2. Without Radiation – removal of the four radiation variables.
3. Without Time – removal of the four cyclical time features (hour_sin, hour_cos, day_sin, day_cos).
4. Without Weather – removal of temperature, humidity, wind speed, wind direction (sin/cos), and daily rainfall.
5. Without Wind – removal of wind speed and wind direction sin/cos.
6. Radiation + Time Only – retention of only the four radiation variables and the four time variables.

Table 3. Feature importance obtained from XGBoost (aggregated over time lags)

Feature	Importance
radiation_global_horiz	0.4293
radiation_global_tilted	0.1664
hour_sin	0.1384
hour_cos	0.1014
temperature	0.0249
day_cos	0.0242
humidity	0.0232
wind_dir_sin	0.0220
wind_dir_cos	0.0200
radiation_diffuse_horiz	0.0153
radiation_diffuse_tilted	0.0152
daily_rainfall	0.0115
day_sin	0.0083
wind_speed	0.0000

2.8. SHAP Explainability Analysis

To enhance model interpretability, SHAP (SHapley Additive exPlanations) [32][33] analysis was applied to the final XGBoost model. SHAP values were computed using a subset of the test dataset (500 samples) and subsequently aggregated across the temporal window to obtain a per-original-feature importance score. Three types of visualisations were generated: a SHAP bar plot (aggregated absolute SHAP values per original feature), a SHAP summary plot (scatter plot showing the distribution of SHAP values for the top 20 time-lagged features), and a SHAP waterfall plot (detailed decomposition of a single prediction).

2.9. Visual Diagnostics

For the XGBoost model, additional diagnostic plots were created to visually assess prediction quality: a scatter plot of actual versus predicted power (with a diagonal reference line), a residuals plot (sequence of prediction errors over the test set to detect systematic bias), and a time series comparison (overlay of actual and predicted power for the first 1000 test samples to visually evaluate temporal tracking).

3. RESULTS AND DISCUSSION

3.1. Comparative Model Performance

The performance of the four prediction models on the 2025 test set is summarized in Table 4. Each value is the mean $\pm$ standard deviation over three independent runs.

Table 4. Comparative performance of forecasting models

Model	R ²	RMSE (W)	MAE (W)	MAPE (%)
LSTM	0.9647 $\pm$ 0.0026	88.40 $\pm$ 3.30	36.20 $\pm$ 2.90	22.63 $\pm$ 1.24
GRU	0.9512 $\pm$ 0.0058	103.90 $\pm$ 6.30	39.70 $\pm$ 3.50	24.09 $\pm$ 2.25
Random Forest	0.9075 $\pm$ 0.0001	143.34 $\pm$ 0.04	52.89 $\pm$ 0.04	31.73 $\pm$ 0.02
XGBoost	0.9463 $\pm$ 0.0022	109.20 $\pm$ 2.20	39.80 $\pm$ 0.40	19.18 $\pm$ 0.14

As presented in Table 4, the LSTM model demonstrated the highest predictive accuracy ($R^2 = 0.9647$, $RMSE = 88.40$ W), confirming its superior capability in capturing temporal dependencies. Conversely, Random Forest yielded the weakest baseline ($R^2 = 0.9075$, $RMSE = 143.34$ W). Under the 36-step sliding window which generates 504 lagged inputs, tabular ensemble models faced an expanded feature space prone to high collinearity and the curse of dimensionality. However, empirical findings revealed a sharp divergence in mitigation: XGBoost showed exceptional resilience to overfitting, achieving a robust R^2 of 0.9463 and the lowest overall MAPE (19.18% plus or minus 0.14%) due to its built-in L1/L2 regularization and sparsity-aware splitting. In contrast, Random Forest's random feature sampling at each split point frequently selected sub-optimal, highly collinear lagged candidates, thereby degrading its structural predictive capacity.

3.2. Feature Importance

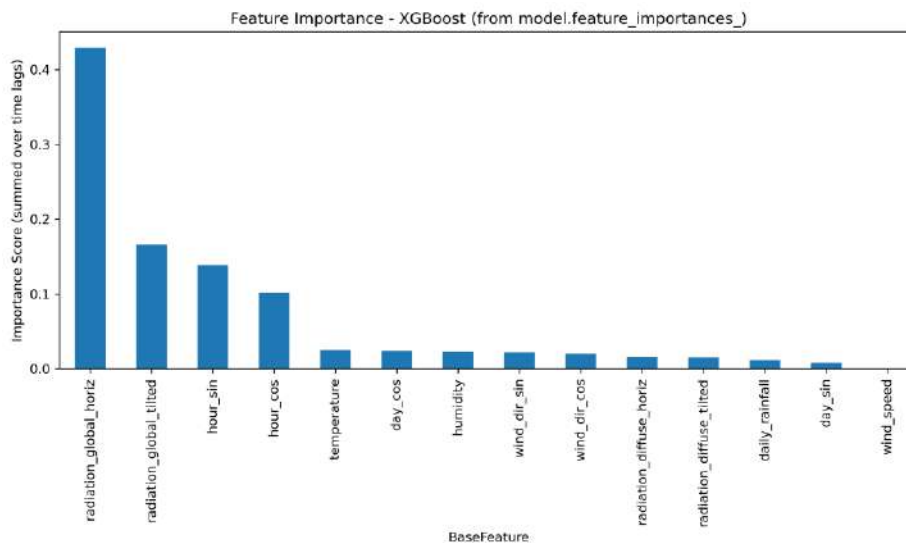


Figure 1. Feature importance from XGBoost (aggregated over time lags).

Figure 1 shows the feature importance from XGBoost (aggregated over time lags). Global horizontal radiation is the dominant factor (importance 0.4293), followed by global tilted radiation (0.1664) and hour sine (0.1384). Wind speed shows negligible importance (≈ 0.0000). These results are physically consistent with PV energy conversion principles.

3.4 Ablation Study

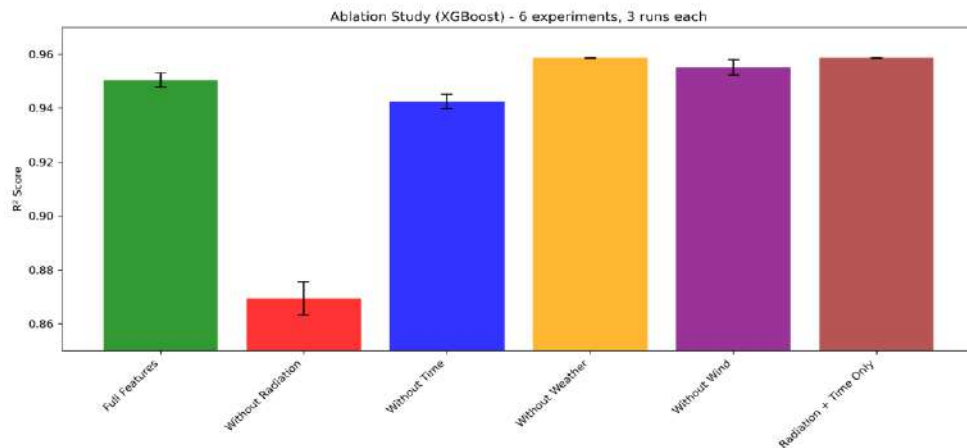


Figure 2. shows the ablation study results (R^2 for six feature sets).

Table 5. Mean absolute SHAP values

Rank	Feature	Mean SHAP
1	Radiation Global Horizontal	0.131
2	Day Cos	0.122
3	Radiation Global Tilted	0.078
4	Hour Cos	0.028
5	Wind Direction Sin	0.025
6	Radiation Diffuse Horizontal	0.018
7	Temperature	0.017
8	Radiation Diffuse Tilted	0.016
9	Humidity	0.014
10	Hour Sin	0.012

Table 6. Ablation study results (XGBoost, mean $R^2 \pm$ std over 3 runs)

Feature Set	Num Features	$R^2 \pm$ std	% Change
Full Features	14	0.9505 ± 0.0027	0.00
Without Radiation	10	0.8694 ± 0.0062	-8.53
Without Time	10	0.9424 ± 0.0027	-0.85
Without Weather	8	0.9587 ± 0.0003	+0.87
Without Wind	11	0.9552 ± 0.0029	+0.50
Radiation + Time Only	8	0.9587 ± 0.0003	+0.87

The most severe performance degradation occurs when radiation variables are removed (R^2 drops from 0.9505 to 0.8694, a -8.53% change). Removing time features causes only a minor decrease (-0.85%). Interestingly, removing weather variables (temperature, humidity, wind, rainfall) slightly improves R^2 (+0.87%), suggesting that some of these variables introduce noise. The Radiation + Time Only configuration achieves the highest R^2 (0.9587), indicating that irradiance and temporal information alone are sufficient for accurate prediction.

3.5 SHAP Explainability

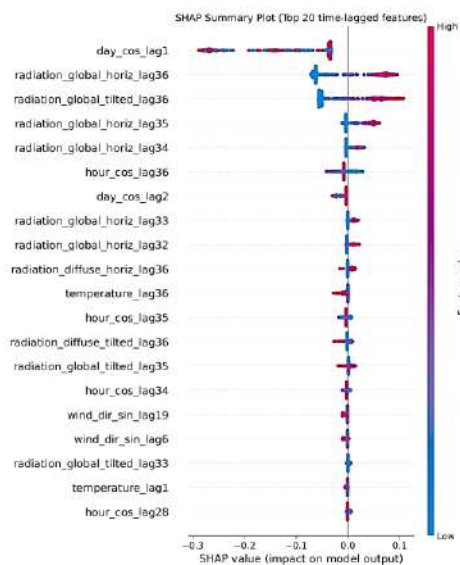


Figure 3. SHAP summary plot (top 20 time lagged)

Figure 3 presents the SHAP summary plot, which provides a comprehensive overview of the contribution of the most influential features to the XGBoost model predictions. The results indicate that solar irradiance variables, particularly global horizontal radiation and global tilted radiation, have the strongest impact on photovoltaic power forecasting. Higher irradiance values are generally associated with positive SHAP values, leading to increased predicted power output, whereas lower irradiance values contribute negatively to the prediction. Temporal features, especially `day_cos` and `hour_cos`, also exhibit substantial influence, reflecting the seasonal and diurnal patterns inherent in photovoltaic power generation. In contrast, variables such as wind speed and daily rainfall show relatively small SHAP contributions, indicating a limited effect on forecasting performance. Overall, the SHAP analysis confirms that irradiance and temporal information are the primary drivers of PV power prediction and supports the findings obtained from the feature importance and ablation analyses, thereby enhancing the interpretability and reliability of the proposed forecasting framework.

4. CONCLUSION

In this study, three years of actual operational data (2023–2025) from the DKASC database were used to create and assess four forecasting models for photovoltaic (PV) power prediction: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Random Forest (RF), and XGBoost. A sliding window of 36 time steps (three hours) was employed to capture temporal dependencies, and a comprehensive feature engineering process was carried out, resulting in fourteen input variables that included multiple irradiance components, meteorological measurements, wind characteristics, daily rainfall, and cyclical time features (hour and day of year). All models were trained on 2023 data, validated on 2024 data, and tested on unseen 2025 data, with each experiment repeated three times to report mean $\pm$ standard deviation.

The LSTM model achieved the highest overall performance, attaining an R^2 score of 0.9647, the lowest RMSE (88.40 W), and the lowest MAE (36.20 ± 2.90 W). XGBoost, while slightly lower in R^2 (0.9463), delivered the best MAPE (19.18%), demonstrating its strength in relative-error minimization. GRU performed competitively ($R^2 = 0.9504$), whereas Random Forest yielded the weakest results, indicating limited capability in capturing complex nonlinear temporal patterns.

SHAP analysis identified global horizontal radiation as the most influential variable, followed by `day_cos`, global tilted radiation, and `hour_cos`. Time features contributed significantly, while wind speed and daily rainfall had negligible impact. The ablation study confirmed that removing radiation variables caused a drastic drop in R^2 (−8.53%), whereas eliminating weather variables (temperature, humidity, wind, rainfall) slightly improved performance, suggesting that some meteorological variables may

introduce noise. The ‘Radiation + Time Only’ configuration achieved the highest R^2 (0.9587), indicating that irradiance and temporal information alone are sufficient for accurate PV power forecasting.

More sophisticated like transformer-based models (like Informer and Temporal Fusion Transformer), which have demonstrated potential in long-sequence forecasting, may be investigated in future research. Multi-step ahead forecasting and probabilistic forecasting to quantify prediction uncertainty are also valuable directions. Furthermore, future work will explore advanced feature extraction techniques to alleviate the dimensionality of the sliding window for tabular models. Finally, deploying the best-performing model (LSTM or XGBoost) in a real-time edge computing environment for on-site PV power prediction would constitute a practical extension of this research.

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Evaluation of STIESIA E-Learning User Experience Using User Experience Questionnaire in the Implementation of Blended Learning

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ABSTRACT

This study evaluates user experience (UX) of STIESIA Surabaya's e-learning platform within its blended learning program, with the aim of identifying specific strengths and gaps. Using a quantitative descriptive-evaluative design, researcher distributed User Experience Questionnaire (UEQ) to 90 Accounting and Management students, each with at least one semester of platform use. After screening 96 initial submissions, researcher analyzed 90 verified responses against a UEQ benchmark of more than 20.000 products. All six dimensions scored positively in absolute terms. Perspicuity rated highest (1.33 Above Average), followed by Attractiveness (1.20) and Efficiency (1.13), and Stimulation (1.13), all above average. Dependability (1.00) and Novelty (0.43) fell Below Average against benchmark. An independent t-test found no significant differences between programs. Platform handles core pragmatic tasks well but shows relative weakness in novelty and dependability, which points to a need for user-centered investigation before any institution-wide redesign.



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1. INTRODUCTION

Blended learning is now a common model across Indonesian universities, combining face to face instruction with online components to give students more flexibility in accessing course materials and activities[1]. Some research suggest a mix of 70-80% online and 20-30% in person instruction works well in certain contexts[2], but exact ratio matters less than whether supporting platform is one students can actually use. At STIESIA, blended learning means regular classroom sessions supplemented by mandatory online activities: content delivery, assignment submission, discussion forums, and assessments, all run through a dedicated e-learning platform.

COVID-19 forced most institutions to move fully online within weeks. Blended models that followed were often built with little time to check whether underlying platforms actually worked[3]. STIESIA Surabaya, a private university with roughly 1.500 active students, runs its blended programme on a home-grown e-learning platform. Having a platform in place, however, does not guarantee that students learn well from it. Prior research shows that poor platform design leads students to disengage, get frustrated, and find workarounds that defeat purpose of blended learning in first place[4].

ISO 9241-210 defines user experience as everything a person perceives, feels, and concludes when interacting with a system[5]. In an e-learning context, those responses are not separate from learning,

they shape how much students engage with material and how much stays with them. A study from UAE found that student's overall judgment of whether blended learning was working for them was closely tied to how well platform itself held up[6]. That finding has a practical consequence: assessing platform's UX is not an optional audit. It is the only way to know what students are actually experiencing when they log in.

This study asks four questions: (1) How does STIESIA's e-learning platform score across six UEQ dimensions? (2) How do students perceive blended learning experience platform is meant to support? (3) which dimensions receive highest and lowest ratings? and (4) What patterns of strength and weakness emerge from dimensional scores? Fourth question stays descriptive by design, focused on interpreting score patterns rather than claiming what causes them. Any insight into underlying causes comes from open-ended survey responses, analysed through thematic coding to identify recurring themes.

Study uses User Experience Questionnaire (UEQ), developed by Martin Schrepp[7]. Instrument covers three pragmatic dimensions (Perspicuity, Efficiency, and Dependability) and two hedonic dimensions (Stimulation, and Novelty), plus an overall Attractiveness score [8]. Students complete it in three to five minutes, which made total sampling across full cohort practical. UEQ also comes with an international benchmark database, so STIESIA's results can be compared against data from more than 20.000 commercial and non-commercial products rather than read in isolation[9].

Scores run on a -3 to +3, and official UEQ guidelines use two separate interpretations. First concerns practical significance: scores above +0.8 count as positive, scores between -0.8 and +0.8 as neutral, and scores below -0.8 as negative. Second is benchmark based classification, which places a score into one of five categories, Excellent, Good, Above Average, Below Average, or Bad, using percentile cutoffs specific to each dimension and to the benchmark dataset's version[10]. These two interpretations answer different questions: first tells you whether a score is favourable in absolute terms, second tells you where platform stands relative to a large reference sample. This study reports both, using official UEQ Data Analysis Tool (www.ueq-online.org. version 14 2024) to compute means, confidence intervals, and benchmark comparisons[11]. Data were collected through a quantitative, descriptive-evaluative design using total sampling.

2. RESEARCH METHOD

This study used a quantitative descriptive-evaluative approach to assess user experience (UX) on STIESIA Surabaya's e-learning platform in a blended learning context. Main instrument was the User Experience Questionnaire (UEQ), a validated tool with 26 pairs of opposing adjectives rated on a 7 point scale (-3 to +3), covering six dimensions: Attractiveness, Perspicuity, Efficiency, Dependability, Stimulation, and Novelty. Table 1 lists each dimension with its corresponding indicators and item numbers.

Table 1. Parameter UEQ

Variable	Indicator	Number Indicator
Attractiveness	Annoying / Enjoyable	1
	Bad / Good	12
	Unlikeable / Pleasing	14
	Unpleasant / Pleasant	16
	Unattractive / Attractive	24
	Unfriendly / Friendly	25
Perspicuity	Not understandable / Understandable	2
	Difficult to learn / Easy to learn	4
	Complicated / Easy	13
	Confusing / Clear	21
Efficiency	Slow / Fast	9
	Inefficient / Efficient	20
	Impractical / Practical	22
	Cluttered / Organized	23

Variable	Indicator	Number Indicator
Dependability	Unpredictable / Predictable	8
	Obstructive / Supportive	11
	Not secure / Secure	17
	Does not meet expectations / Meet Expectations	19
Stimulation	Inferior / Valuable	5
	Boring / Exciting	6
	Not interesting / Interesting	7
	Demotivating / Motivating	18
Novelty	Dull / Creative	3
	Conventional / Inventive	10
	Usual / Leading edge	15
	Conservative / Innovative	26

2.1. Population and Sample

Institutional population comprises all active students at STIESIA Surabaya (approximately 1.500). accessible population, however, was defined more narrowly: all students enrolled in two courses taught by researcher during odd semester of 2025/2026 academic year, one in the Accounting programme and one in the Management programme, who had used e-learning platform for at least one prior semester. This accessible frame totalled 90 students across two course sections.

Because this number was relatively small, a total sampling (census) approach was applied: all 90 eligible students were invited to participate ($n=N=90$). Intent was to maximise data coverage within this specific cohort, not to claim representativeness of entire institutional student body[12]. Sampling frame was chosen for practical reasons: manageable data access, researcher's first-hand knowledge of platform use in these course, and a semester long research timeline. Including both Accounting and Management sections also allowed for exploratory cross programme comparisons.

Drawing sample from researcher's own classes introduces potential convenience selection bias and may limit generalizability to other courses, instructors, or semesters. To reduce authority or coercion effects, participation was entirely voluntary, and questionnaire was administered anonymously through an external platform (Google Forms) with no students identifiers linked to responses. Student were told, both invitation on the first page of the form, that participating or withdrawing would have no effect on their course grades or academic standing.

2.2. Instrument and Data Collection

Data were collected using UEQ questionnaire, distributed online via Google Forms. Form had three sections: respondent demographics, 26 UEQ items, and open-ended questions on contextual factors in blended learning experience.

Before full distribution, a pilot test was run with 10 respondents drawn from same accessible population but not enrolled in two target course sections. Pilot checked item clarity, readability, and estimated completion time. No major wording changes were needed, minor formatting adjustments improved display on mobile devices. These 10 pilot respondents were excluded from final analysis to avoid data contamination. Main data collection ran for four weeks, with reminder prompts sent in second and third weeks to sustain response rates.

Institutional permission was obtained before data collection began. All participants gave informed consent via a checkbox on the first page of the online form. Respondents were assured of anonymity, data confidentiality, and right to withdraw at any point without consequence. Only aggregated, non identifiable data are reported.

	1	2	3	4	5	6	7		
annoying	☐	☐	☐	☐	☐	☐	☐	enjoyable	1
not understandable	☐	☐	☐	☐	☐	☐	☐	understandable	2
creative	☐	☐	☐	☐	☐	☐	☐	dull	3
easy to learn	☐	☐	☐	☐	☐	☐	☐	difficult to learn	4
valuable	☐	☐	☐	☐	☐	☐	☐	inferior	5
boring	☐	☐	☐	☐	☐	☐	☐	exciting	6
not interesting	☐	☐	☐	☐	☐	☐	☐	interesting	7
unpredictable	☐	☐	☐	☐	☐	☐	☐	predictable	8
fast	☐	☐	☐	☐	☐	☐	☐	slow	9
inventive	☐	☐	☐	☐	☐	☐	☐	conventional	10
obstructive	☐	☐	☐	☐	☐	☐	☐	supportive	11
good	☐	☐	☐	☐	☐	☐	☐	bad	12
complicated	☐	☐	☐	☐	☐	☐	☐	easy	13
unlikable	☐	☐	☐	☐	☐	☐	☐	pleasing	14
usual	☐	☐	☐	☐	☐	☐	☐	leading edge	15
unpleasant	☐	☐	☐	☐	☐	☐	☐	pleasant	16
secure	☐	☐	☐	☐	☐	☐	☐	not secure	17
motivating	☐	☐	☐	☐	☐	☐	☐	demotivating	18
meets expectations	☐	☐	☐	☐	☐	☐	☐	does not meet expectations	19
inefficient	☐	☐	☐	☐	☐	☐	☐	efficient	20
clear	☐	☐	☐	☐	☐	☐	☐	confusing	21
impractical	☐	☐	☐	☐	☐	☐	☐	practical	22
organized	☐	☐	☐	☐	☐	☐	☐	cluttered	23
attractive	☐	☐	☐	☐	☐	☐	☐	unattractive	24
friendly	☐	☐	☐	☐	☐	☐	☐	unfriendly	25
conservative	☐	☐	☐	☐	☐	☐	☐	innovative	26

Figure 1. Indicator and Scale UEQ

2.3. Data Analysis

Responses were cleaned for outliers and internal consistency using UEQ Data Analysis Tool[10], and each score was converted from 7-point scale to the -3 to +3 range. Dimensional averages were then computed with 95% confidence intervals and benchmarked against UEQ reference database (over 20.000 products), which classifies performance into five tiers: Excellent (>1.75), Good (0.80-1.75), Above Average (0.52-0.80), Below Average (0.00-0.52), and Bad (<0.00)[9]. An independent samples t-test was run to compare UX perceptions between Accounting and Management groups, and open-ended responses on blended learning context were analyzed descriptively[13].

3. RESULTS AND DISCUSSION

Data were collected via an online Google Form over four weeks, with reminder prompts sent in the second and third weeks to encourage participation. A total of 96 initial submissions were received. After screening for completeness and potential duplicates, six responses were excluded, resulting in a final verified sample of 90 respondents fully matching defined accessible population. Final sample comprised 50 Accounting students (55,6%) and 40 Management students (44,4%), as shown in Table 2. This verified sample serves as basis for all subsequent analyses.

Table 2. Respondent Profile

Study Program	Frequency (n)	Percentage (%)
S1 Akuntansi	50	55,6%
S1 Manajemen	40	44,4%
Total	90	100%

3.1. Evaluation of E-Learning User Experience

A total of 90 verified responses were processed using UEQ Data Analysis Tool (Version 14, obtained from official website in July 2026) at www.ueq-online.org. Tool converts raw 1-7 scale values to a -3 to +3 transformed scale and computes item level and dimension level descriptive statistics.

Item	Mean	Variance	Std. Dev.	No.	Left	Right	Scale
1	1.2	1.8	1.3	90	annoying	enjoyable	Attractiveness
2	1.5	1.4	1.2	90	not understandable	understandable	Perspicuity
3	0.7	2.7	1.7	90	creative	dull	Novelty
4	1.1	2.6	1.6	90	easy to learn	difficult to learn	Perspicuity
5	1.6	2.3	1.5	90	valuable	inferior	Stimulation
6	0.7	1.5	1.2	90	boring	exciting	Stimulation
7	0.9	1.7	1.3	90	not interesting	interesting	Stimulation
8	0.1	2.0	1.4	90	unpredictable	predictable	Dependability
9	0.3	2.5	1.6	90	fast	slow	Efficiency
10	0.0	2.3	1.5	90	inventive	conventional	Novelty
11	1.5	1.5	1.2	90	obstructive	supportive	Dependability
12	1.4	1.8	1.3	90	good	bad	Attractiveness
13	1.3	1.3	1.1	90	complicated	easy	Perspicuity
14	0.9	1.5	1.2	90	unlikable	pleasing	Attractiveness
15	0.4	1.9	1.4	90	usual	leading edge	Novelty
16	1.4	1.4	1.2	90	unpleasant	pleasant	Attractiveness
17	1.4	2.2	1.5	90	secure	not secure	Dependability
18	1.3	1.8	1.3	90	motivating	demotivating	Stimulation
19	1.0	1.7	1.3	90	meets expectations	does not meet expectations	Dependability
20	1.5	1.2	1.1	90	inefficient	efficient	Efficiency
21	1.4	1.9	1.4	90	clear	confusing	Perspicuity
22	1.3	1.9	1.4	90	impractical	practical	Efficiency
23	1.4	2.0	1.4	90	organized	cluttered	Efficiency
24	0.9	1.6	1.3	90	attractive	unattractive	Attractiveness
25	1.4	1.5	1.2	90	friendly	unfriendly	Attractiveness
26	0.6	1.9	1.4	90	conservative	innovative	Novelty

Figure 2. Item Average

Three lowest scoring items were item 10 Inventive vs Conventional (0.0, Novelty dimension), item 8 Unpredictable vs Predictable (0.1, Dependability dimension), and item 9 Fast vs Slow (0.3, Efficiency dimension)

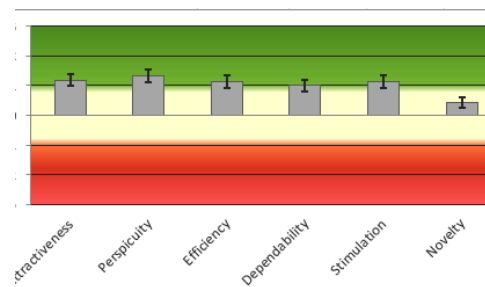


Figure 3. 6 UEQ

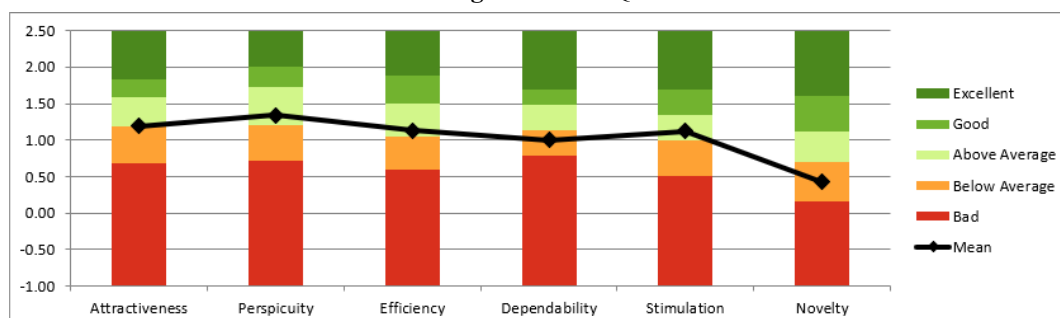


Figure 4. Benchmark UEQ

Under standard UEQ absolute interpretation, scores between -0.8 and +0.8 count as neutral in practical terms. These three item scores fall in that range, so they indicate neither strong dissatisfaction nor positive endorsement. Students do not perceive platform as notably conventional, unpredictable, or slow, but they do not rate these aspects as strong points either.

All six dimension means were positive. Two separate interpretive lenses apply to these results. First is absolute interpretation, or practical significance, scores above +0.8 count as positive, scores between -0.8 and +0.8 as neutral, and scores below -0.8 as negative. Second is benchmark classification, which places each score against a reference database of more than 20,000 product evaluations built into Version

14 of the tool. In this classification, Above Average means 25% of products in database score higher and 50% score lower, while Below Average means 50% score higher and 25% score lower.

Table 3 reports dimension means, standard deviations, 95% confidence intervals, benchmark classifications, and percentile interpretations.

Table 3 UEQ Benchmark Classification

UEQ Dimension	Mean	Std. Dev	95% CI	Classification	Interpretation
Attractiveness	1.20	1.24	[0.94, 1.46]	Above Average	25% score higher, 50% score lower
Perspicuity	1.33	1.23	[1.07, 1.59]	Above Average	25% score higher, 50% score lower
Efficiency	1.13	1.25	[0.87, 1.39]	Above Average	25% score higher, 50% score lower
Dependability	1.00	1.28	[0.73, 1.27]	Below Average	50% score higher, 25% score lower
Stimulation	1.13	1.28	[0.86, 1.40]	Above Average	25% score higher, 50% score lower
Novelty	0.43	1.42	[0.13, 0.73]	Below Average	50% score higher, 25% score lower

In absolute terms, Perspicuity (1.33), Attractiveness (1.20), Efficiency (1.13), Stimulation (1.13) and Dependability (1.00) all exceed +0.8 threshold, which confirms a practically positive perception on each. Students find platform easy to learn, visually acceptable, efficient for routine tasks, reasonably motivating, and sufficiently reliable. Against benchmark, first four dimensions rank Above Average, platform outperforms median product in reference database on these measures.

Dependability (1.00) is positive in absolute terms but falls Below Average against benchmark. Low score on predictability (Item 8 = 0.1) suggests that occasional inconsistencies in system feedback or navigation responses may mildly undermine user confidence. This does not point to a critical failure, but it does mark an area worth refining.

Novelty (0.43) is lowest scoring dimension. It sits inside neutral range in absolute terms (between -0.8 and +0.8) and Below Average against benchmark. Students do not actively dislike platform's creativity or innovation. They simply do not experience it as modern or cutting-edge. This matches Santoso, who found that educational platforms often prioritize functional pragmatism over hedonic qualities such as visual originality and contemporary interaction design[14]. Score points to room for interface improvement rather than to user dissatisfaction or a barrier to learning.

3.2. Comparative Analysis

To check whether UX perceptions differed between Accounting and Management students, an independent samples t-test was run for each of six UEQ dimensions. Shapiro-wilk test and Q-Q plots assessed normality, Levene's test checked homogeneity of variances, and assumptions held reasonably well across all scales. Table 4 reports group descriptive statistics, mean differences, 95% confidence intervals, test statistics, and effect sizes (Cohen's d).

Table 4. Comparative Analysis

UEQ Dimension	Accounting Mean (SD)	Management Mean (SD)	Mean Diff	95% CI of Diff	t-value	df	p-value	Cohen's d
Attractiveness	1.21 (1.24)	1.19 (1.25)	0.02	[-0.50, 0.54]	0.08	88	0.938	0.02
Perspicuity	1.35 (1.23)	1.31 (1.24)	0.04	[-0.48, 0.56]	0.15	88	0.881	0.03
Efficiency	1.14 (1.25)	1.12 (1.26)	0.02	[-0.50, 0.54]	0.08	88	0.938	0.02
Dependability	1.02 (1.28)	0.98 (1.29)	0.04	[-0.49, 0.57]	0.15	88	0.881	0.03
Stimulation	1.12 (1.27)	1.14 (1.30)	-0.02	[-0.55, 0.51]	-0.08	88	0.938	-0.02
Novelty	0.44 (1.42)	0.42 (1.43)	0.02	[-0.57, 0.61]	0.07	88	0.948	0.01

Across all six dimensions, p-values exceed 0.05, and 95% confidence intervals for mean differences cross zero. Cohen's d effect sizes are negligible, ranging from 0.01 to 0.03.

These results need a cautious reading. Failing to reject null hypothesis does not prove two groups are identical or practically indistinguishable. It only means that, within this specific cohort and sample, data do not support a program based distinction.

Sampling frame itself limits how far this reading can go, it comprised two courses taught by same researcher. Shared course content, similar assignment structures, or instructor specific effects could produce this uniformity and mask real program level differences that exist elsewhere. At most, findings show that within this semester and these two courses sections, students from both programs reported comparable UX perceptions. This offers preliminary evidence that UX issues such as low novelty relative to benchmark are unlikely to be tied strongly to academic discipline. It does not establish that a single institution wide intervention will benefit all students equally across every course, instructor, or academic year[15].

4. CONCLUSION

STIESIA Surabaya's e-learning platform shows positive pragmatic usability across most UEQ dimensions: Perspicuity (1.33), Attractiveness (1.20), Efficiency (1.13), and Stimulation (1.13) all score above +0.8 and rank Above Average against benchmark, while Dependability (1.00) and Novelty (0.43) are positive to neutral in absolute terms but Below Average against reference database. Comparative analysis found no statistically significant differences between Accounting and Management students in this sample, but that absence of significance should not be read as proof of program wide uniformity, given limited sampling frame (two courses, one instructor, one semester) and potential confounding factors involved. These results offer a diagnostic baseline rather than a prescriptive roadmap: UEQ identifies where platform falls short but does not reveal which specific interface features or functional issues drive Novelty and Dependability scores. Rather than move straight to a broad visual redesign, institution should first run task-based usability testing and semi structured interviews with a more diverse student sample, expand survey to additional courses and instructors, and use those qualitative findings to guide targeted, pilot tested improvements before any institution-wide rollout.

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Optimal Solar PV Capacity Planning in Bangka Power System Using Grey Wolf Optimizer

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ABSTRACT

This study develops a simplified optimization-based framework to determine the optimal Solar Photovoltaic (PV) capacity for the Bangka power system by combining an annual cost-minimization model with the Grey Wolf Optimizer (GWO). Annual electricity demand is supplied by PV and system-level fossil-based generation, while total annual cost comprises annualized PV investment, PV operation and maintenance (O&M), and fossil generation costs. Three scenarios are evaluated: a baseline without PV, a fixed-PV capacity of 50 MW, and a GWO-optimized PV capacity bounded between 0 and 150 MW. The calculations and GWO procedure are implemented in Python 3.10 using 30 wolves, 100 iterations, and 20 independent runs. All runs converge to the upper feasible capacity of 150 MW. At this capacity, PV generation reaches 236.52 GWh/year, representing 15.6% of annual electricity demand, compared with 78.84 GWh/year or 5.2% in the fixed-PV scenario. Fossil generation cost decreases from 181.73 to 153.35 million USD/year. After including 13.75 million USD/year in annualized PV investment and 2.25 million USD/year in PV O&M costs, the total annual system cost reaches 169.35 million USD/year, yielding net savings of approximately 12.38 million USD/year relative to the baseline. Annual CO₂ emissions decrease from 1211.54 to 1022.32 ktCO₂/year, corresponding to a reduction of approximately 189.22 ktCO₂/year. Within the adopted annual model assumptions, the 150 MW configuration provides the lowest cost and emissions among the evaluated alternatives and represents a boundary optimum.



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1. INTRODUCTION

The increasing demand for electricity, combined with the need to reduce greenhouse gas emissions, has accelerated the transformation of power systems worldwide [1]. In many developing regions, including Indonesia, electricity generation remains largely dependent on fossil fuel-based technologies, particularly coal and diesel power plants [2]. This dependency leads to high operational costs due to fuel consumption and contributes significantly to carbon emissions [3]. Therefore, integrating renewable

energy into existing power systems has become an essential strategy to support sustainable and low carbon energy transitions.

Regional and island power systems present distinct challenges compared to large interconnected grids [4]. The Bangka Belitung power system, for instance, operates as a semi-isolated system with limited interconnection capacity and a strong reliance on local generation units. Based on recent system data, the total installed capacity in the Bangka system is approximately 242 MW without transfer and increases to about 342 MW with power transfer from Sumatra. The system peak load reaches around 225 MW, indicating relatively tight operational margins [5]. In addition, a significant portion of generation is still supplied by diesel and small-scale thermal units, which are characterized by high fuel costs and emissions. These characteristics make the system particularly sensitive to changes in generation mix and highlight the importance of optimal capacity planning.

Solar Photovoltaic (PV) represents a promising renewable energy option for the Bangka Belitung region due to the high total solar irradiance in the Bangka Belitung Islands, which reaches approximately 4.95 kWh/m² day [6], as well as its modular deployment capability. The average daily load profile shows a peak demand of approximately 198.89 MW and annual energy consumption of about 1514.42 GWh [5], indicating a substantial opportunity for integrating solar based generation. However, determining the appropriate capacity of PV integration remains a critical challenge. Excessive PV capacity may lead to curtailment [7] or operational inefficiencies [8], while insufficient capacity may not significantly reduce fossil fuel dependency [9]. Therefore, an optimization-based approach is required to determine the optimal PV capacity that balances cost, reliability, and environmental performance.

Optimization techniques have been widely applied in power system planning to identify cost effective solutions [10]. While conventional optimization methods are effective for structured problems, they may become less flexible when dealing with nonlinear relationships and complex search spaces [11]. In this context, metaheuristic algorithms offer a practical alternative due to their simplicity and ability to explore a wide range of solutions [12]. Among these approaches, the Grey Wolf Optimizer (GWO) is a nature inspired metaheuristic algorithm that simulates the social hierarchy and cooperative hunting behavior of grey wolves [13]. The algorithm has attracted considerable attention in engineering optimization because of its strong convergence capability, balanced exploration and exploitation mechanisms, and ease of implementation [14].

This study aims to determine the optimal Solar PV capacity for the Bangka Belitung power system using the GWO and to evaluate its impact on system cost, fossil fuel consumption, and CO₂ emissions. Three scenarios are investigated, namely the baseline system without PV integration, a fixed PV capacity scenario, and a GWO-optimized PV capacity scenario. By focusing on a regional island power system with real operational characteristics, this study provides practical insights into renewable energy integration and system efficiency improvement. The remainder of this paper is organized as follows. Section 2 describes the proposed methodology, including the system model, mathematical formulation, and GWO algorithm. Section 3 presents and discusses the optimization results, while Section 4 concludes the study by summarizing the main findings and their implications for regional power system planning.

2. RESEARCH METHOD

An optimization-based framework is developed to determine the optimal Solar PV capacity for the Bangka power system by integrating a cost-minimization model with the GWO. The framework incorporates the objective function, system constraints, optimization procedure, and performance indicators to evaluate the economic and environmental performance of the optimized system.

2.1. Problem Formulation

This study addresses the determination of the optimal Solar PV capacity for the Bangka power system within a cost-minimization framework. The system is represented by a simplified annual aggregated model in which electricity demand is assumed to be known over the planning period and is supplied by two generation sources, namely Solar PV and fossil-fuel-based generation. This representation captures the fundamental trade-off between renewable energy integration and conventional generation while maintaining computational efficiency. The installed PV capacity, K_{PV}

(MW), is treated as the primary decision variable, whereas conventional generation operates as the balancing source to satisfy the remaining demand.

The annual electricity demand is denoted by E_{demand} (GWh/year), while PV generation, E_{PV} , is determined by the installed PV capacity, the PV capacity factor (CF_{PV}), and the annual operating hours (H). Fossil generation, E_{fossil} , supplies the unmet demand after accounting for PV generation, thereby ensuring energy balance throughout the planning horizon. Based on this formulation, the optimization problem evaluates the economic performance of different PV capacity levels and is subsequently solved using the GWO, as described in the following sections.

2.2. Objective Function

The optimization problem aims to minimize the total annual system cost, which represents the combined economic impact of Solar PV installation and fossil based electricity generation [15]. The total cost consists of three main components, namely the annualized PV investment cost, PV operation and maintenance cost, and fossil generation cost, as expressed in Eq. (1). This formulation captures the economic interaction between capital intensive renewable deployment and variable cost conventional generation. The objective function is expressed in annual monetary terms to ensure consistency among all cost components. As a result, the optimization identifies the most cost effective balance between PV integration and fossil based generation.

$$C_{\text{total}} = C_{PV, \text{ann}} + C_{PV, O\&M} + C_{\text{fossil}} \quad (1)$$

In Eq. (1), C_{total} denotes the total annual system cost expressed in USD/year. The first component, $C_{PV, \text{ann}}$, represents the annualized investment cost of Solar PV and is defined in Eq. (2). This cost converts the upfront capital expenditure (CAPEX) into an equivalent annual value using the capital recovery factor. The second component, $C_{PV, O\&M}$, accounts for the annual operation and maintenance cost of PV systems, as defined in Eq. (3). The third component, C_{fossil} , represents the cost of fossil-based electricity generation, which depends on the amount of fossil generation required to meet demand. Together, these components form a comprehensive representation of the system cost.

The annualized PV investment cost is calculated as:

$$C_{PV, \text{ann}} = K_{PV} \times CAPEX_{PV} \times CRF \quad (2)$$

In Eq. (2), K_{PV} is the installed PV capacity (MW), $CAPEX_{PV}$ is the capital cost (USD/MW), and CRF is the capital recovery factor (dimensionless). The multiplication of these terms results in a cost expressed in USD/year, which is consistent with Eq. (1). The use of annualized cost allows a fair comparison between investment and operational expenditures. This formulation ensures that long term capital costs are properly integrated into the annual cost structure. Therefore, Eq. (2) provides a realistic representation of PV investment cost within the optimization framework.

The PV operation and maintenance cost is defined as:

$$C_{PV, O\&M} = K_{PV} \times C_{PV}^{O\&M} \quad (3)$$

where $C_{PV}^{O\&M}$ is the O&M cost expressed in USD/MW/year. As shown in Eq. (3), the resulting unit is USD/year, which is consistent with Eqs. (1)-(2). This cost component captures the ongoing operational expenses associated with PV systems. Although typically smaller than capital costs, it contributes to the total system cost and must be included in the optimization. The linear relationship between capacity and O&M cost simplifies the formulation while maintaining accuracy. Thus, Eq. (3) ensures that operational costs are appropriately accounted for.

The fossil generation cost is calculated as:

$$C_{\text{fossil}} = E_{\text{fossil}} \times C_{\text{fossil}}^{\text{var}} \quad (4)$$

where E_{fossil} represents fossil-based electricity generation in MWh/year, while C_{fossil} denotes its system-level variable generation cost in USD/MWh. Fossil generation supplies the residual annual demand after accounting for PV generation; therefore, increasing PV capacity directly reduces fossil generation cost.

All cost components in Eq. (1) are expressed in consistent units of USD/year, ensuring dimensional coherence of the objective function. This consistency allows direct summation of all cost terms without additional conversion factors. The formulation establishes a clear relationship between capacity decisions and system cost. As a result, the optimization process can effectively identify the most economical level of PV integration. This objective function serves as the basis for evaluating and comparing different scenarios.

2.3. System Constraints

The optimization model is subject to a set of constraints that ensure the physical feasibility and operational consistency of the power system. These constraints describe the relationship between electricity demand, Solar PV generation, and fossil-fuel-based generation within an aggregated annual framework using consistent units. The primary constraint is the annual energy balance, which requires total electricity generation to satisfy annual electricity demand, as expressed in Eq. (5):

$$E_{PV} + E_{fossil} = E_{demand} \quad (5)$$

where E_{PV} , E_{fossil} , and E_{demand} are expressed in GWh/year. This equality ensures that all electricity demand is supplied without unmet demand or excess generation.

Solar PV generation is determined by the installed PV capacity, capacity factor, and annual operating hours, as given in Eq. (6):

$$E_{PV} = K_{PV} \times CF_{PV} \times H \quad (6)$$

where K_{PV} is the installed PV capacity (MW), CF_{PV} is the PV capacity factor, and H denotes the annual operating hours (8760 h/year). To ensure technical feasibility, the installed PV capacity is constrained within predefined limits:

$$0 \leq K_{PV} \leq K_{PV,max} \quad (7)$$

where $K_{PV,max}$ is the maximum allowable PV capacity (MW), representing practical limitations such as land availability, grid capability, and investment constraints.

Together, these constraints define the feasible search space explored by the optimization algorithm while maintaining energy balance and realistic PV deployment. Consequently, the optimization produces technically feasible and operationally consistent solutions for evaluating the economic and environmental performance of different PV integration levels.

2.4. Grey Wolf Optimizer

The optimization problem is solved using the GWO, a population-based metaheuristic inspired by the social hierarchy and cooperative hunting behavior of grey wolves. Each candidate solution represents an installed Solar PV capacity within the bounds defined in Eq. (7), and its quality is evaluated using the total annual cost objective in Eq. (1). During the optimization process, the three best candidate solutions are designated as the alpha (α), beta (β), and delta (δ) wolves. These leading wolves guide the remaining search agents toward promising regions of the solution space while maintaining a balance between exploration and exploitation.

The distance between a search agent and a leading wolf is calculated using Eq. (8), while the position of the search agent relative to that leader is updated using Eq. (9):

$$D = |C \cdot X_p - X| \quad (8)$$

$$X(t+1) = X_p - A \cdot D \quad (9)$$

where X is the current wolf position and X_p denotes the position of a leading wolf, namely α , β , or δ . The coefficient vectors A and C , which control the movement and search behavior of the wolves, are calculated using Eqs. (10) and (11), respectively:

$$A = 2ar_1 - a \quad (10)$$

$$C = 2r_2 \quad (11)$$

where r_1 and r_2 are random vectors in $[0, 1]$, while a decreases linearly from 2 to 0 throughout the iterations. This decreasing parameter gradually shifts the search from global exploration to local exploitation. Because the model contains one decision variable, the search space is one-dimensional and corresponds to the installed PV capacity, K_{PV} .

The influences of the alpha, beta, and delta wolves are combined to determine the updated position of each search agent using Eq. (12):

$$\begin{aligned} \mathbf{X}_1 &= \mathbf{X}_\alpha - \mathbf{A}_1 \cdot \mathbf{D}_\alpha \\ \mathbf{X}_2 &= \mathbf{X}_\beta - \mathbf{A}_2 \cdot \mathbf{D}_\beta \\ \mathbf{X}_3 &= \mathbf{X}_\delta - \mathbf{A}_3 \cdot \mathbf{D}_\delta \\ \mathbf{X}(t+1) &= \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3} \end{aligned} \quad (12)$$

In Eq. (12), D_α , D_β , and D_δ are calculated by applying Eq. (8) to the respective leading-wolf positions, while A_1 , A_2 , and A_3 are determined using Eq. (10). The updated wolf position is obtained from the average influence of the three leading wolves. After every update using Eq. (12), the candidate PV capacity is projected onto the feasible region defined in Eq. (7). The objective function in Eq. (1) is then reevaluated, and the process continues until the maximum number of iterations is reached. The best feasible solution at convergence is selected as the installed PV capacity that minimizes the total annual system cost.

2.5. Scenario Evaluation and Computational Implementation

All three scenarios were evaluated using the same annual model, input parameters, and calculation procedures defined in Eqs. (1)–(7). In the baseline scenario, K_{PV} was fixed at 0 MW; in the fixed-PV scenario, it was set to 50 MW; and in the GWO-optimized scenario, K_{PV} was treated as a decision variable bounded between 0 and 150 MW. For each scenario, annual PV generation was calculated using Eq. (6), fossil generation from the energy balance in Eq. (5), and total annual system cost from Eqs. (1)–(4). Annual CO₂ emissions were calculated from fossil electricity generation and the applicable emission factor. The baseline and fixed-PV scenarios were evaluated by direct substitution, whereas the optimized scenario was solved using the GWO implemented in Python 3.10. The GWO employed 30 wolves, 100 iterations, and 20 independent runs, with the lowest-cost feasible solution reported as the optimal PV capacity. Python 3.10 was also used to process the scenario outputs and generate the corresponding figures. To verify numerical accuracy, the GWO solution was cross-checked through direct evaluation of the objective function over the feasible PV-capacity range.

2.6. Input Data and Assumptions

The optimization model uses technical, economic, and algorithmic input parameters representing the annual characteristics of the Bangka power system, as summarized in Table 1. Annual electricity demand and system conditions are based on the Bangka power-system data reported in [5]. Electricity demand is supplied by Solar PV and fossil-based generation, with regional solar resource conditions represented by the PV capacity factor. The technology-cost and PV-lifetime assumptions are adapted from the Indonesian power-sector technology data in [16], while PV investment cost is annualized using a capital recovery factor based on the assumed discount rate and project lifetime. Fossil-based generation is represented using a single system-level variable cost and emission factor, with the emission-factor assumption based on [17], because the model evaluates annual capacity planning rather than unit-level generation dispatch. Within this formulation, chronological variations in electricity demand and generation and unit-level operational constraints are not explicitly modeled.

The installed PV capacity is bounded between 0 and 150 MW, while a capacity of 50 MW is adopted for the fixed-PV scenario. The use of an explicit capacity bound is consistent with the general formulation employed in generation-expansion planning studies [18]. The GWO is implemented using 30 wolves, a maximum of 100 iterations, and 20 independent runs. The lowest-cost feasible solution obtained across these runs is reported as the optimal PV capacity, and the resulting generation, cost, and emission indicators are compared with those of the baseline and fixed-PV scenarios.

Table 1. Input parameters used in the model [5, 16-18]

Parameter	Symbol	Unit	Value
Electricity demand	E_{demand}	GWh/year	1514.42
PV capacity factor	CF_{PV}	-	0.18
PV CAPEX	$CAPEX_{PV}$	USD/MW	960,000
PV O&M cost	$C_{PV}^{O\&M}$	USD/MW/year	7,500
Fossil generation cost	C_{fossil}	USD/MWh	120
Fossil emission factor	EF_{fossil}	tCO ₂ /MWh	0.8
Max PV capacity	$K_{PV,max}$	MW	150
Discount rate	r	-	0.1
PV lifetime	η	year	20
GWO population size	N	-	30
Max iterations	T	-	100
Number of runs	—	-	20

3. RESULTS AND DISCUSSION

The optimization results compare the baseline, fixed-PV, and GWO-optimized PV scenarios in terms of generation mix, total annual system cost, and CO₂ emissions. All figures were produced by the authors in Python 3.10 using outputs from the same annual model: generation was calculated using the energy-balance and PV-generation equations, total cost using Eqs. (1)–(4), and emissions using the fossil-generation-based emission calculation described in Subsection 2.3.

3.1. Electricity Generation Mix

The electricity generation mix across the three scenarios is presented in Figure 1. In the baseline scenario, PV generation is zero and the entire annual demand of 1514.42 GWh is supplied by fossil-based generation. The fixed-PV capacity of 50 MW generates 78.84 GWh/year, calculated as $50 \times 0.18 \times 8760/1000$, and supplies approximately 5.2% of annual electricity demand. Consequently, fossil generation decreases to 1435.58 GWh/year, representing 94.8% of demand. In the GWO-optimized scenario, the installed PV capacity of 150 MW generates 236.52 GWh/year and supplies approximately 15.6% of annual demand, while fossil generation decreases to 1277.90 GWh/year, representing 84.4% of demand.

Relative to the fixed-PV scenario, the optimized configuration increases annual PV generation by 157.68 GWh and raises its generation share from 5.2% to 15.6%, an increase of approximately 10.4 percentage points. This result demonstrates the direct displacement of fossil-based electricity by PV generation within the annual energy-balance model. Because calculated PV generation remains below annual electricity demand throughout the evaluated capacity range, no annual energy curtailment occurs, and fossil generation supplies the residual demand. Consequently, the reduction in fossil generation is directly proportional to the increase in PV output. Although fossil generation remains dominant, the optimized configuration provides the highest renewable contribution among the evaluated scenarios.

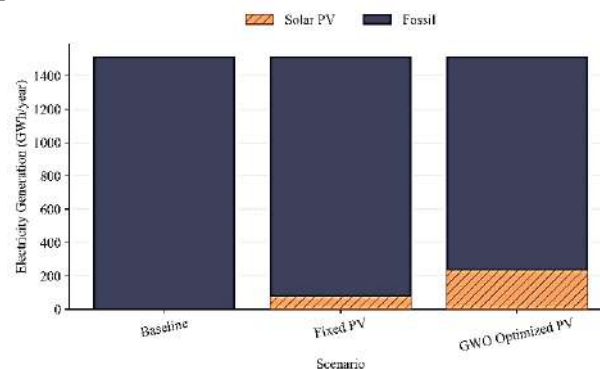


Figure 1. Electricity generation mix calculated from the annual energy-balance model

3.2. Cost Analysis

The annual system cost under each scenario is presented in Figure 2. The baseline cost of 181.73 million USD/year consists entirely of fossil generation cost because no PV capacity is installed. In the fixed-PV scenario, fossil generation cost decreases to 172.27 million USD/year, while annualized PV investment and O&M costs amount to 4.58 and 0.75 million USD/year, respectively. These components produce a total annual system cost of 177.60 million USD/year. In the GWO-optimized scenario, fossil generation cost decreases further to 153.35 million USD/year, while annualized PV investment and O&M costs reach 13.75 and 2.25 million USD/year, respectively. The resulting total cost is 169.35 million USD/year, corresponding to net savings of approximately 12.38 million USD/year relative to the baseline.

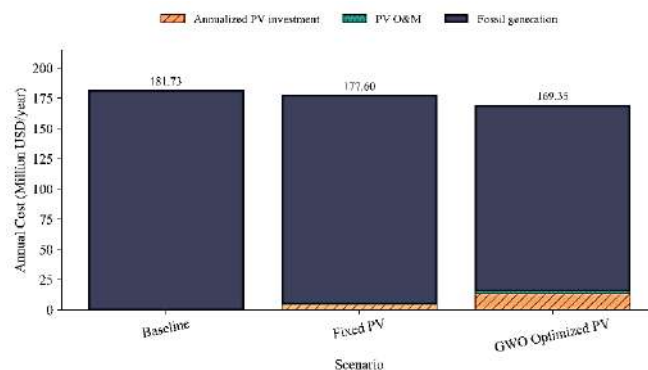


Figure 2. Annual system cost calculated from the model cost components

The cost reduction occurs because the avoided fossil generation cost exceeds the additional annual PV-related expenditure. Within the evaluated capacity range, each additional MW of PV incurs approximately 0.107 million USD/year in annualized investment and O&M costs but avoids approximately 0.189 million USD/year in fossil generation cost. Therefore, total annual system cost decreases by approximately 0.083 million USD/year for each additional MW of PV capacity. This negative marginal change in total system cost explains why the GWO selects the upper feasible capacity of 150 MW and independently corroborates the optimized solution under the adopted assumptions

3.3 Emission Analysis

The annual CO₂ emissions across the evaluated scenarios are presented in Figure 3. The baseline scenario produces 1211.54 ktCO₂/year because its entire electricity demand is supplied by fossil-based generation. Emissions decrease to 1148.46 ktCO₂/year in the fixed-PV scenario and to 1022.32 ktCO₂/year in the GWO-optimized scenario. These results correspond to annual emission reductions of approximately 63.07 and 189.22 ktCO₂/year, respectively, relative to the baseline.

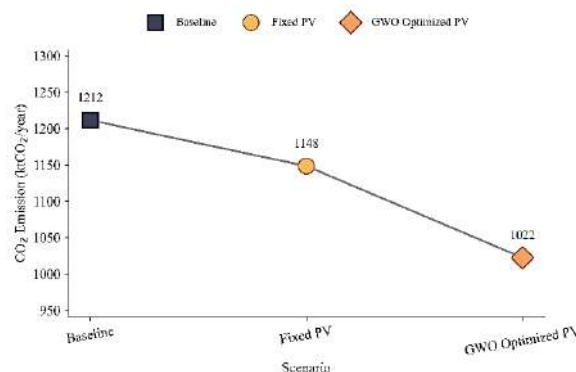


Figure 3. Annual CO₂ emissions calculated from fossil generation and its emission factor

The percentage reductions are approximately 5.2% for the fixed-PV scenario and 15.6% for the optimized scenario, consistent with their respective PV generation shares. This proportional relationship occurs because the model applies a constant fossil emission factor and assigns no operational CO₂

emissions to PV generation. Accordingly, within the adopted model boundary, emission mitigation is directly determined by the amount of fossil-based generation displaced by Solar PV. The optimized scenario provides the greatest environmental benefit because it achieves the largest reduction in fossil generation.

3.4. Cost and Emission Relationship

The relationship between total annual system cost and CO₂ emissions for PV capacities ranging from 0 to 150 MW is presented in Figure 4. Both indicators decrease consistently as PV capacity increases. Each additional MW of PV reduces total annual system cost by approximately 0.083 million USD/year and annual emissions by approximately 1.261 ktCO₂/year. Accordingly, solutions with higher PV capacities move toward the lower-cost and lower-emission region of the figure.

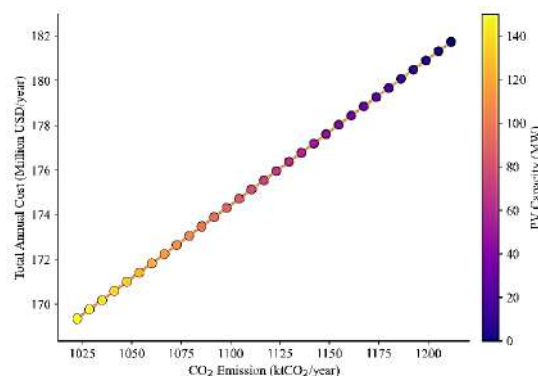


Figure 4. Cost and emission relationship across the evaluated PV-capacity range

No opposing economic-environmental trade-off occurs within the assumptions of the annual model because increasing PV capacity simultaneously reduces both indicators. Therefore, the 150 MW configuration dominates the lower-capacity alternatives and is identified as the boundary optimum. This result is conditional on the specified maximum PV capacity, constant PV capacity factor, adopted technology-cost and emission-factor assumptions, absence of modeled PV curtailment, and exclusion of chronological and unit-level operational constraints. Incorporating these factors into a more detailed model could produce nonlinear relationships or an interior optimum.

4. CONCLUSION

This study develops a simplified optimization-based framework to determine the optimal Solar PV capacity for the Bangka power system using the GWO. Under the adopted annual model assumptions, all GWO runs converge to the upper feasible capacity of 150 MW. At this capacity, PV generation reaches 236.52 GWh/year, representing approximately 15.6% of annual electricity demand, compared with 78.84 GWh/year or 5.2% in the fixed-PV scenario. Fossil generation cost decreases from 181.73 to 153.35 million USD/year; after accounting for approximately 16.00 million USD/year in annualized PV investment and O&M costs, the total annual system cost reaches 169.35 million USD/year. This result corresponds to net savings of approximately 12.38 million USD/year relative to the baseline. Annual CO₂ emissions also decrease from 1211.54 to 1022.32 ktCO₂/year, yielding a reduction of approximately 189.22 ktCO₂/year. Thus, within the evaluated capacity range, the 150 MW configuration provides the lowest system cost and emissions among the evaluated alternatives.

These findings provide system-level insights into the economic and environmental effects of PV capacity expansion in a regional power system where fossil-based generation remains dominant. However, the boundary optimum is conditional on the specified maximum PV capacity, constant PV capacity factor, adopted technology-cost and emission-factor assumptions, and absence of modeled PV curtailment. Because the annual model does not explicitly represent chronological variability, unit-level operation, network constraints, energy storage, or reliability requirements, the results should be interpreted as capacity-planning insights rather than evidence of operational feasibility. Future research may incorporate these elements to evaluate whether more detailed system conditions produce nonlinear relationships or an interior optimal PV capacity.

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Intelligent Mobile-Spatial System for Small Business Digital Innovation in Lubuk Linggau

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ABSTRACT

Micro, small, and medium enterprises (MSMEs) in Lubuklinggau City face digitalization barriers caused by the absence of an integrated, location-based business database and an objective basis for prioritizing digitalization programs. This study designed, built, and tested a mobile- and spatial-based information-system prototype integrating a Geographic Information System, a mobile-first responsive web application, and a Simple Additive Weighting (SAW)-based decision-support module with five digital-readiness criteria, deployed and populated with 50 MSME records across six sub-districts (about 0.51% of the 9,746 MSMEs on the city's official business portal). Three kinds of evidence are reported separately: computational verification, in which system-generated preference values agreed exactly with an independent manual recalculation for all 50 records; software testing, in which 18 functional cases and 8 role-based access-control scenarios passed after two defects found in development-team testing were corrected and re-verified; and preliminary, non-generalizable feedback from a single development-team respondent. Because the active weights are an unelicited uniform placeholder, a sensitivity analysis recomputed rankings under four alternative weight scenarios: 66% of MSMEs changed maturity class under at least one scenario, and one cost-priority scenario retained only 2 of the baseline top-10 MSMEs, showing that the ranking is materially sensitive to weight choice. These results demonstrate implementation correctness and functional behavior under the tested conditions; they do not establish the criteria, weights, or thresholds as a validated policy instrument, nor system-wide technical readiness, both requiring further evaluation described in the conclusion.



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1. INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) are a strategic sector that sustains regional economies through employment absorption and household income growth. Digital transformation has been shown to strengthen daily operations, expand market access, and improve business efficiency [1]; however, most MSMEs still face adoption barriers such as low digital literacy, limited infrastructure, and high implementation costs [2]. In Lubuklinggau City, these barriers are compounded by three

specific problems: MSME data are not yet integrated or location-based, making spatial analysis difficult; business information access for consumers and stakeholders remains limited; and digitalization-program prioritization is not yet grounded in a measurable, objective assessment.

This section synthesizes a narrative, non-systematic review of literature on Geographic Information Systems (GIS) for MSME mapping, mobile applications for MSME management, and spatial decision support; it is not a systematic review with a predefined search protocol, and the resulting gap statement below should be read as a synthesis of the sources examined rather than an exhaustive survey of the field. A GIS is a computer-based system for acquiring, storing, analyzing, and presenting geographically referenced data [3], and it has been used to visualize MSME spatial distribution [4]. Mobile-based applications strengthen MSME operational management and marketing through business-data, promotion, and reporting features [5]. Spatial Decision Support Systems (DSS), which combine data and models to help decision-makers address semi-structured problems [6], can provide strategic, data-driven recommendations for regional MSME development. Table 1 positions the present system against representative examples of each solution category found in the reviewed literature.

Table 1. Positioning of the present system against representative prior systems

System (source)	Data source	Spatial capability	Decision method	Validation reported	Deployment
WebGIS MSME mapping [4]	Field survey	Yes (Leaflet WebGIS)	None (visualization only)	Not reported	Regency-level deployment
Mobile MSME management app [5]	Literature synthesis	No	None	Not reported	Conceptual/reviewed apps
Institutional SAW-DSS [7]	Institutional records	No	SAW	Computational only	Single institution
Present system	Field survey + self-report	Yes (Leaflet WebGIS)	SAW	Computational verification + black-box testing	City-scale prototype, 50 records

Among the sources reviewed, GIS-based MSME mapping studies typically stop at visualization without generating a decision, mobile-application studies rarely incorporate a spatial dimension, and DSS studies for MSMEs are usually not linked to business location; none of the reviewed sources combines all three capabilities in one deployed system, which is the gap this study addresses architecturally rather than through a novel algorithm.

Among multi-attribute decision-making (MADM) methods, Simple Additive Weighting (SAW) computes a weighted sum of normalized performance ratings across criteria for each alternative [6]. SAW has previously been applied to institutional multi-criteria decisions, such as ranking candidates in a staff-recruitment decision support system [7]. SAW was selected over alternatives such as AHP, TOPSIS, or MOORA primarily for its transparency: unlike AHP's pairwise-comparison procedure or TOPSIS's distance-to-ideal-solution calculation, SAW's weighted-sum computation can be reproduced by a stakeholder with a spreadsheet, which was judged important given that the ranking may influence eligibility for a limited assistance program. This choice carries a known trade-off, discussed in the Method and Discussion sections: SAW is fully compensatory, so a severe weakness on one criterion can be masked by strength on others, a property that AHP and TOPSIS do not eliminate but that non-compensatory or veto-threshold approaches are designed to address.

This study addresses the identified gap by designing, building, and testing a prototype mobile- and spatial-based information system that integrates a GIS, a mobile-first responsive web application, and a SAW-based decision-support module, evaluated in the context of MSMEs in Lubuklinggau City. The contribution is scoped specifically as (i) a system architecture and data model that keep spatial attributes and multi-criteria assessment on a single MSME entity, avoiding the record-linkage step that separate mapping and scoring systems require, and (ii) a location-linked recommendation mechanism derived from per-criterion deficits. The study reports computational verification and software-testing evidence for this architecture on 50 real MSME records; it does not claim that the resulting rankings have been validated as a policy instrument, nor does "intelligent" in the title imply learning or adaptive behavior

beyond the deterministic, rule-based SAW computation, a scope limitation stated here to align the terminology with the evidence presented.

2. RESEARCH METHOD

This study used a Research and Development (R&D) approach with a prototyping model, integrating software engineering, Geographic Information System (GIS) development, and Decision Support System (DSS) design. The prototyping model was chosen because prospective users find it difficult to articulate their needs in the abstract, yet provide sharp, actionable feedback once they can interact with a working interface [8]. The research therefore proceeded through iterative cycles of requirements gathering, rapid design, prototype construction, user evaluation, and refinement; the prototype was deployed to a working environment for the data collection and testing reported here, a deployment status distinguished from a production system released for unsupervised public use.

2.1. Research Stages

The research was carried out through eight stages: problem identification and literature review; collection of MSME and spatial data through field observation and surveys; data validation; requirements analysis and prototype design; system development using React and TypeScript with a cloud-based backend and the Leaflet digital mapping library; implementation of the SAW method; system testing; and refinement together with reporting.

Reconstructed from the project's version-control history, the prototype underwent 18 commits across a 52-hour window immediately preceding and overlapping data collection (2026-08-15 16:38 to 2026-08-17 20:29, UTC+7), which can be grouped into four development iterations. Iteration 1 (15-16 August, morning) produced the initial working prototype and resolved production-deployment defects (database-schema migration, environment configuration). Iteration 2 (16 August, afternoon-evening) added region-management functionality and fixed two defects surfaced during this phase: a coordinate-entry field dropping the minus sign, and a business-detail page that stalled indefinitely on "Loading..." when access was denied - the latter matching, by commit message and timestamp, the access-control defect independently reported in Section 3.5. Iteration 3 (17 August, morning) added self-service MSME registration without login (enabling the owner-self-reported records described above); within 30 minutes, its route and on-screen label were both revised (from "/daftar-mandiri" and "Register Your MSME" to "/kuesioner" and "Your MSME Profile"), consistent with immediate naming feedback during first use rather than a separate elicitation session. Iteration 4 (17 August, afternoon-evening) corrected a dashboard display defect and a pagination defect and added an administrative user-access feature; these three commits followed the 13:37 computation run reported in Section 3.2 and therefore postdate, rather than affect, the reported 50-record results. No formal meeting minutes, elicitation protocol, or named stakeholder attribution beyond what is inferable from commit timing and messages were kept; the full 18-commit log with hashes, timestamps, and messages is provided as Supplementary Material S3 for independent verification.

2.2. Participants and Research Setting

The system serves three user roles that also correspond to the study's participant groups: administrators, who manage criteria, weights, and user accounts; surveyors, who collect and validate field data; and MSME owners, who view their own business data and recommendations. The research setting was Lubuklinggau City, South Sumatra Province, Indonesia.

Reconstructed from the system's audit log, field data collection was concentrated on 2026-08-17 (169 of 176 logged record-level actions), preceded by an initial pilot batch on 2026-08-16 and followed by a small number of late self-entered records on 2026-08-18 and 2026-08-19; the log distinguishes surveyor-entered actions from owner-self-entered ("mandiri") actions, independently corroborating the two collection modes described below.

As of the data-collection period, the city's official MSME directory (Linggau Smart Service portal, <https://lss.lubuklinggaukota.go.id/frontend/umkm>) listed 9,746 registered MSMEs across 8 sub-districts. The final analytic sample comprised 50 MSMEs distributed across 6 of these 8 sub-districts, representing approximately 0.51% of the registered population. The remaining two sub-districts had not yet been reached by field surveyors when data collection was concluded for this study; their absence

reflects incomplete field coverage rather than a deliberate exclusion criterion. Given this coverage and the purposive selection described below, the sample should be read as a feasibility demonstration of the system on real records, not as a statistically representative cross-section of the city's MSME population, and all prevalence figures reported in the Results section are specific to this sample. Data collection was conducted by two field surveyors, who divided sub-districts between them; in a subset of cases, business owners were asked to complete the digital-readiness questionnaire directly on the system themselves rather than through a surveyor interview. Because the two surveyors worked on non-overlapping sub-districts and did not double-score a common set of MSMEs, inter-rater agreement was not measured, and consistency across surveyors and self-reported entries relied on the standardized rubric described in the Instruments subsection rather than on a formal reliability statistic; this is acknowledged as a limitation in the Conclusion. MSMEs were included if the business operated at a fixed, geolocatable premise within the city, was actively operating, and the owner or manager consented to participate.

Because the system records business identity and precise geolocation and exposes this information through maps and role-scoped API responses, participants were informed before data collection that their business information and location would be recorded and managed within the system. This study was conducted as part of an academic project with the awareness and oversight of Universitas Bina Insan; a separate independent ethics-committee review was not obtained, and consent was collected as verbal, informed awareness of data collection and system storage rather than a signed instrument that separately itemized map publication, retention period, or anonymization options. This falls short of a documented informed-consent and data-governance protocol, and we report it explicitly as a limitation: consent to participate in data collection is not equivalent to documented consent to publish precise geolocation, and future iterations of this work should obtain formal institutional ethics review and an explicit, itemized consent instrument before expanding data collection or public-facing deployment.

2.3. Instruments and Data Sources

Data were collected using an MSME registration form (business identity, location, and category) and a digital-readiness assessment form covering five criteria: business owner digital readiness (C1), social-media utilization (C2), presence of online business channels (C3), digital transactions (C4), and implementation cost (C5). The first four criteria are benefit-type criteria, while the fifth is a cost-type criterion, confirmed operationally as follows: a higher raw C5 score corresponds to lower implementation cost on a 1-5 rubric scale, so C5 is normalized as a cost-type criterion using the minimum-based rule in equation (1) even though its scoring direction already runs from expensive (1) to inexpensive (5); each criterion was scored on this 1-5 scale using a standardized rubric administered identically to surveyor-collected and owner-self-reported records to keep assessments as consistent as the instrument allows across collection modes. The complete wording of all five rubrics is given in Table 2; each rubric was authored by the development team by adapting general digital-readiness indicators to the MSME context and was not separately validated by an external panel or piloted for content validity prior to use, a limitation acknowledged in the Conclusion.

Table 2. Digital-readiness rubric (1-5 scale) for all five criteria

Criterion	1	2	3	4	5
C1 Owner readiness	Never used digital tools for business	Owens a smartphone, personal use only	Uses basic apps (chat, calculator) occasionally for business	Regularly uses several digital apps for business	Independently uses varied digital apps, open to learning new ones
C2 Social media	No business social-media account	Has an account, inactive	Posts business content irregularly	Posts regularly on a fairly fixed schedule	Posts on a fixed schedule and interacts with customers
C3 Online presence	No online channel at all	Listed on one channel, unmanaged	Listed on one channel, actively managed	Listed on two channels, actively managed	Listed on more than two interlinked channels

Criterion	1	2	3	4	5
C4 Digital transactions	Cash only	Digital payment accepted incidentally	One digital payment channel offered consistently	More than one digital payment channel, used routinely	Majority of transactions digital and recorded
C5 Implementation cost	Very high cost for next digitalization step	High cost	Moderate cost	Low cost	Very low or no cost required

2.4. Data Analysis Technique

Multi-criteria analysis was performed using the Simple Additive Weighting (SAW) method [6]. Let $A = \{A_1, \dots, A_m\}$ denote the m MSMEs (alternatives) and $C = \{C_1, \dots, C_n\}$ the $n = 5$ criteria, with raw score x_{ij} for alternative i on criterion j . Weights w_j satisfy $0 \leq w_j \leq 1$ and $\sum w_j = 1$ for $j = 1..n$. Each criterion is normalized according to its type, as shown in equation (1).

$$rij = x_{ij} / \max_i(x_{ij}) \text{ for benefit criteria; } rij = \min_i(x_{ij}) / x_{ij} \text{ for cost criteria} \quad (1)$$

The preference value of each alternative is computed as the weighted sum of the normalized matrix, as shown in equation (2), where V_i is the preference value of the i -th MSME, w_j is the weight of the j -th criterion, and rij is the normalized value of the i -th MSME on the j -th criterion.

$$V_i = \sum (w_j \times rij), \text{ for } j = 1 \text{ to } n \quad (2)$$

Because $\max_i(x_{ij})$ and $\min_i(x_{ij})$ in equation (1) are taken over the current alternative set, normalized scores - and therefore V_i and the resulting ranks - are defined relative to whichever MSMEs are included in a given computation run; adding or removing an MSME can shift the reference maximum or minimum on a criterion and change other alternatives' normalized scores and ranks even though their own raw values are unchanged. Records with an incomplete rubric score on any criterion are excluded from the run rather than imputed, and no zero-denominator case arises in equation (1) because the 1-5 rubric floor excludes a raw value of zero. Ties in V_i are resolved by standard competition ranking: alternatives with an identical V_i receive the same rank, and the next distinct value skips the number of tied alternatives - the rule that produced the skipped rank reported in the Results.

Independent computational verification was performed by an author who re-implemented equations (1) and (2) in a separate spreadsheet from the exported raw x_{ij} values, working from the system's stored raw scores rather than a blinded dataset; agreement was defined as a difference of no more than 0.0001 in V_i and an identical rank order. This procedure verifies that the software correctly implements the stated formulas; it is computational verification, not decision-model validation, and does not by itself establish that the chosen criteria, weights, or thresholds reflect stakeholder priorities or predict a meaningful external outcome, a distinction maintained throughout the Results and Discussion. Functional black-box testing and role-based access-control testing were carried out by the development team directly against the deployed prototype, covering both user-interface interaction and direct calls to the application programming interface (API), in order to verify that rules were enforced on the server side rather than merely hidden in the interface [9]; no independent or third-party security tester was engaged, and the scope of security-relevant testing performed is stated precisely in the Results.

3. RESULTS AND DISCUSSION

This section reports three distinct kinds of evidence - system design, computational verification of the SAW implementation, and software testing - followed by preliminary, non-generalizable user feedback and a discussion that relates these findings, and their limits, to prior research.

3.1. System Design and Implementation Results

The system was built on a four-layer architecture - presentation, map, service and logic, and data - serving three user roles with tiered access rights: administrator, surveyor, and MSME owner, as illustrated in Fig. 1. The main modules include MSME data management, versioned criteria-and-weight management, the SAW computation engine, a Leaflet-based distribution map, and a recommendation bank that the administrator can edit without redeploying the application. Access rights were designed so

that an MSME owner can view only their own business data, while surveyors and administrators receive access commensurate with their respective authority.

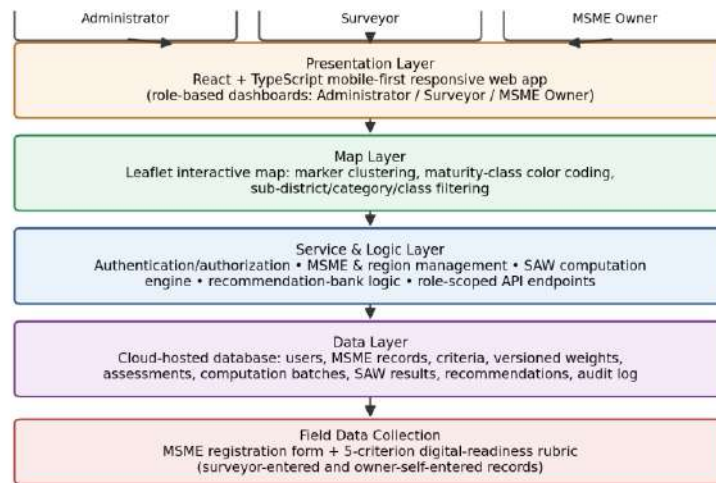


Figure 1. Four-layer system architecture with role-based access and field data-collection flow

The recommendation-bank content mapping each criterion-and-class combination to a specific suggested action was authored directly by the development team, drawing on general MSME digital-assistance practice rather than a documented expert panel; conflicting recommendations across simultaneously deficient criteria are resolved by listing all triggered suggestions rather than by an automated prioritization rule, and the quality or relevance of the recommendations has not been separately validated with MSME owners or assistance-program staff, a gap noted alongside the user-acceptance limitation in the Conclusion.

3.2. SAW Computation Verification Results

The weight set active during data collection was uniform (0.20 for each criterion) and the maturity-class thresholds were set at 0.66 and 0.33; both are provisional placeholders adopted because definitive weights and thresholds have not yet been elicited from stakeholders through the stakeholder focus-group process anticipated in the project design, and neither has a theoretical or empirical basis beyond this uniform default. Consequently, the class counts and rankings reported below describe how the current placeholder configuration behaves on this sample; the following subsection reports a sensitivity analysis quantifying how much this specific configuration matters. All raw criterion values for the 50 MSMEs were exported and independently recomputed using equations (1) and (2), then compared against the preference values stored by the system, following the verification protocol described in the Method section. The verification results are summarized in Table 3.

Table 3. Summary of SAW computation verification on 50 MSMEs

Aspect	Result
MSMEs verified	50
V values in agreement (difference ≤ 0.0001)	50 (100%)
Highest V value	0.8800
Lowest V value	0.2900
High class (placeholder threshold)	21 MSMEs
Medium class (placeholder threshold)	27 MSMEs
Low class (placeholder threshold)	2 MSMEs

All 50 preference values agreed exactly with the manual recalculation, confirming that the software correctly implements equations (1) and (2) as specified; this is computational verification of the implementation, not validation of the ranking's decision quality. A worked example illustrates the full computation: for one MSME (a photography studio) with raw scores $C1=5$, $C2=5$, $C3=3$, $C4=4$, $C5=1$, and sample extremes $\max(C1..C4)=5$ and $\min(C5)=1$, equation (1) gives $r=(1.000, 1.000, 0.600, 0.800, 1.000)$, and equation (2) gives $V_i = 0.20 \times (1.000 + 1.000 + 0.600 + 0.800 + 1.000) = 0.880$, matching the highest value in Table 3. Three MSMEs shared an identical V value (0.8667) and were jointly assigned

rank 2 under the standard competition-ranking rule defined in the Method section, with the next distinct value skipping to rank 5. Two MSMEs fell below the 0.33 placeholder threshold into the Low class. The complete 50-record raw-score matrix and computation output are available from the corresponding author on reasonable request.

3.3. Sensitivity Analysis Across Alternative Weight Scenarios

Because the active weights are an unelicited placeholder (Section 3.2), the exported 50-record raw-score matrix was used to recompute rankings and classes under four alternative weight scenarios in addition to the reported uniform baseline, using the identical equations (1) - (2) and thresholds (0.66/0.33): a readiness-weighted scheme emphasizing C1 (0.35/0.15/0.15/0.15/0.20), a cost-priority scheme emphasizing C5 (0.10/0.10/0.10/0.10/0.60), an online-presence-priority scheme emphasizing C3 (0.15/0.15/0.40/0.15/0.15), and a transaction-priority scheme emphasizing C4 (0.15/0.15/0.15/0.40/0.15). Table 3b summarizes the resulting class distribution and the overlap between each scenario's top-10 ranked MSMEs and the baseline top-10.

Table 3b. Class distribution and top-10 overlap under alternative weight scenarios

Scenario	High	Medium	Low	Top-10 overlap with baseline
A. Uniform (reported baseline)	21	27	2	10/10
B. Readiness-weighted (C1-heavy)	22	26	2	9/10
C. Cost-priority (C5-heavy)	10	38	2	2/10
D. Online-presence-priority (C3-heavy)	17	29	4	9/10
E. Transaction-priority (C4-heavy)	23	25	2	10/10

The ranking is materially sensitive to weight choice: 33 of the 50 MSMEs (66%) change maturity class under at least one of the four alternative schemes relative to the reported baseline, and the cost-priority scenario in particular reshuffles the top tier so severely that only 2 of the baseline top-10 MSMEs remain in the top-10 (Table 3b). The readiness- and transaction-priority scenarios are comparatively more stable (9/10 and 10/10 overlap), suggesting the baseline ranking is more sensitive to how much weight is placed on cost and online presence than on owner readiness or digital transactions specifically, though this pattern is observed on the current 50-record sample and is not claimed to generalize beyond it. This empirically confirms, rather than merely asserts, that the uniform placeholder weight materially shapes which MSMEs are classified as high-priority or high-maturity, and that eliciting definitive weights from stakeholders before using the ranking for assistance decisions (Section 4) is not a procedural formality but a substantive requirement: a materially different set of MSMEs would be flagged for assistance depending on which criterion stakeholders choose to emphasize. The full scenario-by-scenario class assignment for all 50 MSMEs is provided in Supplementary Material S2.

3.4. Functional and Security Testing Results

Black-box testing was conducted by the development team through both interface interaction and direct API calls to verify server-side rule enforcement; no independent or third-party tester was engaged, a scope limitation noted in the Method section. Two defects were found during initial development-team testing - the absence of duplicate-MSME detection and a page that failed to display an error message when access was denied - both of which were fixed and then re-verified in a separate regression run using an identical reproduction procedure; the totals in Table 4 report that post-fix regression run, so the 100% pass rate reflects successful correction rather than a first-pass quality metric.

Table 4. Recapitulation of post-fix regression testing

Testing category	Cases	Passed (post-fix)
Functional (black-box)	18	18 (100%)
Role-based access control	8	8 (100%)

Each of the 18 functional cases has a documented requirement ID, precondition, input, expected result, observed result, tester, environment, and status; this per-case log is reproduced in full in the Supplementary Material accompanying this submission, given the manuscript's page limit. Role-based access-control testing covered the eight scenarios in Table 5, verified down to the API response level:

an MSME-owner account received a null maturity-class value for every MSME other than its own, indicating that this specific field is filtered server-side rather than only concealed in the interface.

Table 5. Role-based access-control testing scenarios

Role	Scenario	Result
Surveyor	Admin-only menus hidden from the sidebar	Passed
Surveyor	Direct URL access to an admin-only page	Blocked, explicit message
Surveyor	Direct calls to admin-only API endpoints	403 Forbidden
Surveyor	Access to MSME data within surveyor authority	Passed
MSME owner	Own-business dashboard displays safely	Passed
MSME owner	Direct URL access to ranking/list pages	Blocked, explicit message
MSME owner	Map hides other MSMEs' maturity class	Passed, field-level null
MSME owner	Opening another MSME's detail page	403 Forbidden, explicit message

These eight scenarios assess object-level authorization for the maturity-class field and role-scoped page access only; they should not be characterized as comprehensive security testing. No formal threat model was developed, and the following were not tested in this study: authentication and session-management robustness beyond normal login, input validation and injection resistance, rate limiting, transport-layer security configuration, logging and audit-trail integrity, backup and recovery, and broader geolocation-privacy leakage beyond the maturity-class field. These are identified as required future work before any claim of comprehensive security assurance.

3.5. Preliminary User Feedback

A 15-item questionnaire covering perceived usefulness, ease of use [10], functional suitability, map-module usefulness, and recommendation usefulness was administered to a single respondent, a development-team administrator, who scored all items at the maximum value. A single respondent who participated in system development cannot yield interpretable evidence of user acceptance: the result is subject to self-assessment bias, provides no variance to assess response consistency, and does not constitute a substantive finding. It is reported here only as a preliminary data point, not as evidence of user acceptance, pending a properly powered study with an independent, adequately sized sample of administrators, surveyors, and MSME owners, including reported response scale, scoring, content validity, and reliability - none of which can be established from a single respondent.

3.6. Discussion

The results show that GIS, mobile-first application, and SAW-based DSS integration can be implemented on a single shared database so that ranking results can be visualized spatially without a separate record-linkage step, addressing the architectural gap identified in the reviewed literature, where GIS-based MSME mapping studies typically stop at visualization without producing a decision [3], [4]. The post-fix 100% pass rate on the tested functional and access-control cases indicates that those specific cases behave as specified after correction; it does not by itself establish general technical readiness, which would additionally require performance and concurrent-load testing, reliability and recovery testing, device and browser compatibility, responsive-layout verification, degraded-network behavior, accessibility testing, and independent usability evidence, none of which has yet been conducted. The compensatory property of SAW observed in this dataset - for example, the worked-example MSME attained its highest score partly through a perfect cost-criterion score offsetting a mid-range value on C3 - is a structural property of the additive model itself rather than an empirical discovery of this study. Its policy implication is that a severe weakness on one essential criterion can be fully offset by strengths elsewhere, which may be undesirable if a program requires a minimum standard on every criterion for eligibility; because this system's output may influence assistance allocation, whether a veto threshold, minimum-eligibility rule, or a non-compensatory ranking method such as those noted in the Introduction is needed should be decided with stakeholders before the ranking guides real allocation decisions, rather than assumed away by displaying per-criterion values alongside the aggregate score. The still-uniform, unelicited criteria weighting and thresholds remain the principal limitation of this study; all ranking

results should be read as a demonstration of system behavior, not a validated policy recommendation, until definitive weights and thresholds are established and sensitivity-tested with stakeholders.

4. CONCLUSION

This study designed, built, and tested a prototype mobile- and spatial-based information system that integrates a Geographic Information System, a mobile-first responsive web application, and a Simple Additive Weighting-based decision-support module for MSME digital-readiness assessment in Lubuklinggau City. Computational verification on 50 MSME records showed exact agreement between the system's preference values and an independent manual recalculation, and 18 functional test cases together with 8 role-based access-control scenarios passed in a post-fix regression run after two defects found during development-team testing were corrected. These results demonstrate that the software correctly implements the specified formulas and behaves as intended on the tested cases; they do not demonstrate improvement in MSME digital innovation, decision quality, program targeting, or user outcomes, and no causal or impact claim is made here pending a comparative field evaluation or longitudinal outcome study.

A specific technology-readiness-level rating is not asserted in this study: no formal TRL rubric was applied against documentary evidence, and the current provisional weights, single-respondent preliminary feedback, and untested performance, reliability, and independent-security dimensions would likely not satisfy a mid-range TRL claim if formally assessed. The system is, at this stage, more accurately described as a functionally verified prototype rather than a technically validated, deployment-ready decision tool. Several limitations should be addressed before the ranking output informs real assistance decisions: definitive criteria weights and class thresholds have not been elicited from stakeholders, and the sensitivity analysis reported above shows this matters substantively — 66% of MSMEs change maturity class under at least one of four alternative weight scenarios tested; the 50-record sample (about 0.51% of the city's 9,746 registered MSMEs, per the Method section) was collected purposively by two field surveyors without inter-rater reliability testing, and two of eight sub-districts were not yet reached; user-acceptance evidence currently consists of a single, non-independent respondent; and security testing was performed only by the development team against a narrow set of authorization scenarios, without a formal threat model or independent testing. Future work should prioritize, in roughly this order: eliciting definitive stakeholder weights and thresholds through a focus-group process and re-running the sensitivity analysis on that elicited configuration; an adequately powered, independent user-acceptance study across all three roles; independent or third-party security testing against a documented threat model; formal institutional ethics review and an itemized consent and data-retention protocol given the geolocation data involved; and extending field coverage to the remaining sub-districts with a longitudinal design to observe whether digital-maturity classes change following assistance.

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Design and Development of a Smart Energy Management System Based on Hybrid Demand Side Management for 1100 Wp Off Grid Solar Power Plant Battery Optimization

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ABSTRACT

Off-Grid solar power plant systems often face battery life degradation due to deep discharge cycles. This research aimed to design a Smart Energy Management System (SEMS) based on an ESP32 microcontroller and PZEM-017 sensors to monitor and control load dispatch. The system supplied a 3,420 Wh daily load using 1,100 Wp solar panels and a 25.6V 100Ah (2,560 Wh) LiFePO4 battery. The applied strategy was Hybrid Demand Side Management (DSM), integrating Load Shifting and Load Shedding. Test results indicated the sensors operated exceptionally well with an average error rate of 1.44%. The system successfully executed Load Shifting by directly powering heavy loads during abundant solar production ($P_{pv} > 500W$). Conversely, it executed priority Load Shedding by disconnecting non-essential loads during power-saving mode ($20\% \leq SoC \leq 50\%$). Furthermore, the system automatically switched the power source to the utility grid when the battery reached a critical condition $SoC < 20\%$. The evaluation proved this system effectively prevented 100% deep discharge and limited the maximum Depth of Discharge (DoD) to 80%, significantly extending the LiFePO4 battery's cycle life.



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1. INTRODUCTION

The utilization of off-grid solar power plants has become a strategic solution for achieving energy independence, particularly in remote areas. In off-grid systems, the sustainability of the power supply relies heavily on energy storage units (batteries) [1]. However, batteries represent the highest investment cost and are the most vulnerable component to performance degradation caused by poor discharging management. Operating heavy electrical loads when battery capacity is running low frequently triggers a deep discharge condition. This practice massively reduces the battery's cycle life, especially if the Depth of Discharge (DoD) limit is continuously violated [2], [3].

Various studies related to Automatic Transfer Switch (ATS) systems in solar power plants generally still employ conventional, non-selective logic [4]. Such systems unilaterally shift the entire electrical load to the utility grid (PLN) when the battery reaches its minimum voltage limit, without classifying load priorities. Furthermore, energy inefficiency frequently occurs due to the battery's round-trip losses (approximately 15% - 20%) during the charge-discharge cycles. System efficiency can be

significantly improved through a direct self-consumption strategy, which involves operating high-power loads directly during peak solar energy production [5]. Nevertheless, the absence of real-time solar irradiance data often causes users to miscalculate the peak power period, resulting in a massive current draw from the battery during cloudy weather.

To address this gap, the integration of Internet of Things (IoT) devices into the Energy Management System (EMS) instruments is absolutely necessary [6], [7]. While several previous studies have implemented smart sensors in solar power systems, the majority focused solely on remote monitoring functions without executing autonomous load-side management actions based on actual real-time data[8], [9].

Therefore, this research developed a Smart Energy Management System (SEMS) based on the ESP32 microcontroller and the PZEM-017 high-precision DC parameter reader module. This system offers novelty through the implementation of an automated Hybrid Demand Side Management (DSM) algorithm. Unlike conventional ATS, this algorithm utilizes the actual power value (P_{pv}) from the solar panels to trigger Load Shifting during the day, and analyzes the estimated State of Charge (SoC) of the LiFePO4 battery using polynomial regression to perform priority Load Shedding at night. This hybrid approach aims to maximize the self-consumption ratio while drastically extending the economic cycle life of the battery by keeping the DoD within safe limits.

2. RESEARCH METHOD

This research was conducted comprehensively to design, develop, and validate a Smart Energy Management System (SEMS) intended for an off-grid solar power plant. The research methodology was divided into several key stages, as illustrated in the research flowchart.

The research methodology was divided into several key stages: system architecture design, hardware integration, algorithm development based on Hybrid Demand Side Management (DSM), and experimental evaluation. The object of this research was an off-grid solar installation located in Palembang, South Sumatra, which utilized two 550 Wp monocrystalline solar panels (total 1,100 Wp) and a 25.6V 100Ah LiFePO4 battery as the primary energy storage unit.

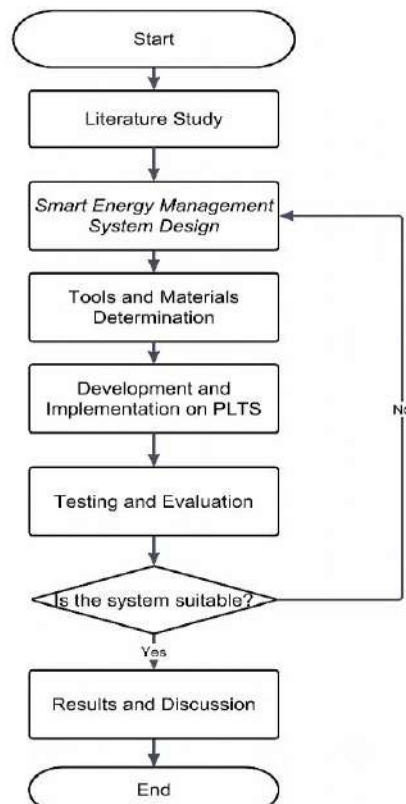


Figure 1. Research flow

2.1. System Architecture and Hardware Integration

The system architecture, as illustrated in the block diagram, consists of three main stages: input, process, and output. The input stage comprises the solar panels acting as the primary energy source and the utility grid (PLN) functioning as a backup. The processing stage is the core of the Smart Energy Management System (SEMS). The main control center utilizes an ESP32 microcontroller, which processes sensor data and executes the switching logic[10]. The data acquisition system relies on two precision PZEM-017 (DC) instruments connected via a Modbus RTU (RS485 to TTL) communication interface to ensure accurate voltage and current tracking [11].

The first sensor (PZEM-017 1) is installed at the solar panel output with the assistance of a 100A shunt resistor to monitor Voltage, Current, and Generation Power (P_{pv}). The second sensor (PZEM-017 2) is installed at the battery terminal to read voltage fluctuations and charge/discharge currents. The power control execution (actuator) at the output stage is managed using a 5V/10A 4-Channel Relay module that connects or disconnects the 220V AC line from the inverter to the priority loads, non-priority loads, and regulates the backup source interlock from the utility grid (PLN).

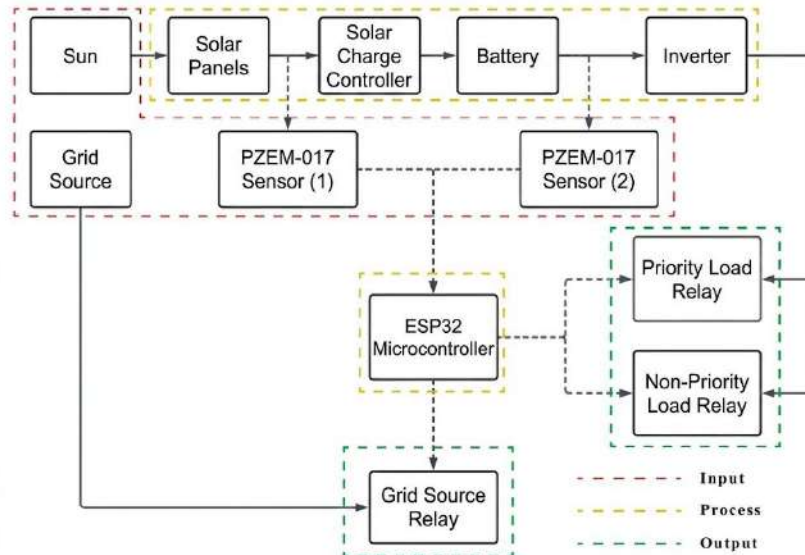


Figure 2. SEMS hardware block diagram

2.2. Algorithm and Hybrid DSM Strategy

The State of Charge (SoC) estimation of the LiFePO4 battery on the ESP32 does not use a linear percentage mapping. Instead, it utilizes a 4th-Order Polynomial Regression computation:

$$SoC = aV^4 + bV^3 + cV^2 + dV^1 + e \quad (1)$$

This mathematical approach (1) was specifically selected to accurately accommodate the highly flat plateau characteristic of the LiFePO4 battery's voltage drop curve. The Hybrid DSM algorithm continuously loops, utilizing the PV power (P_{pv}) and the battery SoC to execute three main operational scenarios:

1. Load Shifting Strategy: If the system detects abundant solar power production where $P_{pv} > 500W$, the status of both the Priority Relay and Non-Priority Relay will be connected (ON). The solar panel power is maximized to supply all heavy loads through direct consumption, shifting energy usage from nighttime to daytime.
2. Load Shedding Strategy: If the solar power generation decreases ($P_{pv} < 500W$), the system shifts its reliance to the battery and continuously evaluates the SoC:
 - Safe Mode ($SoC > 50\%$): All priority and non-priority loads are kept ON.
 - Power-Saving Mode ($20\% \leq SoC \leq 50\%$): The ESP32 automatically disconnects the Non-Priority Relay (OFF) to conserve energy. Essential priority loads continue to receive power (ON) from the battery.

3. Critical Protection Strategy ($SoC < 20\%$): The interlock algorithm is triggered. The inverter line is completely disconnected, and the system automatically switches to the Grid Source Relay contactor (ON). This serves as an absolute protection mechanism (limiting the Depth of Discharge to 80%) to safeguard the battery from experiencing a damaging 100% deep discharge.

2.3. System Evaluation Setup

The experimental testing was divided into two phases. The first phase focused on validating the accuracy of the instrumentation. The voltage and current readings from both PZEM-017 sensors were compared against calibrated standard measuring instruments (a digital multimeter and a clamp meter) to determine the percentage error. The maximum allowable error margin was set at $\leq 2\%$, following industrial standards.

The second phase evaluated the reliability of the control logic. The tests involved simulating various solar power and battery SoC conditions to observe the ESP32's response. The success criteria were based on the accurate execution of relay transitions corresponding to the predefined thresholds for Load Shifting, targeted Load Shedding, and the final safety switch to the utility grid.

3. RESULTS AND DISCUSSION

Testing was conducted to validate the precision of the PZEM-017 sensor data acquisition and the reliability of the Hybrid DSM control logic in responding to actual fluctuations in energy production and battery capacity.

3.1. Sensor Stability and Accuracy Validation

The accuracy of electrical data reading is highly crucial, considering that a voltage computation error on the LiFePO4 battery could trigger incorrect relay switching. Prior to operation, both PZEM-017 units underwent a software-based zero-offset calibration stage to eliminate parasitic impedance (-0.6A on the solar side and -0.5A on the battery side).

Sensor stability testing was conducted for 7 consecutive days, compared with standard, calibrated measuring instruments (Digital Multimeter). The testing results are summarized in Table 1.

Table 1. Average sensor accuracy testing results (7 Days)

Day	Test Point	Parameter	Standard Measuring Instrument	PZEM-017 Sensor	Difference	Error (%)
1	Sensor 1 (PV)	Voltage (V_{DC})	75,90 V_{DC}	77,3 V_{DC}	1,40	1,84%
		Current (A)	5,20 A	5,3 A	0,10	1,92%
	Sensor 2 (Battery)	Voltage (V_{DC})	26,41 V_{DC}	26,7 V_{DC}	0,29	1,10%
		Current (A)	15,42 A	15,6 A	0,18	1,17%
2	Sensor 1 (PV)	Voltage (V_{DC})	75,20 V_{DC}	75,6 V_{DC}	0,40	0,53%
		Current (A)	1,06 A	1,1 A	0,04	3,77%
	Sensor 2 (Baterai)	Voltage (V_{DC})	24,43 V_{DC}	24,5 V_{DC}	0,07	0,29%
		Current (A)	4,41 A	4,5 A	0,09	2,04%
3	Sensor 1 (PV)	Voltage (V_{DC})	80,00 V_{DC}	81,4 V_{DC}	1,40	1,75%
		Current (A)	2,89 A	2,9 A	0,01	0,35%
	Sensor 2 (Baterai)	Voltage (V_{DC})	27,08 V_{DC}	27,4 V_{DC}	0,32	1,18%
		Current (A)	7,23 A	7,4 A	0,17	2,35%
4	Sensor 1 (PV)	Voltage (V_{DC})	79,50 V_{DC}	80,7 V_{DC}	1,20	1,51%
		Current (A)	4,01 A	4,1 A	0,09	2,24%
	Sensor 2 (Baterai)	Voltage (V_{DC})	27,32 V_{DC}	27,5 V_{DC}	0,18	0,66%
		Current (A)	9,08 A	9,2 A	0,12	1,32%
5	Sensor 1 (PV)	Voltage (V_{DC})	73,70 V_{DC}	74,8 V_{DC}	1,10	1,49%
		Current (A)	6,29 A	6,4 A	0,11	1,75%
	Sensor 2 (Baterai)	Voltage (V_{DC})	28,16 V_{DC}	28,3 V_{DC}	0,14	0,50%
		Current (A)	7,68 A	7,8 A	0,12	1,56%
		Voltage (V_{DC})	85,70 V_{DC}	87,3 V_{DC}	1,60	1,87%

Day	Test Point	Parameter	Standard Measuring Instrument	PZEM-017 Sensor	Difference	Error (%)
6	Sensor 1 (PV)	Current (A)	4,82 A	4,9 A	0,08	1,66%
	Sensor 2 (Baterai)	Voltage (V_{DC})	27,87 V_{DC}	28,2 V_{DC}	0,33	1,18%
		Current (A)	12,36 A	12,5 A	0,14	1,13%
7	Sensor 1 (PV)	Voltage (V_{DC})	85,40 V_{DC}	86,5 V_{DC}	1,10	1,29%
		Current (A)	6,17 A	6,3 A	0,13	2,11%
	Sensor 2 (Baterai)	Voltage (V_{DC})	27,96 V_{DC}	28,1 V_{DC}	0,14	0,50%
		Current (A)	18,09 A	18,3 A	0,21	1,16%
Average Error (%)						1,44%

Based on Table 1, the average overall error percentage of the reading system was 1.44%. According to the Indonesian National Standard (SNI IEC 60051-1:2011), the error tolerance limit for industrial-grade panel electrical instruments is in the range of $\pm 1.5\% - 5\%$ [12]. The error value of 1.44% indicates that the SEMS instrumentation is highly precise and possesses valid high reliability as a reference for the DSM algorithm. Furthermore, power quality testing at the Hybrid Inverter output also demonstrated highly stable Alternating Current (AC) voltage regulation ranging from 229.3VAC to 230.3VAC, with an extreme error tolerance below 0.30%.

3.2. Evaluation of the Hybrid DSM Algorithm

The control logic execution test was performed by manipulating field parameters to observe the relay switching response. Table 2 illustrates the scenarios successfully handled by the ESP32 microcontroller.

Table 2. Verification of hybrid DSM relay execution

No	Test Parameter	Condition during Testing	Relay			Compliance
			Priority	Non-Priority	PLsN	
1	Active Load Shifting (Abundant solar production) $P_{PV} > 500W$ $SoC \geq 50\%$	$P_{PV} = 552 W$ $SoC = 80\%$	ON	ON	OFF	Match
2	Normal Operation (Night/Cloudy, Safe Battery) $P_{PV} \leq 500W$ $SoC \geq 50\%$	$P_{PV} = 338 W$ $SoC = 80\%$	ON	ON	OFF	Match
3	Load Shedding (Battery energy saving) $P_{PV} \leq 500W$ $20\% \leq SoC \leq 50\%$	$P_{PV} = 218 W$ $SoC = 50\%$	ON	OFF	OFF	Match
4	Critical Condition (Protection) (Deep Discharge Prevention) $P_{PV} \leq 500W$ $SoC < 20\%$	$P_{PV} = 10 W$ $SoC = 19\%$	OFF	OFF	ON	Match

During hot daytime scenarios $P_{PV} > 500W$, the system successfully executed the Load Shifting strategy. Heavy loads such as an iron or a washing machine (non-priority) continued to receive electricity from the abundant solar energy, preventing this power from being wasted.

Towards evening or during heavily overcast weather ($P_{PV} \leq 500W$), the algorithm relied on the battery value. When the battery reached 50% SoC, the Load Shedding phase was activated. The system immediately and autonomously disconnected the Non-Priority Relay, while the Priority Relay remained ON. This action shed excess load, significantly slowing down the State of Charge (SoC) decline rate at night.

As the final layer of protection, when the battery hit an SoC below 20%, the system identified a critical condition. The interlock algorithm completely halted current draw from the inverter and automatically transferred the household load to the PLN utility line.

3.3. Impact on Battery Cycle Life

In conventional Off-Grid solar installations, uncontrolled current draw at night often causes the battery voltage to hit its lowest point (0% SoC or 100% DoD). Referring to the electrochemical characteristics of Lithium Iron Phosphate (LiFePO₄) cells [7], forcing ion extraction up to 100% DoD applies contraction stress on the electrodes, limiting the cell's lifespan to around ± 4.000 cycles [13].

Through the implementation of the designed SEMS, the system absolutely performs automatic braking and transfers the load to the grid at the 20% SoC threshold. This means the Depth of Discharge rate is successfully limited to 80%. Restricting ion movement within this safe mechanical zone, both empirically and theoretically, prevents early cell damage and projects the LiFePO₄ battery's cycle life to increase significantly to approximately ± 6.000 cycles [14]. Assuming 1 cycle per day, this system is capable of extending the economic lifespan of the battery by more than 5 additional years compared to conventional systems.

4. CONCLUSION

This research has successfully designed and implemented a Smart Energy Management System (SEMS) to address the risk of battery wear in a 1100Wp Off-Grid solar system. Based on empirical testing, the PZEM-017-based measurement devices operated with high precision, recording an average error of 1.44%, fully complying with instrument quality standards. The ESP32 microcontroller proved reliable in executing the Hybrid DSM logic, autonomously optimizing excess energy production through Load Shifting during the day and conserving power through priority Load Shedding at night. The utmost effectiveness of this system lies in its proven ability to absolutely secure the LiFePO₄ battery from deep discharge conditions. Based on empirical validation where the system consistently and autonomously transferred the electrical load to the backup utility grid exactly at the 20% SoC threshold, the maximum Depth of Discharge was physically locked at 80%. By strictly enforcing this verified operational boundary, theoretical and electrochemical data project the battery's cycle life to be drastically extended to approximately $\pm 6,000$ cycles. This smart intervention not only maintains electrical continuity but provides a strong empirical basis for an economic lifespan extension of over 5 years compared to conventional systems.

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Review on Resilience-Oriented Strategies Power Systems Facing Extreme Natural Disaster

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ABSTRACT

Natural disasters significantly impact electricity services worldwide, making power grid resilience a crucial research topic. This article presents a literature review focusing on resilience-oriented strategies for electric power systems facing extreme natural disasters. Employing the Preferred Reporting items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, fifty-eight relevant articles were selected and analyzed. The reviewed literature was categorized into three distinct operational stages of disasters: pre-disaster, during-disaster, and post-disaster. In the pre-disaster stage, the focus was placed on proactive infrastructure hardening and robust planning. During disasters, the priority shifted to real-time threat monitoring and active risk mitigation. Post-disaster recovery relied heavily on functional technologies, including distributed generation islanding, microgrid clustering, and optimal energy management coordinated with the deployment of emergency repair crews. The analysis revealed critical challenges, such as the lack of standardized metrics, limited transmission-distribution coordination studies, and a scarcity of multi-disaster modeling. Finally, future research directions were identified, emphasizing control stability in low-inertia microgrids and the integration of interconnected civil infrastructures to accelerate power system restoration.



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1. INTRODUCTION

The ability of an electric power system to withstand, respond to, and recover from catastrophic events is a basic criterion for defining power system resilience. Resilience is frequently characterized by high-impact low-probability (HILP) [1]. Environmental and human threats, including cyberattacks, can trigger this type of event. As the driving force behind all living activities worldwide, the electrical system plays a vital role but is highly susceptible to natural calamities such as hurricanes, earthquakes, floods, geomagnetic storms, etc. [2]. Many countries are now grappling with efforts to strengthen the resilience of power grids that have been operating for decades and were not originally designed to withstand extreme weather or natural disasters. Research reveals that natural disasters are the primary source of extensive blackouts, representing approximately 52% of occurrences [1]. An analysis of major power outages in the US in 2008 showed that out of 933 power outage incidents between 1984 and 2006, approximately 44% were weather-related [3,4]. In February 2021, the southern US experienced a catastrophic winter storm that caused generator outages and rolling blackouts in Texas and neighboring states. The devastating impact was economic damage to communities and loss of life due to the power grid. Consequently, measures must be taken to address these vulnerabilities and mitigate future losses. Motivated by this, the authors aim to review strategies for maintaining power system resilience in the

face of extreme natural disasters.

Natural disasters pose a significant concern to the continuity of electricity services in Europe and worldwide, as evidenced by data from the 2003, 2011, and 2014 flood centers, that consequently prompted Europeans to start doubting their dependability and safety of their electricity grids facing natural disasters [5]. Similar concerns are occurring in Asia [6], and Africa [7]. Global climate change is affecting electrical availability throughout the continent, with natural disasters damaging economies [8]. The impact of these disasters on electricity system service will jeopardize the activities of other important sectors such as industry and transportation, public health, security, communications, businesses, and households [3]. Figure 1 shows the importance of electricity services in supporting the operation of important sectors in improving a country's economy.

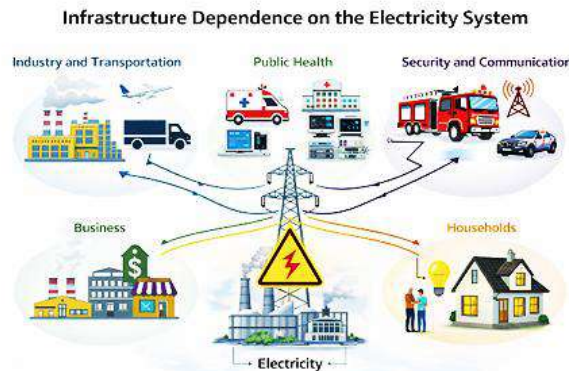


Figure 1. A visual depiction of the interdependence between electricity services and other infrastructure

With the increasing incidence of a natural disaster and extreme weather events, the resilience of the electricity grid infrastructure to deal with them has become crucial [9]. Since, it is not possible for humans to control all extreme events from natural disasters that will impact the occurrence of contingencies in the transmission and distribution system. Therefore, it is essential to implement additional strategic efforts beside the existing electricity master plans to maintain electricity supply during a disaster and to facilitate quick recovery [10]. By modernizing infrastructure using technologies cutting-edge smart grid, such as distributed energy resources (DER), isolated microgrid formation, and resource allocation for recovery, along with an agile team of technicians, the electrical system resilience can be significantly enhanced [11]. This article provides an outline of the essential systematic strategies that can achieve grid resilience during the preparation phase, during, and post-emergency incident phases [9].

This paper aims to deliver a comprehensive analysis of power system resilience by: (1) integrating notions the resilience stage, (2) classifying resilience strategies based on pre-, during-, and post-disaster phases, (3) assessing modeling and evaluation methodologies in transmission and distribution systems, and (4) pinpointing potential research directions. In understanding the meaning of resilience, several related sources are reviewed.

Various sources [12, 13], [10] demonstrate how difficult to describe the meaning of power system resilience. There is no globally accepted definition. However, it is generally understood that initiatives to enhance power system resilience seek to make the electricity network resilient to external disturbances. The concept and analysis related to this subject are presented by the author in [14]. Meanwhile, a review of the concept and assessment of resilience generally is available in [10], [14, 15]. These articles provide a strong foundation for developing research concepts on power resilience in the future. Figure 2 represents the concept of power systems resilience value using a trapezoidal graph. Classify resilience strategies based on pre-disaster, during-disaster, and post-disaster phases, depicted according to time periods (t). From time t_0 to t_1 , system is predicated on the N-1 reliability criterion. At t_1 , a natural disaster strikes the grid. The period from t_1 to t_2 indicates resilience period, which is expected be able to handle power supply disruptions more effectively than conventional reliability systems. From t_2 to t_3 , rapid response and adaptation strategies to the natural disaster are implemented; then, period t_3 to t_4 , further recovery strategies involving microgrid clustering can be immediately applied in an effort to approach the optimal condition of the system performance levels, while full recovery occurs from t_4 to t_n period after the existence of repair teams and the most efficient allocation of repair resources.

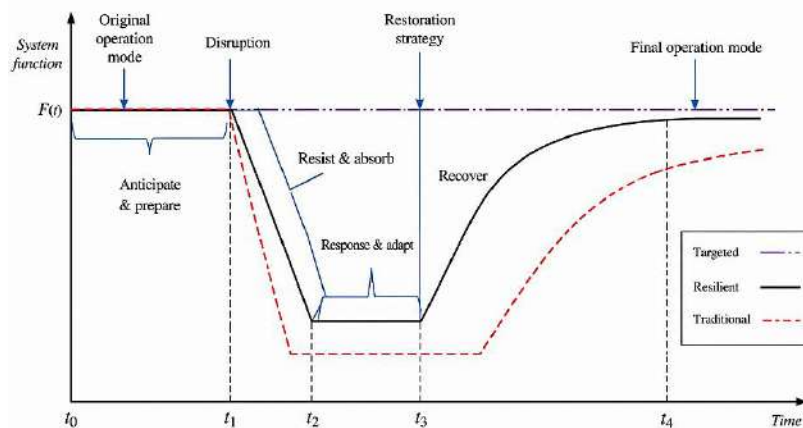


Figure 2. Performance of the trapezoidal system resistance to time [9], [16]

Based on this, resilience is defined as the ability of an electric power system to anticipate, withstand, adapt to, and rapidly recover from high-impact, low-probability (HILP) catastrophic events. As stated in [10], there are many studies on resilience uses reliability measures, such as the system mean duration of interruption (SAIDI), the system mean frequency of interruption (SAIFI), and the customer mean duration of interruption (CAIDI). These measures were taken without taking into account major outages disruption caused by extreme weather. The reliability of the electricity in stable weather conditions may not be sufficient to handle natural disasters. Therefore, it is important to implement standard resilience measures that can handle all possible disruptions due to extreme weather on critical infrastructure, based on a three-stage improvement strategy as illustrated in Figure 2, the resilience trapezoid graph. Therefore, having a robust electricity system that is able to efficiently prepare for future emergency conditions and its impact on increasing the effectiveness of operational scheduling. The strategy aims to naturally respond occurrences affecting the grid and mitigating the impact of future extreme weather events to improve network operational services.

2. RESEARCH METHOD

The applied method focuses on power system resilience evaluating. Strength assessment or evaluation is the initial strategies that needs to be taken before achieving power grid resilience. The evaluation methods used consist of qualitative and quantitative approaches. The quantitative approach includes three types: analytical techniques, statistical analysis of blackout history, and simulation method to improving the system resilient from natural disasters, as described in [10]. The results of the assessment the electric system resilience can be a guide in realizing concrete efforts and assisting system operators in planning and making operational decisions. Table 1 shows operational strategies planning for system resilience. As a basic concept in defining power system resilience, the aspects covered start from the operational period of the power system, as illustrated Fig.1 to the resilience measures implemented following a crisis. When a natural disaster impacts the grid, the subsequent frequently asked questions often yield insights for enhancing power resilience system.[9].

Question 1: What are the categories of resilience stage, and what types of measures are used in resilience assessment are needed to evaluate the power system grid in an emergency situation? These categories can provide information for formulating indicators to assess resilience improvement.

Question 2: At what level in the power system hierarchy can a power flow disturbance occur?

Question 3: What model can appropriate to address this issue to make problem-solving?

Question 4: Which phases does the resilience need to be improved?

All these questions serve as assesment criteria for research focused on increased power system resilience. Operational Strategies Planning, as shown in Table 1.

Table 1. Operational strategies planning for resilience of power system [9]

Term	Formulating operational strategies	
	Fortification measures	Strategies for operational resilience
Short term	Planning for reserves	Accuracy of location and intensity estimates.
	Installed black-start capabilities	Demand-side management
	Mobilization of repair team members	Rapid topology system reconfiguration
	Installation of Distributed Energy Resources (DER)	Microgridisland
	Collaboration with neighboring networks and repair teams	The existence of an automated protection and control system: generation and load shedding, system segmentation
Long term	Arboricultural pruning / vegetation control	Monitoring: enhancement situational awareness; sophisticated information systems and visualization.
	Underground installation of distribution and transmission cables	Guarantee communications capability
	Enhancing poles and structures with more durable, resilient materials	Microgrids with local generation (PV, wind, biomass)
	Improve the performance of substations and place them in areas that are not prone to flooding.	Using protection mechanisms and advanced control, including system integrity protection schemes (SIPS)
	The existence of backup transmission lines is carried out through additionally on transmission facilities.	Evaluation of disasters & establishment of priorities. Risk management and assessment to detect and mitigate the threats posed by disaster.

Assessing modeling and evaluation methodologies in transmission and distribution systems as shown in Table 2 below:

Table 2. Detailed list of the selected references

Disaster	References Number	Papers Overview				
		Classification	Lines		Model	
			Transmission	Distribution	Power Flow	Multi Agent
Before	[17] [18] [19] [20] [21] [22][23] [24] [25] [26]	Planning	✓	✓	✓	
	[27] [28]	Operation	✓	✓		✓
During	[29]	Operation		✓		
After	[7] [10] [24] [30] [31] [32] [33]	Evaluation		✓	✓	
	[34] [35] [36]	Strategy	✓	✓		

3. RESULT AND DISCUSSION

To directly answer the main research question (RQ1 to RQ4), this section provides a systematic literature analysis. The discussion is divided into three stages of system resilience, each providing: methodology, power vulnerability hierarchy, optimization and modeling techniques, and resilience strategies. Based on Figure 2, resilience is classified into three stages, as described below.

3.1. Pre-Interruption Stage

This stage represents the conditions before a disaster occurs, and is crucial for achieving power system resilience, it includes the following:

1. Role in Power System Resilience

This stage serves as a critical first layer in power system resilience, influencing its ability to withstand disaster-induced disruptions with a low probability of failure. Strategic implementation can realize a reduction in the frequency and duration of disruptions which will result in an increase in the system reliability index [37], lowering operational and recovery costs, and enhancing system

readiness to be able to face extreme disasters such as earthquakes, floods, storms, and cyber threats. Increasing renewable energy penetration. At this stage will also support the transition to a smart, adaptive, and self-sufficient grid. This procedure enables the anticipation, mitigation, and absorption of disruptions without interrupting power flow system services.

2. The Electricity Transmission Systems Pre-Interruption Phase

This section answers RQ 2, and in this stage, system planners will think about possible failures and to make the system ready. The research problem is frequently structured into two optimization phases. The first phase is all about making system parts stronger against expected weather conditions. The second phase looks at how the fortification strategies have improved network performance after "if scenarios" simulations to find system weaknesses during emergencies. The method for this phase is explained in the literature [23], [27], [24] recently made the electricity grid more resilient by doing a risk-based security evaluation. This evaluation method makes it easier to include risk or vulnerability analysis in security assessments that focus on risk. It uses what we know about current threats to understand important system scenarios and improve operator readiness. Phase 1 mainly uses this method, as shown in Figure 1. Researchers around the world are putting more and more effort into predicting the most dangerous possible events and finding the parts that are most likely to fail. You can find more models that are similar in references [39–41].

3. Prevention of Initial Power Supply Interruption on Distribution Systems level

This section answers RQ 2. The application of the defender-attacker-defender (DAD) model to distribution networks in [19], [20], [22] represents a decision in an effort to strengthen the distribution network. This model was developed in response to the maximum attack in research [41] correlated with the increasing frequency of disturbances caused by natural weather events. Optimal network reconfiguration and distributed energy resource (DER) island optimization are techniques for strengthening the system; therefore, considering the occurrence of natural disasters in relation to distribution line strengthening is very important. Various efforts can be made such as the placement of distributed energy resources (DER), pile excavation in robust construction efforts, vegetation management, and the application of resilience-enhancing techniques. Distribution system reconfiguration can be effectively carried out by changing the islanding procedure which will provide the opportunity to supply more electrical energy as needed and have an impact on reducing distribution system losses. [20].

3.2. During-Interruption Stage

This stage represents the conditions during a disaster occurs that people who plan and run electricity transmission and distribution systems try to figure out how often and in what ways their networks are attacked. This thorough understanding is essential for identifying the severity and nature of these attacks as a foundation for developing effective and resilient strategies [9]. Consequently, this phase examines research from two overarching viewpoints: natural occurrences and anthropogenic assaults. System planners look at the effects of natural disasters like storms, earthquakes, and floods on damage to components. They then come up with models to manage these attacks. Another way to get ready is to figure out what the worst things that could happen to the electricity system are and which parts of the network are most likely to be attacked. The literature and these sources contain more detailed explanations [43–46].

3.3. Post-Interruption Stage

At this stage, the rapid recovery of the electrical system becomes the most crucial aspect of the resilience enhancement strategy and need to be improved (this section answers RQ 3 and RQ 4). The distribution system area is directly impacted by disasters from several events. Therefore, the main research focus for post-disaster recovery conditions is on the distribution network. Through the growth of smart network technology, strategic innovations can be generated to address disruptions caused by disasters. From several studies, three main recovery schemes have been formulated that can be used to achieve optimal load recovery after a contingency occurs, which will be briefly discussed below:

1. Efficient Network Reconfiguration and DG Islanding:

In the face of unexpected disruptions, effective long-term measures are needed, such as grid reconfiguration and the implementation of distributed generation islanding (DG islanding) on power system lines. This method has been proven to be an effective strategy in avoiding and

repairing power outages to critical areas during emergencies [41], [17], [46]. A study [45], [47] has produced a network reconfiguration algorithm that considers "electrical connectivity" by prioritizing "non-black-start generators" and critical load to accelerate the recovery the transmission network after a natural disaster. Another researcher [48] introduces a model with "a sequential Monte Carlo" risk-based approach, through the separation strategies with creating gaps in the transmission line that require the least power exchange. The black-start component on each island will ensure a sufficient power supply to meet load demands. This concept also represents a strategic effort to restore power distribution during emergencies, reduce the risk of power loss, utilize renewable energy, and power quality improving [17], [41]. Restructuring the network and establishing interconnected distributed generation islands has demonstrated increasing the resiliency of the electric power systems network to harsh weather by alleviating cascading disturbances on power lines during natural catastrophes via the creation of microgrids [49]. Additional information concerning the diverse methodologies employed for this work within the electric power distribution system is available in publications [51, 52], offering a more comprehensive insight for interested readers.

2. Optimal Energy Management Scheme (OEMS):

The use of OEMS is an effort to restore power from an outage without changing the network configuration. This system uses advanced energy managements system (EMS) to improve network performance after a power outage. The OEMS can manage various resilience resources in the electrical system, from power generation, energy storage, and demand response to electrical loads, to ensure the microgrid functions properly. The algorithms used in energy management are divided into two categories. There are centralized and decentralized EMS [9]. The centralized energy management model was created using mathematical calculations and run through numerical simulations. Efforts to restore electricity supply services through mixed integer programming modeling that can be adapted to various operational constraints have been developed in previous research [52]. This model helps system operators plan and make decisions about how to run the system by creating a well-coordinated sequence of steps for controlling adjustable switches, energy storage systems, and distributed resources. The capability of such a tool has been demonstrated in other studies [54, 55] which indicate that the electricity system can be more robust if it considers the coordination of microgrids in isolation mode to maintain critical loads during emergencies. Conversely, in a decentralized energy management approach, each party making improvements, such as DERs and microgrids, independently optimize its operations and exchange information within local entities. Chen and his colleagues [52] addressing different operational restrictions on distributed generation and economic efficiency in the electrical market using a second-order conical programming paradigm. Abdelhamid et al. [54] examined the administration of extensive electrical networks extending hundreds of kilometers through the integration of multiple microgrids, employing a decentralized multi-agent control strategy to tackle the complexities inherent in large power systems. This study shows that adding a microgrid with multi-agent-based control makes the power system more resilient. Another study [55] said that the integration of multiple microgrids into a distribution system can substantially improve the utilization of distributed energy resources (DERs). This strategy is an effort to optimize operations through the implementation of microgrids connected to a system bus that has been modeled as a cyber communication network that is regulated in the form of an algorithm that has the ability to withstand disturbance conditions. This network would allocate the necessary power to local entities during emergency power supply situations, distribution systems use an EMS to lower network operating costs by adding tiered microgrids [17], [57].

3. Efficiency Allocation of Repair Resources with Teams

The last phase simulation, designed to assist the transmission and distribution system restore power as quickly as possible after a disruption, is to deploy the best recovery resources and repair teams. This is because power restoration involves efficient network restructuring and the separation of distributed generation systems, which are still not optimal as seen in the period t_3 to t_4 in Figure 2. The most effective deployment of resources and repair teams is associated with the end of the resilience graph, namely from t_4 to t_n . Reliability analysis often assumes that damaged components have recovered after a specific repair period. However, in an effort to increase resilience, Power supply can be restored better and faster through the deployment of repair teams that act proactively using limited restoration resources [58]. The integration of "mobile emergency generators" (MEGs)

and “prosumer communities” (PCs) is a combination of heat and power generation (CHP) units, electric boilers (EB), photovoltaic (PV) sources, and demand response (DR) is a strategy to improve recovery to post-disaster demand by looking at the capacity of resource capabilities to respond to demand more flexibly. Currently, efforts to accelerate emergency power recovery when extreme circumstances occur include risk-based evaluations to strengthen resilience, repair team dispatch arrangements, and resource deployment. In this phase, the identified challenge is a two-stage dispatch model with initial placement and real-time allocation, in realizing the efficiency of time delivery of repair resources using mixed integer linear programming, for example the use of mobile generators.

4. CONCLUSION

This article presents a comprehensive analysis of power system resilience strategies against extreme natural disasters, based on 58 studies identified through a thorough review using the PRISMA method. Addressing four research questions, the review classifies various resilience strategies into three critical stages. In the pre-disaster stage, actions focus on proactive infrastructure fortification and robust planning optimization to minimize the risk of initial failure. The during-disaster stage prioritizes real-time threat monitoring and immediate risk mitigation. For the post-disaster stage, rapid load restoration is achieved through functional technologies such as distributed generation islanding, microgrid clustering, and the implementation of Optimal Energy Management Schemes (OEMS) integrated with the efficient deployment of emergency repair teams. This comprehensive synthesis establishes a structured framework to guide both academics and practitioners. Future research should aim to address remaining critical challenges, including the standardization of resilience metrics, the expansion of transmission-distribution coordination studies, the development of multi-hazard modeling, the resolution of control stability issues in low-inertia microgrids, and the integration of interconnected civil infrastructure such as telecommunications and transportation systems to accelerate overall power restoration.

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