International Journal of Advances in Applied Sciences (IJAAS)
Vol. 15, No. 2, June 2026, pp. 622~633
ISSN: 2252-8814, DOI: 10.11591/ijaas.v15.i2.pp622-633

Multi-level redundancy with internet of things battery supply for fault mitigation in grid-tied photovoltaic systems

Habib Satria[1], Muhammad Fadlan Siregar[1], Indri Dayana[1], Dadan Ramdan[1], Muhammad Irwanto[2,3], Syafii[4]
[1]Department of Electrical Engineering, Faculty of Engineering, Universitas Medan Area, Medan, Indonesia
[2]Center of Excellence for Health Based on IoT and Renewable Energy, Department of Electrical Engineering, Faculty of Science and Technology, Universitas Prima Indonesia (UNPRI), Medan, Indonesia
[3]Fellow of Center of Excellence for Renewable Energy, Faculty of Electrical Engineering and Technology, Universiti Malaysia Perlis, Arau, Malaysia
[4]Department of Electrical Engineering, Faculty of Engineering, Universitas Andalas, Padang, Indonesia

Article Info

Article history:

Received Nov 11, 2025
Revised Apr 26, 2026
Accepted May 23, 2026

Keywords:

Dynamic IoT monitoring
Fault mitigation
Machine learning
Multi-level redundancy
System protection

ABSTRACT

The development of grid-tied photovoltaic (PV) systems in tropical regions remains a strategic focus for achieving sustainable clean energy. However, energy conversion efficiency is often hampered by fluctuations in panel surface temperature and electrical faults. To ensure long-term system reliability, this study implements a multi-level redundancy architecture integrated with dynamic internet of things (IoT) monitoring for fault mitigation in grid-tied PV systems. The system employs a machine learning (ML) method using the k-nearest neighbors (KNN) algorithm for thermal classification, achieving an accuracy of 84% in identifying normal (25 °C to 35 °C) and overheating conditions. Furthermore, an electrical redundancy layer is designed with an automatic tripping mechanism that activates when the current exceeds a 1.30 A threshold, demonstrating a rapid response latency of 150 ms. To ensure monitoring resilience, the system is supported by a dedicated 18650 Li-ion battery backup. The implementation results confirm that this multi-level protection framework effectively monitors real-time energy usage, prevents critical component damage, and enhances the overall safety of household-scale PV installations. This research provides a scalable and intelligent solution for fault mitigation, supporting the broader adoption of renewable energy in tropical environments.

Corresponding Author:

Habib Satria
Department of Electrical Engineering, Faculty of Engineering, Universitas Medan Area
Kolam St, No.1, Medan-20223, Indonesia
Email: habib.satria@staff.uma.ac.id

1. INTRODUCTION

Indonesia’s solar energy potential is enormous, opening up significant opportunities for breakthroughs in grid-connected photovoltaic (PV) installations. Its favorable climate and abundant natural resources have led to the rapid advancement of PV utilization, driven by its environmental friendliness and ease of operation [1]–[3]. Therefore, the development of PV for public use must be properly utilized [4], [5]. However, significant challenges in the field hamper the PV energy conversion process, particularly dust accumulation and excessive heat on the panel surface, which exhibit a linear relationship in reducing conversion efficiency [6], [7]. These conditions negatively impact the distribution of energy from PV to household electrical loads, resulting in suboptimal panel efficiency [8]–[10]. Meanwhile, the implementation of grid-connected PV systems [11]–[13] is highly sought after due to its potential to reduce electricity bills and provide a solution amidst economic challenges. Complex issues that must be considered are fault mitigation and protection system control in grid-connected PV installations. Common damages such as overloads, direct lightning strikes, or potential house fires often occur due to standard installations that do not comply with the electrical safety provisions and procedures established by the International Electrotechnical Commission (IEC) standards [14]–[16]. This non-compliance is crucial for the safety and optimization of household electrical installations and equipment usage, and impacts the instability of PV energy conversion in home power supplies [17], [18]. Despite recent advances in internet of things (IoT)-based monitoring using sensors such as the PZEM-004T and ESP8266, most existing systems focus on only one layer of protection (thermal or electrical only) and often lack automatic fault mitigation. There is a clear research gap in integrating these two layers into a unified architecture that remains operational during power outages. Therefore, to ensure the safety and reliability of PV systems, an approach that integrates multiple layers of protection, or multi-level redundancy, is needed.

The first step in addressing this issue is optimizing PV energy conversion by recognizing and managing panel surface temperature patterns. Machine learning (ML) methods were chosen for their rapid and effective pattern recognition, particularly from image data captured using thermovision technology [19]–[21]. The recorded data was processed using the k-nearest neighbors (KNN) algorithm to determine accuracy, precision, recall, and F1-score [22]. This data processing provides solutions to temperature issues, such as identifying temperatures outside the ideal range of 25 °C to 35 °C, allowing the system to immediately provide information to optimize electrical energy conversion [23]. Furthermore, to implement an effective multi-level redundancy layer, the functionality of the grid-connected PV protection system was optimized through integrated dynamic IoT monitoring. The system utilizes the PZEM-004T sensor module to read vital parameters such as voltage, current, active power, and energy consumption [24]. This technology is enhanced with an IoT system, utilizing the ESP8266 module, which enables real-time electrical energy monitoring. To ensure system resilience, a dedicated battery backup supply is integrated to maintain monitoring functions during critical interruptions. Overall, this system is designed to provide electrical protection for grid-connected PV users. This means that when an overload or excessive current occurs (such as an automatic disconnection based on readings outside the set electrical parameters), the system will automatically cut off the current [25]. Based on this, this research contributes to an integrated thermal redundancy layer using KNN-based classification with thermovis data, followed by an electrical redundancy layer through IoT-based automatic relay protection, and a battery-powered control system for uninterrupted monitoring. This monitoring data can be accessed through PC and Android applications, providing a comprehensive solution for optimizing energy conversion from PV and ensuring safe electricity use in grid-connected installations. This integrated approach significantly improves the reliability and safety of household-scale PV systems in tropical regions.

2. METHOD

The thermal redundancy layer relies on dynamic IoT monitoring and ML to ensure early fault detection. The dataset used in this study consists of 300 thermovision images, which were captured under varying environmental conditions to record temperature patterns on the surface of the PV panels. To evaluate the model's performance and avoid selection bias, the dataset was split into a training set of 210 images and a testing set of 90 images, following both 70:30 and 80:20 distribution ratios for comparative validation in the developed pattern recognition method. The dataset partitioning was performed randomly to ensure a uniform distribution of classes and features across both subsets. The training set was utilized to develop the diagnostic model, while the testing set served as a benchmark to evaluate the model's generalization capability on unseen data. This process is then executed using the KNN algorithm with a parameter of k =3, effectively classifying temperature conditions as either normal (25 °C–35 °C) or overheating. This classification provides a real-time response for thermal damage mitigation. The installation positioning is carefully performed using the azimuth and elevation point method to ensure ideal panel orientation, which is crucial for energy conversion efficiency as shown in Figure 1.

Criteria that support optimal system operation and thermal redundancy layer. These criteria include a review of environmental parameters and the physical condition of the panels. Monitoring on measurements for PV installations and an introduction to solar cell patterns to convert PV energy into electrical energy are shown in Figure 2.

The monitoring system captures environmental data to evaluate system performance. Figure 2(a) illustrates the trends of the coefficient of performance (CoP) (ΔT) during the heating and cooling cycles, which is critical for understanding thermal behavior. Meanwhile, Figure 2(b) displays the continuous measurements of the temperature source [°C], showing the stability of the ambient conditions. For the fault mitigation process, the thermal redundancy layer relies on image acquisition. Figure 2(c) represents the captured thermal pattern of a solar cell under normal temperature conditions, serving as the baseline for the system. In contrast, Figure 2(d) highlights the solar cell temperature pattern during hot or overheating conditions, where potential damage is identified. These captured images are then processed using the KNN algorithm to classify the health status of the PV system based on these specific patterns.

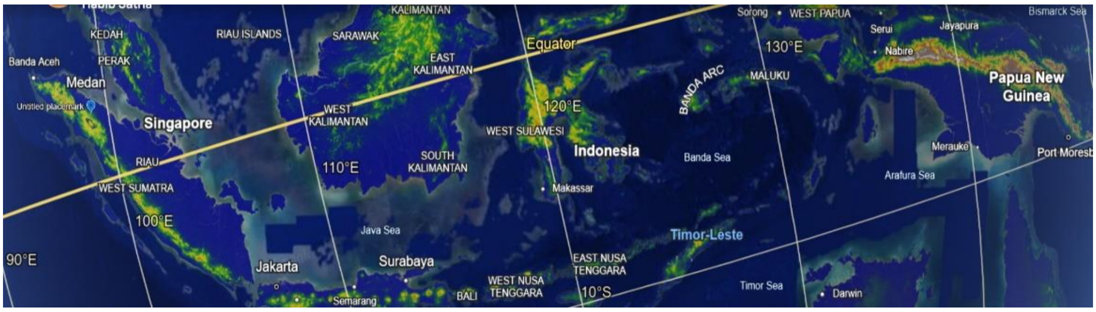
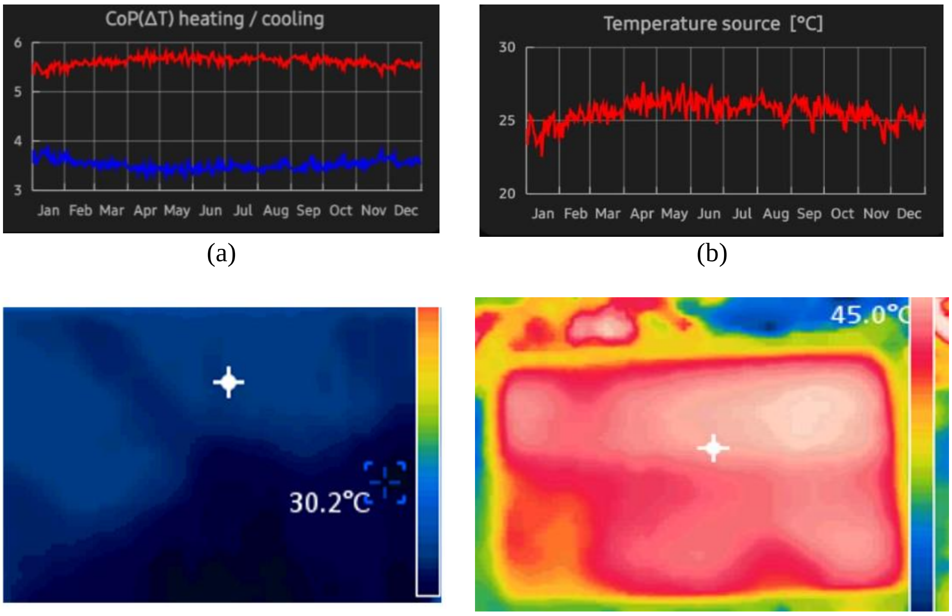


Figure 1. Strategic location of on grid PV installation in North Sumatra region



(a) (b)

(c) (d)

Figure 2. Monitoring on measurements for PV installations and introduction of solar cell patterns to convert PV energy into electrical energy, (a) CoP (ΔT) heating/cooling, (b) temperature source [°C], (c) solar cell temperature conditions when the surface temperature is normal, and (d) solar cell temperature conditions when the surface temperature is hot

The final stage of the methodology focuses on the implementation of the electrical redundancy layer through an IoT-based protection system for grid-tied PV systems. The model is developed using PZEM-004T sensor connected via an ESP8266 module for real-time monitoring of vital electrical parameters. To ensure control system resilience, a dedicated 18650 Li-ion battery backup is integrated to provide a secondary power level, ensuring the IoT monitoring unit remains active during grid faults. The protection system is equipped with a relay control as a disconnect mechanism. The relay is set to automatically trip when the sensor detects an excessive current of 1.30 A or other abnormal conditions. Experimental validation shows that the relay tripping mechanism achieves an average response time latency of approximately 150 ms, ensuring rapid fault isolation and installation safety. All data from both redundancy layers are integrated and monitored in real-time via PC and Android applications. The architecture diagram of the grid-tied PV system integrated with the dynamic IoT-based electrical redundancy protection system for damage mitigation is shown in Figure 3.

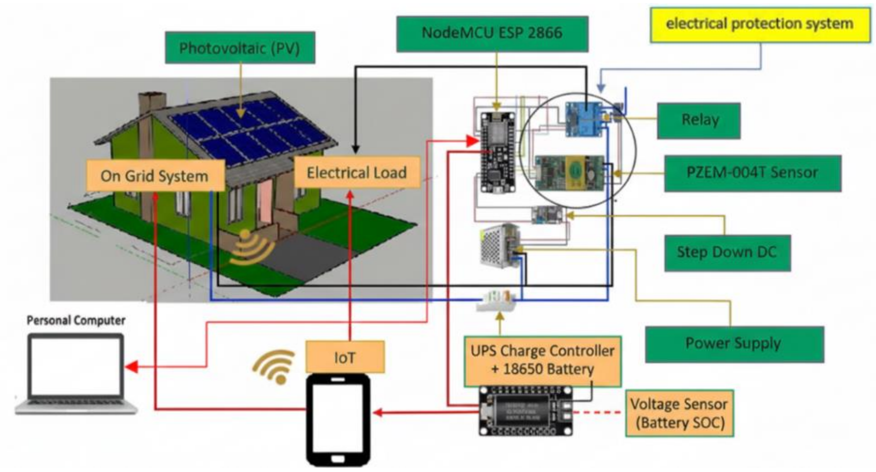


Figure 3. Resilient multi-level redundancy architecture featuring 18650 Li-ion battery backups for uninterruptible dynamic IoT monitoring

The integrated sensor protection system design is implemented as a crucial layer of multi-level redundancy to prevent damage to electrical equipment and as a detector for power outages. The system operates using an IoT connection on a grid-connected PV installation, as illustrated in Figure 3. Technically, this dynamic IoT monitoring is built around a node microcontroller unit (NodeMCU) microcontroller (ESP8266). The system's power supply installation involves connecting voltage at the common collector (VCC) and ground (GND) via a step-down module to the Vin and GND pins on the NodeMCU, ensuring a stable power supply. The NodeMCU serves as the main processing unit to monitor, control, and activate the protection layer. The PZEM-004T module is connected to the NodeMCU via the RX and TX pins to read vital electrical parameters (voltage, current, active power, and energy) in real-time. This data forms the basis of the dynamic monitoring system. A relay is connected to the NodeMCU and serves as the main breaker. The system is configured to operate on a household-scale active power of 900 VA. When the sensor detects an electric current exceeding the safe limit of 1.30 A, the NodeMCU will activate the relay, which will then trigger the miniature circuit breaker (MCB) system to cut off the electric current. This fast mechanism is a crucial layer of electrical redundancy. In addition to the protection function, the voltage, current, and power data on the grid-connected PV system can be monitored in real-time through the IoT system connected to the NodeMCU ESP8266, with light emitting diode (LED) indicators indicating the activation of the protection system and an active WiFi connection.

The electrical redundancy layer operates on the principle of an adaptive overcurrent relay (OCR). The relay tripping time (T) is determined by the magnitude of the fault current (I_{fault}) compared to the set pick-up current (I_{pick}). The equation used to calculate the OCR relay tripping time is as in (1).

$$T = \left[\frac{A}{\frac{I_{Fault}}{I_{Pick}}^{B}-1}\right] \text{TMS} \tag{1}$$

Then, to classify the PV panel temperature into normal (c1) or Hot (c2) conditions, the ML model uses the KNN algorithm. KNN works based on the majority classification rule, where the class of the test data is determined by the majority class of it is KNN. Mathematically, the KNN majority classification rule is defined as in (2).

$$Y - \frac{\arg max}{c\in Dom(Y)} \sum_{X_{i\in KNN(T)}} I(Y_i = c) \tag{2}$$

The performance of the KNN algorithm can then be improved by applying a weighted classification rule. This method can assign greater weight to the nearest neighbors of the test data, thereby increasing sensitivity to local anomalies. One implementation of distance-based weighted classification is shown in (3).

$$Y - \frac{\arg max}{c\in Dom(Y)} \sum_{X_{i\in KNN(T)}} I(Y_i = c)\left(1 - \frac{d(X_i,X)}{d_{MAX}}\right) \tag{3}$$

3. RESULTS AND DISCUSSION

PV is a major supplier to reduce household electricity consumption, which is essential to minimize electricity bills. The development of grid-connected PV using IoT technology is an innovative solution in efficient and environmentally friendly energy management today. This study tested the implementation of multi-level redundancy for damage mitigation through the integration of intelligent protection systems and thermal performance monitoring. Dynamic IoT monitoring is set up with NodeMCU ESP8266 as the central controller, receiving power data from the PZEM-004T module. Wi-Fi connection allows real-time monitoring and analysis of electrical load power via smartphones and personal computers. The test results cover several main aspects. First, the reliability of the NodeMCU ESP8266 microcontroller is validated by measuring the transmitted data (kb) and received data (bytes) parameters. Second, the thermal redundancy layer is tested by capturing panel image data to recognize hot and normal temperature patterns using ML, enabling control of damaging overheating. Third, the electrical redundancy layer was validated by testing the accuracy of the PZEM-004T voltage, current, and power measurements compared to a standard multimeter. Finally, after data accuracy was verified, a functional test of the protection system was conducted to measure the relay's optimality as a primary power breaker and connector (with the MCB functioning only as backup protection in abnormal conditions).

3.1. Dynamic internet of things sensor protection system performance and accuracy validation

To connect to the web, this tool uses a NodeMCU ESP8266 microcontroller by considering using PV and without using PV. The NodeMCU ESP8266 microcontroller usage system is calibrated in an effort to ensure the reliability of the data accuracy system sent and received so that it is more valid for use in testing sensors connected to the IoT. The results of the transmitted data (kb) and received data (bytes) measurements in the NodeMCU ESP8266 test are shown in Figure 4.

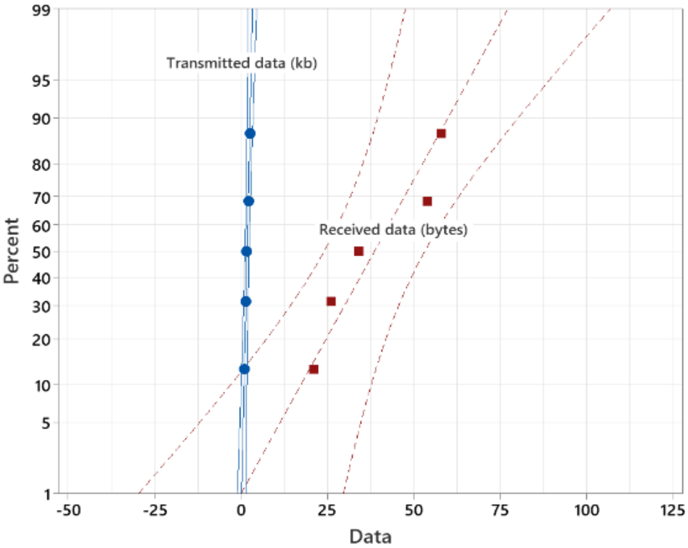
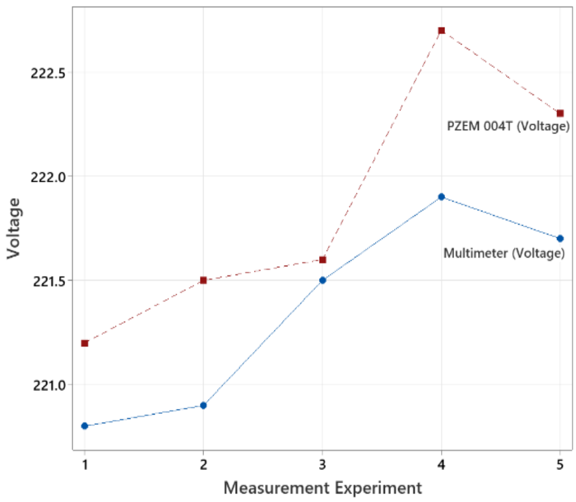


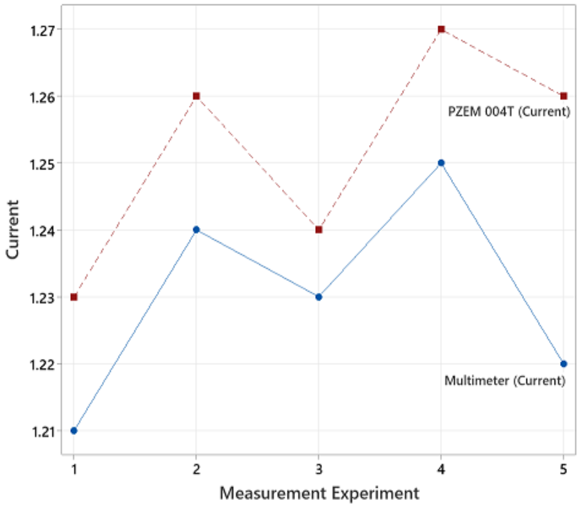
Figure 4. NodeMCU ESP8266 communication reliability validation

Validation of dynamic IoT monitoring begins with reliability testing of the NodeMCU ESP8266 microcontroller as the system's communication core. This testing is crucial as data transmission stability is a prerequisite for real-time damage mitigation decisions. Data from five experiments show an average of 1.74 kb of transmitted data and 38.6 bytes of received data. It is observed that the NodeMCU operation exhibits a consistent and stable response to the data volume. This communication quality is reinforced by the analysis of Figure 4, where the probability plot confirms that the communication data is normally distributed as the P-values for transmitted data (0.476) and received data (0.363) are both greater than 0.05. The high reliability and performance stability of the NodeMCU ESP8266 validate its role as a solid communication foundation for the effective implementation of a multi-level redundancy protection system on grid-connected PV. Then, an accuracy test was conducted using a multimeter to validate the performance of the PZEM-004T module as the main input sensor for the dynamic IoT-based protection system. This validation is essential to measure how accurately the PZEM-004T reads energy conversion parameters (voltage, current, and power) generated by a grid-connected PV system. Sensor accuracy ensures the reliability of data that triggers damage mitigation actions. A comparison of the results of voltage, current, and power parameter measurements between the multimeter as a reference and the PZEM-004T module is presented in Figure 5.

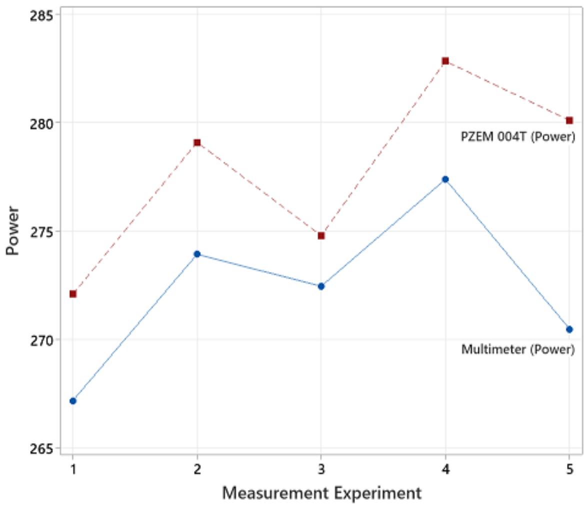
The results of the PZEM-004T sensor calibration test, presented in Figure 5, demonstrate a high level of accuracy when tested against a 900 VA household electrical load connected to a PV installation. The comparison is detailed across three parameters: Figure 5(a) illustrates the voltage measurement correlation with an average error of only 0.23%, Figure 5(b) depicts the current measurement correlation with an average error of 1.79%, and Figure 5(c) shows the power measurement correlation validating the overall energy conversion consistency. This high level of precision is crucial as the sensor serves as the primary input for damage mitigation decisions, with results remaining well within the IEC standard tolerance limits of ±2.5% for voltmeters and ±3.2% for ammeters. Since the sensor accuracy has been validated, the system proceeded to the functional performance testing of the electrical redundancy protection layer by evaluating the relay response time, which achieved a tripping latency of approximately 150 ms. Since the sensor accuracy has been validated, the system proceeded to the functional performance testing stage of the electrical redundancy layer protection system by testing the relay performance, as shown in Figure 6.



(a)



(b)



(c)

Figure 5. Comparison analysis of average percentage error for electrical parameters between the PZEM-004T sensor and a calibrated multimeter (a) voltage measurement consistency, (b) current measurement consistency, and (c) power measurement consistency

The functional performance testing of the electrical redundancy layer aims to validate the system's ability to automatically perform damage mitigation by tripping the relay when the load current exceeds a safe limit. The graph in Figure 6 visualizes the relay action relative to the tripping threshold of 1.30 A. The protection system was shown to function reliably in experiments 1, 2, and 4, the load current was below 1.30 A, and the recorded status was relay on, indicating no false tripping. In contrast, in experiment 3 at 1.35 A and experiment 5 at 1.40 A, the current exceeded the threshold, and the system immediately responded by activating the relay off action, which was confirmed as a relay trip. This fast and timely relay action proves that the electrical redundancy layer works effectively as a smart circuit breaker, which is a crucial success in achieving the damage mitigation goal and supporting the multi-level redundancy architecture.

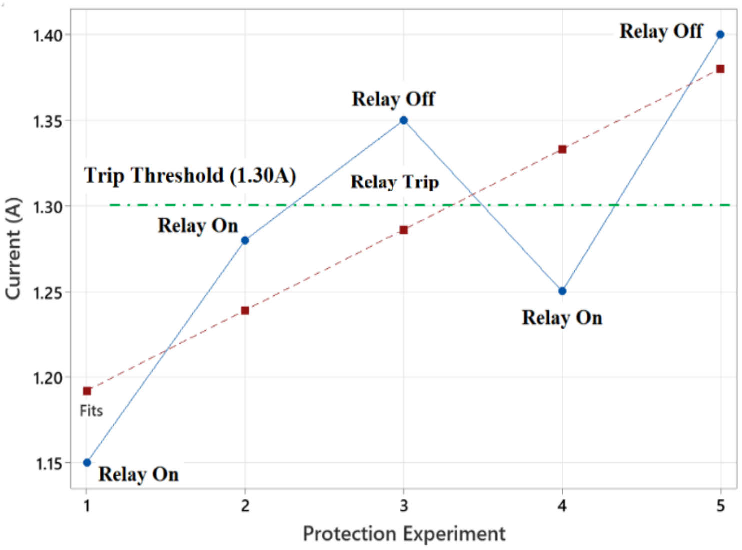


Figure 6. Performance graph of relay tripping action against current threshold (trip threshold 1.30 A), validating the electrical redundancy layer

3.2. User interface design for dynamic IoT monitoring and crash mitigation notification

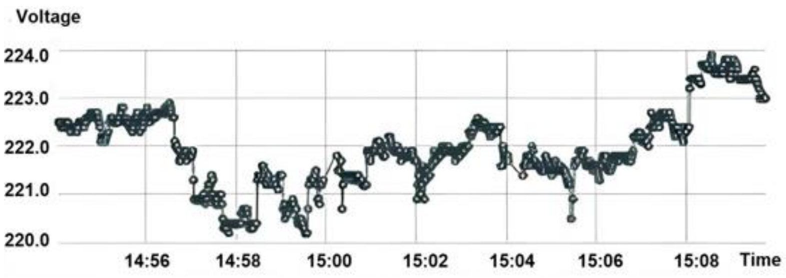
A graphical user interface (GUI) is designed to facilitate dynamic IoT monitoring of grid-connected PV performance. This monitoring is done through a web-based dashboard such as Thinger.io, which is directly connected to the IoT system. The Thinger.io dashboard is not only designed to display basic electrical data such as voltage, current, and power to monitor energy consumption management, but most importantly, it also functions as a multi-level redundancy notification center. The GUI displays the real-time status of both mitigation layers: the tripping relay status (electrical redundancy) and temperature anomaly alerts detected by ML (thermal redundancy). This functional dashboard design is illustrated in Figure 7.

The implementation of the integrated electrical redundancy protection system is visualized through the dynamic IoT monitoring dashboard in Figure 7. This architecture utilizes two separate relays to ensure system reliability, forming the core of the multi-level redundancy framework. Relay 1 functions as the main breaker, while relay 2 acts as a backup protection layer should relay 1 fail to operate during an overcurrent event. The system is specifically programmed to trigger damage mitigation actions when the current exceeds the safe limit of 1.30 A. As shown in the dashboard, vital electrical parameters are tracked in real-time: Figure 7(a) displays voltage fluctuations, Figure 7(b) monitors current surges, and Figure 7(c) tracks power consumption. Beyond real-time monitoring, the integration of IoT via the Thinger.io platform enables the analysis of historical energy consumption and early detection of abnormal surges. This dual-relay mechanism and predictive monitoring capability significantly reduce the risk of damage to electrical components in grid-tied PV systems.

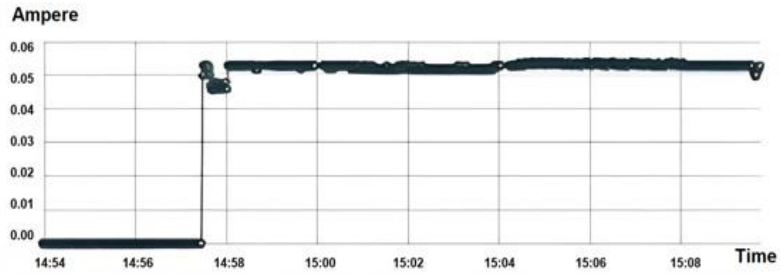
3.3. Machine learning model design for photovoltaic temperature anomaly detection

The use of ML is crucial for determining patterns in energy conversion and detecting temperature anomalies that could potentially cause damage. This thermal redundancy layer is realized through collection of thermal image data obtained from thermovision technology. In this study, a dataset of 300 thermovision images was utilized, consisting of 210 images for the training set and 90 images for the testing set

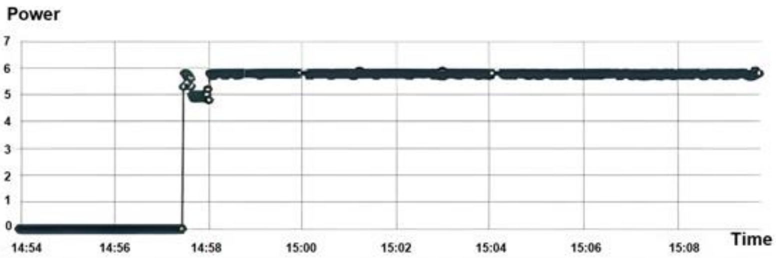
(70:30 ratio). To ensure a uniform distribution of features and avoid selection bias, the dataset partitioning was performed randomly. The main purpose of collecting this PV conversion image data is to analyze the efficiency and impact of weather fluctuations on temperature. The study focused on developing an ML method by selecting the KNN algorithm with a parameter of k=3. The KNN model was trained to classify two main conditions: normal temperature (25 °C to 35 °C) and overheating (hot cell) during energy conversion. The performance of the KNN model was evaluated by comparing predicted data with actual data, as visualized in the performance graph in Figure 8 and the confusion matrix in Figure 9.



(a)



(b)



(c)

Figure 7. Dynamic IoT monitoring dashboard (Thinger.io) view showing the real-time parameter acquisition for damage mitigation: (a) real-time voltage fluctuations, (b) current (Ampere) monitoring during system activation, and (c) power (Watt) consumption data streaming

Figure 8 shows the KNN algorithm serves as a thermal redundancy layer to detect temperature anomalies. Although Figure 8 shows an initial deviation between the actual and predicted data, the model performance is further evaluated using the confusion matrix in Figure 9. The results indicate that the KNN algorithm achieves an accuracy of 84%, with a precision of 0.80, recall of 0.78, and F1-score of 0.78. The 16% misclassification rate primarily occurred during peak solar irradiation hours, where solar reflections on the PV glass surface created “thermal artifacts” that interfered with the thermovision sensor’s readings. Despite this, an 84% accuracy validates the effectiveness of the KNN algorithm for early-stage thermal anomaly detection. This allows for the identification of hotspot risks and decreased energy conversion efficiency, effectively supporting damage mitigation and optimizing the PV maintenance schedule. The IoT-based PV monitoring study found that this research offers a more comprehensive framework by integrating multi-level redundancy architecture (thermal and electrical), which ensures higher reliability than a single-layer monitoring system [26]–[28].

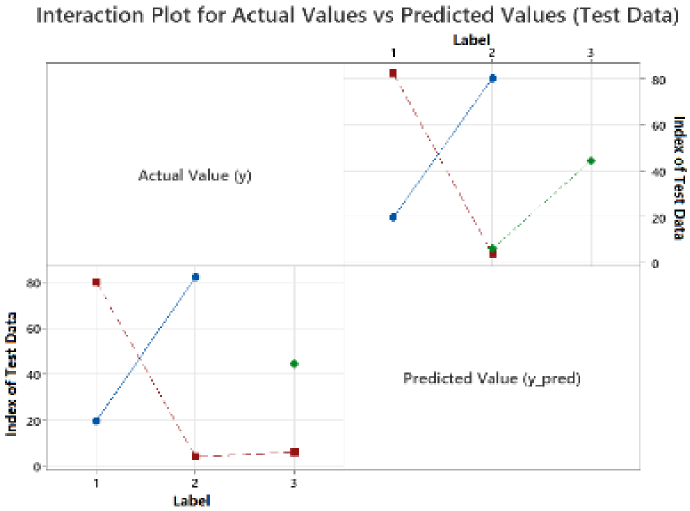


Figure 8. The data model of the output data from the KNN algorithm, plotting the actual and predicted values

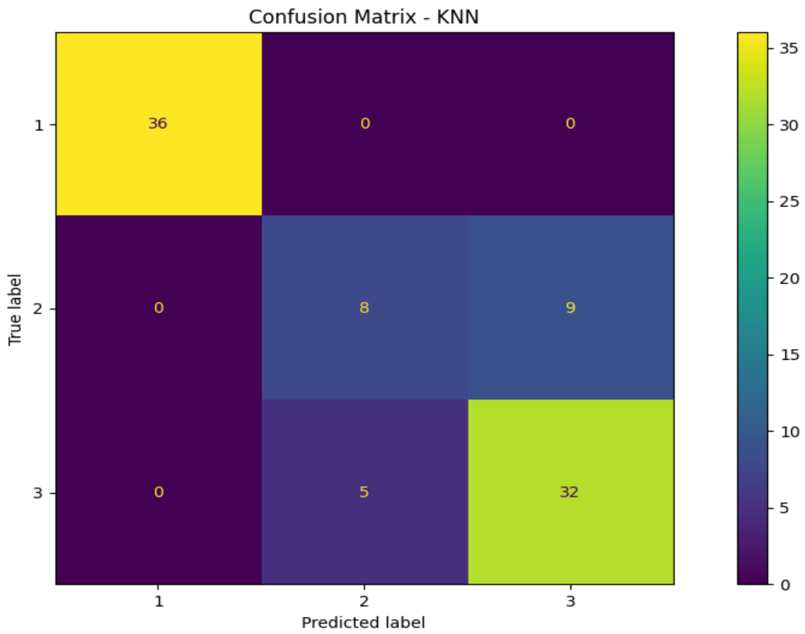


Figure 9. Confusion matrix values in evaluating the number of correct and incorrect data

4. CONCLUSION

This research successfully demonstrates the implementation and validation of a multi-level redundancy protection system supported by dynamic IoT monitoring for grid-tied PV installations. The electrical redundancy layer is proven effective through the validation of the PZEM-004T sensor, achieving an average voltage error of 0.23% and a current error of 1.79%, ensuring reliable input for damage mitigation. The functional performance of relay 1 and relay 2 is confirmed to successfully execute automatic tripping actions when the current exceeds the threshold, with relay 2 providing critical backup protection. Furthermore, the thermal redundancy layer utilizing the KNN algorithm achieves an 84% accuracy in classifying normal (25 °C to 35 °C) and overheating (36 °C to 48 °C) conditions. The integration of these two redundancy layers, supported by real-time GUI monitoring and a dedicated 18650 Li-ion battery backup, collectively improves system reliability and offers a comprehensive solution to minimize risk in PV components. Ultimately, this integrated approach contributes to the advancement of renewable energy engineering by providing a scalable, intelligent, and cost-effective fault mitigation framework, particularly suitable for ensuring the safety and adoption of household-scale PV systems in tropical regions.

ACKNOWLEDGMENTS

The authors would like to thank the Internal Funding Foundation (DIYA) for its grant support. They would also like to express their gratitude to Universitas Medan Area for its support of this research. They also thank our research partners, including Universiti Malaysia Perlis and Universitas Andalas, for their valuable contributions and support.

FUNDING INFORMATION

The authors would like to thank the Internal Fund Foundation (DIYA) for its financial support under grant no. 216/P3MPI/3.1.1/XI/2025. We also thank Universitas Medan Area for its support of this research.

AUTHOR CONTRIBUTIONS STATEMENT

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

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Habib Satria	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓
Muhammad Fadlan Siregar		✓		✓	✓	✓				✓	✓		✓	✓
Indri Dayana	✓	✓		✓	✓		✓			✓	✓		✓	✓
Dadan Ramdan	✓		✓		✓		✓	✓		✓				
Muhammad Irwanto	✓	✓		✓	✓			✓		✓				
Syafii		✓		✓				✓		✓		✓		

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

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research presented in this paper focuses on the development and validation of an engineering system (multi-level redundancy protection system for grid-tied PV). This study does not involve human subjects, animal testing, or clinical trials. Therefore, formal approval from an Institutional Review Board (IRB) or an Ethics Committee was not applicable for this study.

DATA AVAILABILITY

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

REFERENCES

[1] A. E. Hammoumi, S. Chtita, S. Motahhir, and A. E. Ghzizal, "Solar PV energy: from material to use, and the most commonly used techniques to maximize the power output of PV systems: a focus on solar trackers and floating solar panels," *Energy Reports*, vol. 8, pp. 11992–12010, Nov. 2022, doi: 10.1016/j.egyr.2022.09.054.

[2] A. K. Azad and S. Parvin, "Bibliometric analysis of photovoltaic thermal (PV/T) system: from citation mapping to research agenda," *Energy Reports*, vol. 8, pp. 2699–2711, Nov. 2022, doi: 10.1016/j.egyr.2022.01.182.

[3] Y. Jia, G. Alva, and G. Fang, "Development and applications of photovoltaic–thermal systems: a review," *Renewable and Sustainable Energy Reviews*, vol. 102, pp. 249–265, Mar. 2019, doi: 10.1016/j.rser.2018.12.030.

[4] R. Wolniak and B. S.-Zasadzień, "Development of photovoltaic energy in EU Countries as an alternative to fossil fuels," *Energies*, vol. 15, no. 2, p. 662, Jan. 2022, doi: 10.3390/en15020662.

[5] X. Han, Y. Ji, and Y. Yang, "Ferroelectric photovoltaic materials and devices," *Advanced Functional Materials*, vol. 32, no. 14, Apr. 2022, doi: 10.1002/adfm.202109625.

[6] H. Zhou, C. Zhang, and H. Yang, "A new energy frequency adjustment model based on adaptive power control optimization algorithm for photovoltaic power generation systems," *International Journal of Renewable Energy Development*, vol. 14, no. 5, pp. 981–991, 2025, doi: 10.61435/ijred.2025.61125.

[7] A. M. Bassam, K. Sopian, A. Ibrahim, M. F. Fauzan, A. B. Al-Aasam, and G. Y. Abusaibaa, "Experimental analysis for the photovoltaic thermal collector (PVT) with nano PCM and micro-fins tube nanofluid," *Case Studies in Thermal Engineering*, vol. 41, p. 102579, Jan. 2023, doi: 10.1016/j.csite.2022.102579.

[8] J. Zhu, Z. Li, X. Yue, and Y. Nie, "Influence of automatic voltage control on small signal stability of photovoltaic system," *Energy Reports*, vol. 8, pp. 95–104, Aug. 2022, doi: 10.1016/j.egyr.2022.02.134.

[9] A. M. Soomar, A. Hakeem, M. Messaoudi, P. Musznicki, A. Iqbal, and S. Czapp, "Solar photovoltaic energy optimization and challenges," *Frontiers in Energy Research*, vol. 10, May 2022, doi: 10.3389/fenrg.2022.879985.

[10] B. Sutanto *et al.*, "Design and analysis of passively cooled floating photovoltaic systems," *Applied Thermal Engineering*, vol. 236, Jan. 2024, doi: 10.1016/j.applthermaleng.2023.121801.

[11] D. J. Damiri and A. A. Nugraha, "Technical performance and economic feasibility simulation of 200 kwp rooftop solar photovoltaic on grid on industrial estate factory building with helioscope software," *Jurnal Rekayasa Elektrika*, vol. 17, no. 2, Jun. 2021, doi: 10.17529/jre.v17i2.19578.

[12] V. Boscaino *et al.*, "Grid-connected photovoltaic inverters: grid codes, topologies and control techniques," *Renewable and Sustainable Energy Reviews*, vol. 189, Jan. 2024, doi: 10.1016/j.rser.2023.113903.

[13] S. Wang, X. Tang, X. Liu, and C. Xu, "Research on low voltage ride through control of a marine photovoltaic grid-connected system based on a super capacitor," *Energies*, vol. 15, no. 3, Jan. 2022, doi: 10.3390/en15031020.

[14] S. Kawai, K. Shikama, and M. Shimokozono, "Standardization activities related to fiber-optic systems and active devices in international electrotechnical commission," *NTT Technical Review*, vol. 20, no. 4, pp. 74–79, Apr. 2022, doi: 10.53829/ntr202204gls.

[15] D.-M. Kim, S.-K. Park, and S.-G. Park, "A study on the performance evaluation criteria and methods of abdominal ultrasound devices based on international standards," *Safety*, vol. 7, no. 2, Apr. 2021, doi: 10.3390/safety7020031.

[16] S. Sarkar, M. S. Bhaskar, K. U. Rao, P. V, D. Almakhles, and U. Subramaniam, "Solar PV network installation standards and cost estimation guidelines for smart cities," *Alexandria Engineering Journal*, vol. 61, no. 2, pp. 1277–1287, Feb. 2022, doi: 10.1016/j.aej.2021.06.098.

[17] A. Miglioli, N. Aste, C. D. Pero, and F. Leonforte, "Photovoltaic-thermal solar-assisted heat pump systems for building applications: integration and design methods," *Energy and Built Environment*, vol. 4, no. 1, pp. 39–56, Feb. 2023, doi: 10.1016/j.enbenv.2021.07.002.

[18] Z. Liu, Z. Jin, G. Li, X. Zhao, and A. Badiei, "Study on the performance of a novel photovoltaic/thermal system combining photocatalytic and organic photovoltaic cells," *Energy Conversion and Management*, vol. 251, Jan. 2022, doi: 10.1016/j.enconman.2021.114967.

[19] Y. Liu, O. C. Esan, Z. Pan, and L. An, "Machine learning for advanced energy materials," *Energy and AI*, vol. 3, Mar. 2021, doi: 10.1016/j.egyai.2021.100049.

[20] Y. Xu, J. Ge, and C.-W. Ju, "Machine learning in energy chemistry: introduction, challenges and perspectives," *Energy Advances*, vol. 2, no. 7, pp. 896–921, 2023, doi: 10.1039/D3YA00057E.

[21] R. O.-Ajayi, H. Alaka, I. Sulaimon, F. Sunmola, and S. Ajayi, "Machine learning for energy performance prediction at the design stage of buildings," *Energy for Sustainable Development*, vol. 66, pp. 12–25, Feb. 2022, doi: 10.1016/j.esd.2021.11.002.

[22] W. Liu *et al.*, "Machine learning applications for photovoltaic system optimization in zero green energy buildings," *Energy Reports*, vol. 9, pp. 2787–2796, Dec. 2023, doi: 10.1016/j.egyr.2023.01.114.

[23] H. Satria, S. Nisworo, J. Windarta, and R. B. Y. Syah, "Performance of single axis tracker technology and automatic battery monitoring in solar hybrid systems," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 6, pp. 3247–3255, Dec. 2023, doi: 10.11591/eei.v12i6.5506.

[24] A. Dhoke, R. Sharma, and T. K. Saha, "A technique for fault detection, identification and location in solar photovoltaic systems," *Solar Energy*, vol. 206, pp. 864–874, Aug. 2020, doi: 10.1016/j.solener.2020.06.019.

[25] H. Satria, R. Rosnelly, and Wanayumini, "Classification of random forest method on photovoltaic temperature and IoT monitoring for energy conversion," *IET Conference Proceedings*, vol. 2024, no. 30, pp. 380–385, Mar. 2025, doi: 10.1049/icp.2025.0282.

[26] A. Raj, R. Walia, A. K. Gupta, and V. Sharma, "Solar photovoltaic system-fed battery charging with decision-tree-assisted maximum power point tracking," *International Journal of Critical Infrastructures*, vol. 23, no. 2, 2027, doi: 10.1504/ijcis.2027.10069855.

[27] M. T. -Ágreda *et al.*, "Framework for autonomous inspection of PV plants using IoT electronics on each PV panel and UAV collaboration," *Energy Conversion and Management: X*, vol. 26, Apr. 2025, doi: 10.1016/j.ecmx.2025.100878.

[28] B. Aljafari, P. R. Satpathy, S. B. Thanikanti, and N. Nwulu, "Supervised classification and fault detection in grid-connected PV systems using 1D-CNN: simulation and real-time validation," *Energy Reports*, vol. 12, pp. 2156–2178, Dec. 2024, doi: 10.1016/j.egyr.2024.08.008.

BIOGRAPHIES OF AUTHORS

Habib Satria received B.Sc. degree in Electrical Engineering Education from Padang State University in 2016, and M.T. degree in Electrical Engineering from Universitas Andalas, Indonesia, in 2018 and engineer professional (Ir). degree from Universitas Diponegoro, Indonesia, in 2022, and received an M.Kom. degree in Computer Science from Universitas Potensi Utama, Indonesia, with a concentration in artificial intelligence and pattern recognition in 2025. He has also received recognition from ASEAN Engineering in 2024. He is currently a lecture in Department of Electrical Engineering, Universitas Medan Area, Indonesia. His research interests are new and renewable energy, concerning about solar power plant, automatic control system, IoT, real-time simulation, green computing, pattern recognition, and power system. He is a member of the International Association of Engineers (IAENG) and The Institution of Engineers Indonesia. He can be contacted at email: habib.satria@staff.uma.ac.id.

Muhammad Fadlan Siregar received B.Sc. degree in Electrical Engineering from Medan Institute of Technology in 2007, and M.T. degree in Electrical Engineering from the University of North Sumatra, Indonesia, in 2014 and Engineer Professional (Ir). degree from the University of North Sumatra, Indonesia, in 2025. He is currently a lecture in Department of Electrical Engineering, Universitas Medan Area, Indonesia. His research interests are new and renewable energy, IoT, and power system. He is a member of the Institution of Engineers Indonesia. He can be contacted at email: muhammadfadlansiregar@staff.uma.ac.id.

Indri Dayana received B.Sc. degree in Physic from Medan State University in 2004, and M.Si. degree in Physic from the University of North Sumatra, Indonesia, in 2015 and Dr. degree from the University of North Sumatra in 2021. She is currently a lecture in Department of Electrical Engineering, Universitas Medan Area, Indonesia. His research interests are physic, material, energy, and electro. She can be contacted at email: dayanaindri@gmail.com.

Dadan Ramdan received a B.Sc. degree in Instrumentation Physic from the Universitas Padjadjaran in 1988, and M.Sc. degree in Instrumentation Physic from Institut Teknologi Bandung, Indonesia, in 1991, and M.Eng. degree in Production System Engineering from Toyohashi University of Technology, Japan, in 2000 and a Dr. degree from Universiti Sains Malaysia in 2013. He is currently a professor in the Department of Electrical Engineering, Universitas Medan Area, Indonesia. His research metaheuristics hybrid algorithm, computational intelligence, renewable energy, automatic control system, and material science. He can be contacted at email: dadan@uma.ac.id.

Muhammad Irwanto received his Ph.D. degree in electrical system engineering from Universiti Malaysia Perlis (UniMAP), Malaysia in 2012. He is currently a researcher in the Center of Excellence for Health Based on IoT and Renewable Energy, Department of Electrical Engineering, Universitas Prima Indonesia (UNPRI). He is also fellow of Centre of Excellence for Renewable Energy (CERE), Faculty of Electrical Engineering and Technology, Universiti Malaysia Perlis (UniMAP). His research interest includes power electronic, electrical power system stability, solar energy and photovoltaic application system. He can be contacted at email: muhammadirwanto@unprimdn.ac.id or irwanto@unimap.edu.my.

Syafii received a B.Sc. degree in Electrical Engineering from the Universitas Sumatera Utara in 1997, and M.T. degree in Electrical Engineering from Institut Teknologi Bandung, Indonesia, in 2002, and a Ph.D. degree from Universiti Teknologi Malaysia in 2011. He is currently a professor in the Department of Electrical Engineering, Universitas Andalas, Indonesia. His research interests are new and renewable energy, smart grid, and power system computation. He is a member of the IEEE. He can be contacted at email: syafii@eng.unand.ac.id.