Photovoltaic Fault Detection in Remote Areas Using Fuzzy-Based Multiple Linear Regression (FMLR)

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***Abstract*—This research focused on developing and implementing a fault detection model for photovoltaic (PV) systems in remote areas, utilizing a Fuzzy-Based Multiple Linear Regression (FMLR) approach. The study aimed to address the challenges of monitoring PV systems in locations with limited access to conventional power grids and technical resources. The fault detection system integrated environmental parameters such as solar radiation, temperature, wind speed, and rainfall, alongside PV system parameters like panel voltage, current, battery voltage, and inverter performance. Data collection and preprocessing were conducted over a specified period to identify operational patterns under both normal and faulty conditions, ensuring data accuracy through cleaning, normalization, and categorization. The research was conducted in *Pandan Arang* Village, *Kandis* District, *Ogan Ilir* Regency, South Sumatera, Indonesia, contributing to the improvement of reliability and sustainability of renewable energy sources in isolated communities. The total number of data points for 276 rows with 6 attributes each was 1656 records. The MLR model was developed to predict the output power of the PV system, while fuzzy logic was employed to handle uncertainties in the data, offering a more flexible and adaptive decision-making process. The system applied fuzzy rules to determine the charging status (P3), categorizing it into Optimal Charging, Adjusted Charging, Charging Delay, or Fault Alert. The model was tested with real-time data, and its performance was validated through comparison with manual inspections. The results showed that the FMLR-based fault detection system effectively identified faults and optimized the performance of the PV system, making it suitable for remote areas in South Sumatera.**

Keywords*—*Photovoltaic; multiple linear regression; fuzzy; fault detection; remote areas

I. Introduction

Solar energy has become one of the most promising renewable energy sources in addressing global challenges related to energy security and environmental sustainability [1]–[3]. Photovoltaic (PV) systems have been widely implemented, particularly in remote areas where access to conventional power grids is limited. However, the effectiveness of PV systems heavily depends on the performance of solar panels, which can be influenced by various factors, including environmental conditions, dirt accumulation, shading, and component failures [4]–[6].

Fault detection in photovoltaic systems remains a major challenge in ensuring system efficiency and reliability. Undetected or delayed fault identification can lead to reduced energy production, extensive component damage, and increased maintenance costs [7], [8]. Therefore, an efficient and accurate method is required to detect faults in PV systems in real-time, especially in remote areas where technical resources and maintenance capabilities are limited [9]–[12].

The latest research trends focus on improving detection accuracy and enhancing PV system monitoring by integrating multiple data sources, including electrical performance indicators, environmental conditions, and system degradation metrics. Several key studies have significantly contributed to the advancement of fault detection g in photovoltaic (PV) arrays. Jordan & Hansen (2023) introduced a clear-sky detection approach using time-averaged plane-of-array irradiance to assess PV system health under clear-sky conditions, allowing for better identification of environmental factors affecting PV degradation using linear regression [13].

Jufri et al. (2019) developed a hybrid detection model combining regression analysis and Support Vector Machines (SVM) to detect abnormal conditions in PV systems. Their method enhanced fault prediction accuracy by incorporating daylight time and interaction variables between independent parameters, validated through multi-stage k-fold cross-validation [14]. Heinrich et al. (2020) explored machine learning techniques, particularly Logistic Regression, to monitor cleaning interventions in PV modules, ensuring optimized maintenance scheduling [15].

Harrou et al. (2021) utilized Gaussian Process Regression (GPR) and Support Vector Regression (SVR) for fault data modelling, showcasing the flexibility and adaptability of kernel-based learning methods for real-time PV system monitoring [16]. Additionally, Kim et al. (2020) introduced multivariate analysis using least-square regression to detect PV system faults, integrating both electrical and environmental parameters to provide a structured statistical framework for system health assessment [17]. These studies demonstrate the evolution of fault detection methodologies, emphasizing the role of statistical, machine learning, and hybrid approaches in improving PV system reliability and efficiency.

While previous studies primarily focused on machine learning and statistical regression techniques, a hybrid solution that integrates the strengths of fuzzy logic and multiple linear regression can be used for uncertainties decision [18]–[20]. This method is particularly advantageous in handling uncertainties in photovoltaic (PV) system operations in environmental conditions that vary significantly [21]–[23]. By

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effectively modeling nonlinear relationships between multiple independent variables—such as temperature, solar irradiance, wind speed, humidity, and power output—and their influence on fault indicators, this approach enhances the accuracy of fault detection.

Unlike traditional regression models that depend on fixed threshold values, Fuzzy-Based Multiple Linear Regression (FMLR) utilizes fuzzy membership functions to dynamically categorize data, allowing for greater flexibility in identifying faults within PV systems in South Sumatera’s diverse climatic conditions [24]–[26]. Moreover, this method improves fault classification by facilitating gradual transitions between fault states rather than the rigid categorizations typically employed in Support Vector Machines (SVM) and Logistic Regression, ensuring a more adaptive and resilient monitoring system for PV operations in the region [27]–[29].

The remainder of this paper is organized as follows: Section II provides a detailed literature review on the various fault detection methods used in PV system, with a particular focus on the integration of fuzzy logic and MLR. Section III outlines the research methodology, including data collection, preprocessing, and the design of the fault detection model. Section IV presents the experimental setup and the implementation of the photovoltaic system in the remote area. Section V discuss the results and validation of the proposed model, including comparisons with manual inspection data. Finally, Section VI concludes the paper by summarizing the findings and offering recommendations for future work in PV system fault detection.

II. Literature Review

A. Multiple Linear Regression

Regression analysis is a statistical-based method used to analyze the relationship between independent variables (X) and a dependent variable (Y). In the context of fault detection in photovoltaic systems, Multiple Linear Regression (MLR) is often employed to assess the impact of multiple independent variables on system performance. The general equation is expressed as Eq. (1).

$$y = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n \tag{1}$$

In the context of fault detection in photovoltaic systems, the dependent variable (Y) represents the system’s output or fault indicator, while the independent variables (X_1, X_2... X_n) include factors such as panel temperature, solar radiation, wind speed, and other operational parameters. The equation incorporates b_0 as the intercept (constant term) and b_1, b_2... b_n as the regression coefficients, which indicate the relation to each independent variable on the dependent variable.

B. Fuzzy Logic

In photovoltaic fault detection, once all propositions have been evaluated, the output consists of a fuzzy set that represented the contribution of each rule to the final decision that is represented and expressed as Eq. (2).

$$\mu(x_i) = (\mu_{sf}(x_i), \mu_{kf}(x_i)) \tag{2}$$

Value of $\mu_{sf}(x_i)$ denoted the membership value of the fuzzy solution up to the *i-th* rule, indicating how well a specific condition aligns with the defined fuzzy rules for system performance evaluation. Meanwhile, $\mu_{kf}(x_i)$ denoted the membership value of the fuzzy consequent up to the *i-th* rule, reflecting the degree to which the system's response or output is influenced by a given rule.

The input for the defuzzification process in photovoltaic fault detection is a fuzzy set derived from the composition of fuzzy rules, while the output is a crisp numerical value that provides a definitive assessment of the photovoltaic system's performance. Given a fuzzy set within a specific range, a crisp output can be determined using a defuzzification method. When multiple rules contribute to the decision-making process, defuzzification is performed by calculating the centre of gravity (centroid method) to determine the most representative output value. This approach helps in accurately detecting faults in photovoltaic panels, inverters, and power output variations by translating fuzzy logic-based rule evaluations into precise system diagnostics. The final crisp decision can be obtained using centroid-based defuzzification, allowing for proactive fault identification and optimization of photovoltaic energy generation as presented in Eq. (3).

$$C = max(a, b) \tag{3}$$

where, C represents the most significant fuzzy membership value, aiding in the identification and classification of faults in photovoltaic operations.

III. Research Methdology

The research is initiated with a literature review and problem identification, which examined previous studies on fault detection in photovoltaic (PV) systems using artificial intelligence methods such as Fuzzy Logic and Multiple Linear Regression (MLR). This phase identified key challenges encountered by PV systems in remote areas and fault detection is depicted in Fig. 1.

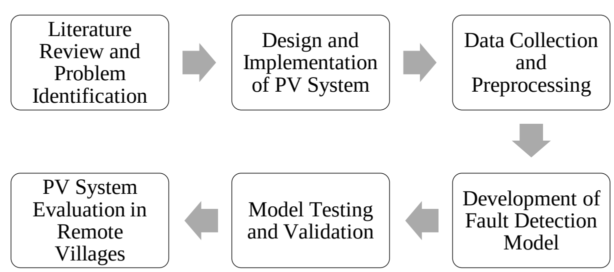


Fig. 1. Research phase.

Data collection and preprocessing were carried out over a specified period to identify operational patterns of the photovoltaic (PV) system under both normal and faulty conditions. The process involved, cleaning the data by eliminating anomalies and noise to ensure its accuracy. Afterward, the data was normalized to ensure compatibility with the regression model and categorized based on the operational conditions of the PV system. The collected environmental parameters included solar radiation intensity, air temperature, humidity, wind speed, rainfall, and panel temperatures (both top and bottom). The total number of data points for 276 rows with 6 attributes each was 1656 data.

The development of the fault detection model for the photovoltaic (PV) system involved several stages, starting from the system setup to the implementation of the fault detection mechanism. Initially, the necessary hardware components, including photovoltaic panels, solar charge controllers, batteries, inverters, and MCBs, were configured. Environmental parameters such as solar radiation, temperature, wind speed, and rainfall, along with system parameters like current, voltage, power, and temperature at various points in the system, were continuously monitored. The fault detection system was designed to trigger alerts based on FMLR and presented in Fig. 2.

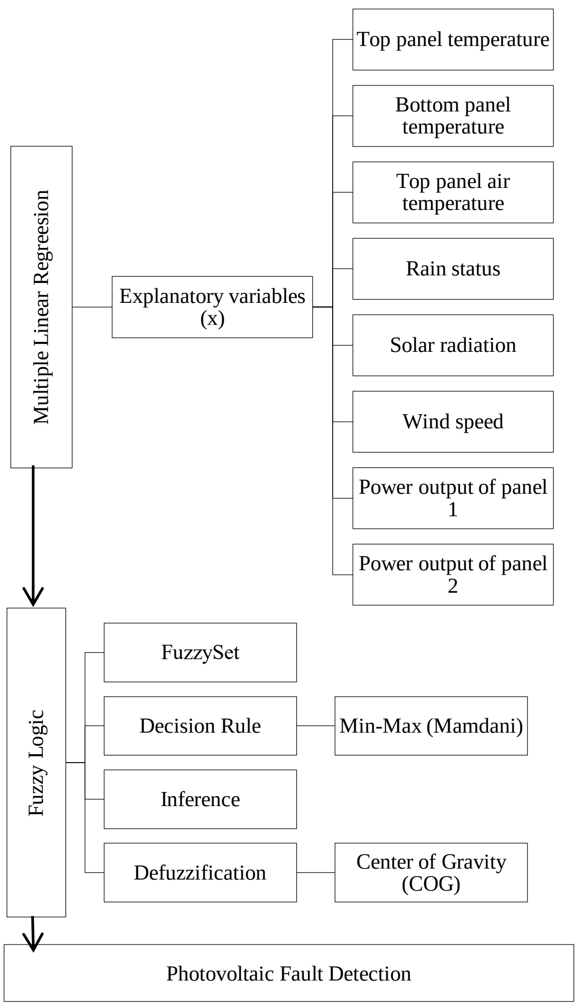


Fig. 2. Photovoltaic fault detection based on FMLR.

The research was conducted using an experimental method by implementing PV system integrated with fault detection. The study took place in Pandan Arang Village, Kandis District and Ogan Ilir Regency with its located in South of Sumatera. Data was collected over a specific period to identify operational patterns in both normal and faulty conditions. This data was preprocessed by eliminating anomalies, normalizing values for compatibility with the regression model, and categorizing it based on operational conditions.

The fuzzy-based multiple linear regression (FMLR) model was designed to enhance the fault detection process in photovoltaic (PV) systems by analyzing the relationships between various environmental and system parameters. These parameters include temperature, solar irradiance, wind speed, humidity, and power output, which directly influence the performance of the PV system. The FMLR model incorporates fuzzy logic to handle uncertainties and nonlinearities in these parameters, offering a more flexible and dynamic approach compared to traditional methods.

The model was trained using historical data collected from the PV system, which included instances of both normal operation and various types of faults. By processing this data, the model learned to identify distinct patterns associated with typical system behavior as well as fault conditions. The use of fuzzy logic rules allowed the model to adapt to varying operational conditions and gradually transition between different system states, rather than relying on rigid, predefined thresholds. This adaptability makes the FMLR model particularly useful for systems that operate in dynamic and unpredictable environments, such as those found in remote or off-grid locations.

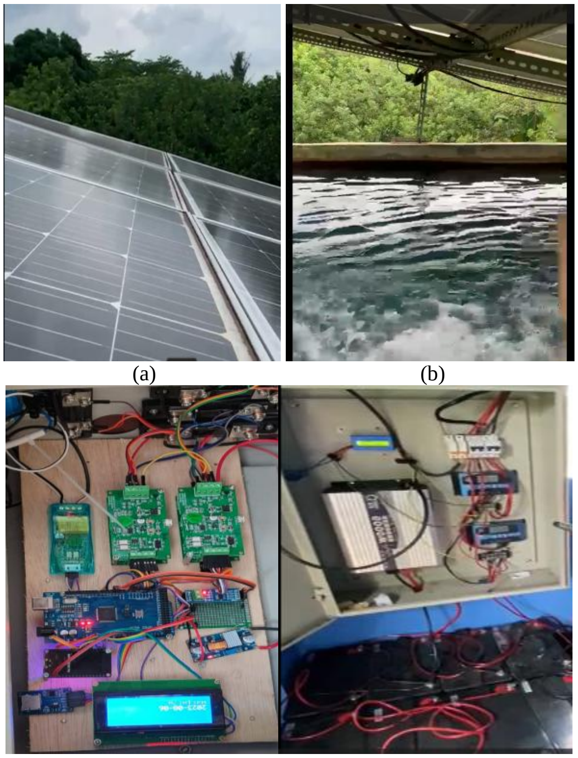
Once trained, the FMLR model was able to classify system conditions into several categories, each reflecting a different state of operation. These categories included “Optimal Charging”, where the system is functioning at peak efficiency, “Adjusted Charging”, which occurs when external factors such as weather conditions require adjustments to the charging process, “Charging Delay”, which is triggered when system temperatures are too high to ensure safe operation, and “Fault Alert”, which indicates that a significant fault has been detected, requiring immediate attention.

The developed model underwent testing and validation using test data to assess its accuracy. The fault detection results were compared with manual PV system inspections to validate the model’s accuracy. The fault detection system was deployed and observed in a remote village in South of Sumatera for to detect fault conditions in real-time.

IV. Research Result

The identification process carried out through a site survey for the placement of the photovoltaic system resulted in the required photovoltaic (PV) components amounting to 6 x 200 WP. The required solar charge controller (SCC) was 2 x 12V 60A, while the battery capacity needed was 8 x 12V 100Ah. Additionally, a single inverter unit with a capacity of 12V 6000-watt peak (WP) was used to support the system. The photovoltaic (PV) panels were installed on top of a water storage tank, arranged in parallel configuration using six panels.

The installation of the PV system followed a parallel PV configuration, where the panels were placed on the roof (rooftop) above the water storage tank. The PV panels were connected to a miniature circuit breaker (MCB) as a protective device before being linked to the solar charge controller (SCC). The SCC was set according to the battery voltage to optimize charging efficiency. From the SCC, the energy was stored in batteries, which were then connected to the inverter. The inverter was also linked to an MCB before converting DC (Direct Current) into alternating current (AC) to power the water pump. The proposed PV system as illustrated in Fig. 3.



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

Fig. 3. PV system in remote areas (a) Solar panels (b) Solar panels integrated to water storage tank (c) IoT for environment paramater control (d) IoT for PV system control.

The implementation of this system ensured that the photovoltaic system provided a stable energy supply for operating essential equipment in the remote area. The use of the Internet of Things (IoT) allowed real-time monitoring and control of the system, enabling efficient management of power generation and consumption. This approach contributed to improving access to renewable energy in isolated rural areas of South Sumatra, where conventional electricity sources were limited or unavailable.

The photovoltaic fault detection for the PV system was designed to optimize the battery charging process by considering various environmental factors and the output power from solar panels. This system integrated sensors, an Arduino Mega, data storage, and fuzzy-based multiple linear regression (FMLR) to provide more accurate decisions regarding photovoltaic fault detection based on battery charging conditions.

The DSS utilized sensors to collect real-time data on environmental parameters such as solar radiation, temperature, and battery voltage. These data were then processed using an Arduino Mega microcontroller, which acted as the main control unit for data acquisition and transmission. The multiple linear regression (MLR) approach was used to predict the output power of photovoltaic in panel 1 (P1) and panel 2 (P2) by utilizing six independent variables, including top panel temperature (X_1), bottom panel temperature (X_2), panel surface temperature (X_3), rain status (X_4), solar radiation intensity (X_5) and wind speed (X_6). The calculation P1 and p2 using MLR approach is presented in Eq. (4) and Eq. (5).

$$P1 = -1.0389+(0.1656\times X1) + (-0.0754\times X2) + (-0.0688\times X3) + (0.4500\times X4) + (-0.0025\times X5) + (13.6189\times X6) \quad (4)$$

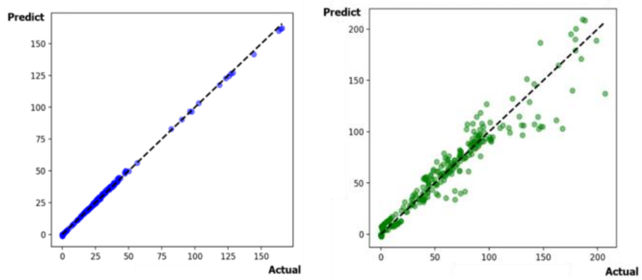
$$P2 = -55.9447+(0.6757\times X1) + (5.0193\times X2) + (-3.5212\times X3) + (-0.9017\times X4) + (0.2040\times X5) + (4.6400\times X6) \quad (5)$$

The fuzzy rules for predicting P_1 and P_2, along with other input data established several important steps. First, the fuzzy sets for the P_1 power output variable and the charging status (P3) variable were defined. Based on the MLR prediction, a fuzzy classification category was generated for predicting P_1 and P_2, which included three levels: Low, Medium, and High. The classification determined based on fuzzy set values in Table I.

TABLE I. FUZZY SET VALUES

Variable	Membership	Value Range
Top Panel Temperature (X_1)	Low	$\leq$ 25°C
	Medium	25°C < T $\leq$ 35°C
	High	> 35°C
Bottom Panel Temperature (X_2)	Low	$\leq$ 25°C
	Medium	25°C < T $\leq$ 35°C
	High	> 35°C
Air Temperature (X_3)	Low	$\leq$ 25°C
	Medium	25°C < T $\leq$ 35°C
	High	> 35°C
Rain (X_4)	Rain	1
	No Rain	0
Solar Radiation (X_5)	Low	$\leq$ 10 W/m²
	Medium	10 < W/m² $\leq$ 100 W/m²
	High	> 100 W/m²
Wind Speed (X_6)	Low	$\leq$ 1 m/s
	Medium	1 < m/s $\leq$ 3 m/s
	High	> 3 m/s
Power Output Panel 1 (P_1) & Power Output Panel 2 (P_2)	Low	$\leq$ 50 Watt
	Medium	50 < Watt $\leq$ 100 Watt
	High	> 100 Watt

The comparison graph between actual data and the multiple linear regression (MLR) model predictions illustrated the relationship between observed power output values and the predicted values generated by the model. The first graph presented the actual data for P_1 (x-axis) against the predicted P_1 values (y-axis), where the blue scatter points were closely aligned with the dashed diagonal line (y = x). This pattern indicated that the model had achieved high accuracy, with minimal error in predicting P_1. Meanwhile, the second graph compared actual P_2 data (x-axis) with its predicted values (y-axis), where the green scatter points appeared more dispersed, though they still largely followed the y = x diagonal line. The visualizations provided insight into the prediction accuracy and reliability of the MLR model is depicted in Fig. 4.



(a) (b)

Fig. 4. Comparison of actual data and MLR model predictions for (a) panel P1 (b) panel P2.

In a photovoltaic system, the value of the battery charging status (P3) functioned to regulate the battery charging level by considering various environmental factors and the operational conditions of the solar panels. This process used fuzzy logic, which enabled the system to dynamically adjust charging decisions based on input values that were not always precise or binary. Fuzzy logic worked by translating environmental variables such as temperature, solar radiation, wind speed, and rainfall into linguistic categories like low, medium, or high. Then, the system applied fuzzy rules in the form of IF-THEN statements, which determined P3 based on the combination of existing variables and represented through pseudocode, as shown in Fig. 5 (Algorithm 1).

Algorithm 1: Decision Rule for PV Fault Detection

```
BEGIN
  INPUT P1, P2, X4, X1, X2, X3, X5, X6

    IF P1 == "low" AND P2 == "high" AND X4 == "no" AND X1
    == "high" AND X2 == "high" AND X3 == "high" AND X5
    == "high" AND X6 == "medium" THEN
    P3 = "Optimal Charging"
    END IF

    …

    IF P1 == "medium" AND P2 == "medium" AND X4 == "no"
    AND X1 == "medium" AND X2 == "high" AND X3 ==
    "medium" AND X5 == "high" AND X6 == "medium" THEN
    P3 = "Optimal Charging"
    END IF

    IF P1 == "high" AND P2 == "high" AND X4 == "no" AND
    X1 == "high" AND X2 == "high" AND X3 == "high" AND
    X5 == "medium" AND X6 == "high" THEN
    P3 = "Optimal Charging"
    END IF

  DISPLAY "Charging Status: ", P3
END
```

Fig. 5. Decision rule for photovoltaic fault detection.

To understand P3 operated in the photovoltaic system, a logical representation was required to illustrate the relationship between input and output variables based on the defined fuzzy rules. Pseudocode could be used to illustrate how environmental variables such as panel power (P1, P2), rainfall (X4), panel temperature (X1, X2), air temperature (X3), solar radiation (X5), and wind speed (X6) interacted in determining the charging status (P3). Each observed variable combination was processed using IF-THEN rules. With the application of fuzzy rules, the system was able to optimize charging when environmental conditions were favorable, adjust the charging mode in response to external disturbances such as rain, and delay or reduce charging to prevent overheating if the panel temperature became too high.

Based on the applied rules, the fuzzy inference system output in fault detection for photovoltaic operations was categorized into four main conditions. The "optimal charging" condition occurred when environmental conditions supported maximum charging, such as high solar radiation, panel temperature within a safe range, and sufficient wind speed to maintain panel temperature stability. The "adjusted charging" condition was applied when external factors influenced the charging process, such as rain, where the system adjusted the charging mode to remain efficient and safe. The "charging delay condition was implemented when panel temperature was too high, potentially causing overheating, leading the system to automatically delay charging to prevent component damage. The "fault alert" condition was triggered when the system detected issues that could cause malfunctions or damage, such as high panel temperature but low solar radiation, which could indicate problems with the panel or electrical system.

In the defuzzification process, the input used was the fuzzy set obtained from the composition of fuzzy rules. This process aimed to determine a crisp value that represented the system output based on the distribution of membership degrees from the various rules that had been previously applied. One of the most commonly used defuzzification methods was the Center of Gravity (COG), where the output value was obtained by finding the central average of all values within the given range. This method calculated the balance point of the fuzzy membership distribution, ensuring that the final result reflected the most representative value based on the applied fuzzy rules.

If the fuzzy inference system generated membership values for multiple output categories such as Optimal Charging, Adjusted Charging, and Charging Delay, then the defuzzification process determined a crisp value among these categories based on their membership weights. Thus, defuzzification enabled the system to translate fuzzy results into concrete actions, such as determining the charging level or detecting potential errors in the photovoltaic system. The structured output in the Arduino Command Line Interface (CLI) environment provided a clear representation of how the fuzzy-based decision support system (DSS) functioned in real-time fault detection is presented in Fig. 6.

```
==================================================
                DSS FAULT DETECTION
==================================================

Enter value for Top Panel Temperature (X1): 39.99
39.99
Enter value for Bottom Panel Temperature (X2):
40.00
40.00
Enter value for Air Temperature (X3): 40.00
40.00
Is it Raining? (1 = Yes, 0 = No) (X4): 0
0
Enter value for Solar Radiation (X5): 500.00
500.00
Enter value for Wind Speed (X6): 4.03
```

```
4.03

-------------------------------------------------
PREDICTION: FUZZY-BASED MULTIPLE LINEAR REGRESSION
-------------------------------------------------
Predicted MLR Value for P1: 53.4406
Predicted MLR Value for P2: 151.7050
Fuzzy Category for P1: Medium
Fuzzy Category for P2: High

-------------------------------------------------
               CHARGING STATUS
-------------------------------------------------
P3 Status: FAULT ALERT

** WARNING **
Please check the **panel condition, environmental
factors, and system configuration** for possible
issues.
```

Fig. 6. Output of Arduino CLI for fault detection.

Fuzzy inference was a rule-based reasoning process used to determine the output based on input variables that had been classified into membership categories. In the fault detection system for IoT-based photovoltaic operations, the fuzzy inference method was applied to link input variables with the charging level and potential system disturbances based on environmental and operational conditions of the solar panels. The method used for fuzzy inference was the MIN-MAX method. Once all propositions had been evaluated, the output contained a fuzzy set that reflected the contribution of each proposition, as shown in Fig. 7.

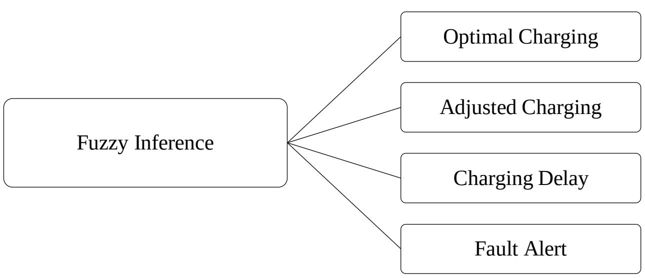


Fig. 7. Fuzzy inference.

The output generated from the Arduino Command Line Interface (CLI) code represented the fault detection process in an IoT-based photovoltaic system using a fuzzy inference model and multiple linear regression (MLR). The system prompted the user to input environmental parameters, including top panel temperature (X_1), bottom panel temperature (X_2), air temperature (X_3), rainfall status (X_4), solar radiation (X_5), and wind speed (X_6). Based on these inputs, the system computed predicted power values (P_1 and P_2) using the MLR model and classified them into fuzzy categories such as Low, Medium, or High. The final step involved evaluating the charging status (P3) using predefined fuzzy logic rules. If an anomaly was detected, the system triggered a Fault Alert, indicating a potential operational issue within the photovoltaic system. The warning message advised further inspection of panel conditions, environmental factors, and system configurations to prevent potential failures or inefficiencies.

V. Conclusion

This research successfully developed and implemented a Fault Detection Model for photovoltaic (PV) systems in remote areas, utilizing the Fuzzy-Based Multiple Linear Regression (FMLR) approach. The model demonstrated its potential to address the challenges of monitoring PV systems in regions with limited access to conventional power grids and technical resources. By integrating environmental parameters such as solar radiation, temperature, wind speed, and rainfall, along with PV system parameters like panel voltage, current, battery voltage, and inverter performance, the system effectively tracked and evaluated the operational conditions of the photovoltaic system. The system was successfully deployed in Pandan Arang Village, Kandis District, Ogan Ilir Regency, South Sumatera, Indonesia, providing a reliable and sustainable solution for enhancing the efficiency of renewable energy sources in isolated communities.

Data collection and preprocessing were carefully executed to ensure the quality and accuracy of the data, with anomalies removed, normalization applied, and data categorized based on operational conditions. The MLR model was used to predict the output power of the PV system, while fuzzy logic enabled the handling of uncertainties in data, offering greater flexibility in decision-making. The system utilized fuzzy rules to determine the charging status (P3), categorizing it into Optimal Charging, Adjusted Charging, Charging Delay, or Fault Alert, ensuring adaptive and responsive fault detection. The developed model was tested using real-time data, and its performance was validated against manual inspections, demonstrating its high accuracy and effectiveness in fault detection.

Future research focused on further validating the proposed fault detection model by conducting long-term field studies in various geographical regions with different climatic conditions. This approach helped assess the model's robustness and adaptability in diverse environments. Additionally, the integration of advanced machine learning techniques, such as deep learning, was explored to improve the model's predictive accuracy and real-time fault detection capabilities. Future studies also investigated the optimization of energy storage and grid integration in remote PV systems to enhance the overall efficiency and sustainability of renewable energy solutions.

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