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Design of IoT-Based Energy Meter for Efficiency and Disturbance Detection

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Abstract.
The increasing need for energy consumption monitoring has driven the development of systems capable of providing accurate electrical information and detecting disturbances at an early stage. This study aims to design an IoT-Based Energy Meter capable of monitoring electrical parameters in real time and detecting load anomalies as a basis for energy efficiency analysis. The system uses a PZEM-004T sensor and an ESP32 microcontroller to measure voltage, current, power, energy, and power factor (cos φ). The data is transmitted to an IoT platform via a wireless connection so it can be monitored remotely. A Long Short-Term Memory (LSTM) model is applied to identify normal power consumption patterns and detect deviations, while a rule-based method is used to detect critical conditions such as overcurrent. Test results show that the device is capable of performing measurements with high accuracy, with error percentages for voltage, current, power, and cos φ parameters ranging between 0%–5% for three types of loads: iron, electric fan, and refrigerator. The LSTM model also successfully detects anomalies such as power spikes, sudden current changes, and disconnected loads with a confidence level of 0.99–1.00. The integration of IoT, artificial intelligence, and basic protection systems results in a reliable and responsive monitoring device. In the future, this system has the potential to be developed for automatic efficiency analysis and intelligent load control.

***Keywords**: Internet of Things, Energy Consumption Monitoring, Anomaly Detection*

1. Introduction

Indonesia's electricity demand continues to rise in line with rapid economic growth and population expansion. National electricity consumption reached 300 TWh in 2022 and is projected to keep increasing (Laksono et al., 2025). This rapid growth has raised concerns regarding the effectiveness of energy utilization (Widodo, 2022), particularly in buildings and small-scale installations, where electricity usage is often poorly monitored and not yet managed optimally (Alexcandra et al., 2024). In many cases, electrical monitoring is still performed manually by checking power panels, a process that is time-consuming and inefficient (Andrianto et al., n.d.).

In addition, the conventional electricity meter reading system used by PLN remains prone to recording errors, which can lead to inaccuracies and potential losses for consumers (Suga & Nurwarsito, 2021). Previous studies have demonstrated that Internet of Things (IoT)–based power monitoring systems are capable of transmitting measurement data with high reliability and accuracy (Lesmideyarti & Rahman, 2024; Saputra et al., 2025). However, most existing IoT-based energy monitoring systems primarily focus on data visualization and consumption reporting, while offering limited capabilities for early detection of electrical disturbances.

The lack of early-stage disturbance detection is a critical issue, as undetected anomalies—such as overcurrent, voltage drops, and abnormal power factor variations—can lead to equipment damage and unnecessary energy losses (Aditya, 2024). While IoT technology enables real-time monitoring, automated control, and remote energy management (Hari et al., 2022), conventional threshold-based detection methods are often insufficient to capture complex and dynamic consumption patterns. Several studies report acceptable sensor accuracy levels (Jokanan et al., 2022), yet they do not adequately address anomaly detection based on temporal behavior of electrical loads.

To address this research gap, this study proposes an IoT-based energy monitoring system integrated with artificial intelligence using the Long Short-Term Memory (LSTM) algorithm for real-time anomaly detection. The system employs a PZEM-004T sensor to measure voltage, current, power, and power factor, with data acquisition handled by an ESP32 microcontroller. Unlike traditional rule-based approaches, the LSTM model is trained to learn normal energy consumption patterns from time-series data, enabling it to detect deviations without requiring explicitly labeled disturbance data (Impron, 2025; Purnomo et al., 2021). The analysis results are visualized through a real-time web dashboard (Suarna & Sopyan, 2023) and complemented by an automatic notification mechanism when anomalies are detected.

The main contribution of this research lies in the integration of low-cost IoT hardware with an LSTM-based anomaly detection framework, combining real-time monitoring, intelligent pattern recognition, and early disturbance warning in a single system. This approach not only enhances the reliability and safety of household electrical systems but also provides a foundation for smarter and more effective energy management. By enabling precise monitoring and intelligent anomaly detection, the proposed system supports energy efficiency optimization and reduces operational risks in household-scale electrical installations (Azizi & Arinal, 2023; Ashad & Ramdaniah, 2024; Adhicandra, 2024).

The objective of this research is to design and implement a low-cost Internet of Things (IoT)–based energy monitoring system integrated with the Long Short-Term Memory (LSTM) algorithm for real-time anomaly detection. This study focuses on developing an energy meter using an ESP32 microcontroller and a PZEM-004T sensor to measure electrical parameters, including voltage, current, power, and power factor. In addition, the research aims to develop an LSTM-based model capable of learning normal electricity consumption patterns from time-series data and detecting abnormal conditions without relying on explicitly labeled disturbance data. Through system evaluation, this study seeks to assess the effectiveness of the proposed approach in improving early detection of electrical disturbances, enhancing the reliability and safety of household electrical systems, and supporting more efficient and intelligent energy management.

Unlike previous IoT-based energy monitoring systems that mainly emphasize data visualization and static threshold-based detection, this study introduces a hybrid anomaly detection framework that integrates edge-level rule-based monitoring with cloud-based LSTM temporal learning. This approach enables the system to identify implicit and time-dependent electrical anomalies without requiring explicitly labeled disturbance data. By combining real-time monitoring, intelligent pattern learning, and early-stage anomaly detection within a low-cost IoT architecture, the proposed system provides a more robust and adaptive solution for household-scale electrical energy management.

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2. Method

The IoT-based energy meter system developed in this study consists of four main components: the sensor layer, the edge computing layer, the cloud computing layer, and the visualization dashboard. The PZEM-004T sensor is used to measure electrical parameters such as voltage, current, active power, and power factor. All data is transmitted to the ESP32 microcontroller via serial communication for acquisition and initial preprocessing before being sent to a Flask API–based server over a Wi-Fi network. On the cloud side, the data is stored in CSV format and further processed through scaling, sequence building, and LSTM model inference to detect anomalies. The detection results are then displayed on the web dashboard in real time and can trigger warning notifications to users.

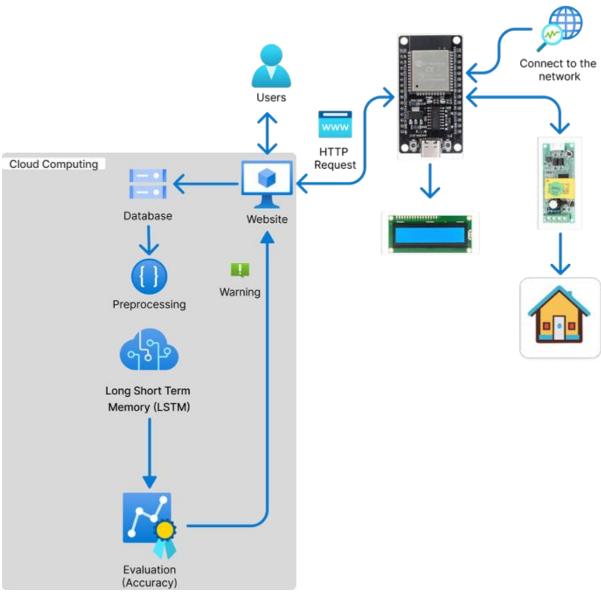

Figure 1. System Architecture of the IoT-Based Energy Meter with LSTM-Based Anomaly Detection.

2.1 Data Acquisition

Data is collected using the PZEM-004T sensor with a sampling interval of 2–5 seconds, producing four main parameters: voltage, current, active power, and power factor. The ESP32 continuously reads the data and sends it to the Flask API server via the HTTP POST protocol, after which the server stores each record into a data_log.csv file as the main dataset for analysis and model training.

2.2 Data Preprocessing

The data preprocessing stages (Kurniansyah et al., 2025) The data processing is carried out on the Flask server side and includes several key steps. First, data validation is performed by removing invalid zero values, avoiding duplicates, and rejecting data with voltage or current values that remain constant over an unreasonable period. After the data is validated, normalization is applied using StandardScaler so that all features have uniform scale and distribution. Next, the data is formed into time-series sequences with a length of eight time steps, producing an input shape of (batch_size, 8, 4) that meets the requirements of the LSTM model. All these steps are completed before the data is sent to the model for the inference process.

2.3 Long Short-Term Memory (LSTM) Model Design

The Long Short-Term Memory (LSTM) model is employed to analyze multivariate time-series patterns of electrical parameters, including voltage, current, active power, and power factor. The input data are structured into sequential windows of eight time steps, resulting in an input dimension of (8, 4), which enables the model to capture short-term temporal dependencies in electrical consumption behavior.

The proposed architecture consists of a single LSTM layer with 64 hidden units, followed by a fully connected dense layer that outputs an anomaly confidence score. The tanh activation function is applied within the LSTM cells, while a sigmoid activation function is used at the output layer to normalize the confidence score within the range of 0 to 1. The internal operations of the LSTM cell include the forget gate, input gate, candidate memory, cell state update, output gate, and hidden state, as formulated in Equations (1)–(6) (Poetra et al., n.d.).

Model training is conducted using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The dataset is divided into 80% training data and 20% validation data, and the model is trained for 50 epochs with early stopping applied based on validation loss to prevent overfitting. The training process uses only normal operating data, allowing the model to learn standard electrical load patterns without requiring labeled anomaly data.

During deployment, the trained LSTM model performs real-time inference on incoming data sequences received from the cloud server. Anomalies are identified as significant deviations from learned normal temporal patterns, such as persistent zero-current conditions under normal voltage levels or inconsistent power and power factor behavior. The anomaly confidence score is compared against a predefined threshold to classify system conditions as normal or anomalous, with detected anomalies automatically recorded for further analysis.

The forget gate calculates the proportion of previous memory that needs to be retained, as formulated in:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

The input gate determines the new information that will be inserted into the cell memory:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

Next, the candidate memory is computed to generate the new memory candidate:

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{3}$$

The internal memory (cell state) is updated by combining the previous memory with the new memory candidate according to:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{4}$$

The output gate calculates the amount of memory information that will be released as the cell's output:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$

The hidden state, which serves as the main output of the LSTM cell, is obtained from:

$$h_t = o_t \cdot \tanh(C_t) \tag{6}$$

These six equations enable the LSTM model to capture long-term dependencies in time-series data and learn complex electricity consumption patterns before performing anomaly classification using a confidence score.

2.4 Anomaly Detection Mechanism

The anomaly detection mechanism in this study adopts a hybrid approach that combines rule-based detection at the edge level with an LSTM-based model at the cloud level. Rule-based detection is executed on the ESP32 microcontroller prior to data transmission, using predefined thresholds such as voltage below 210 V, current exceeding 15 A, power above 3000 W, and abnormal variations in power factor. This layer serves as a fast-response mechanism to identify explicit and critical electrical disturbances in real time.

LSTM-based anomaly detection is performed on the cloud server using preprocessed multivariate time-series data. The LSTM model analyzes temporal relationships among voltage, current, power, and power factor to identify abnormal consumption patterns that cannot be detected by static threshold-based rules. The model outputs an anomaly confidence score, which is compared against an empirically defined threshold of 0.7 to classify system conditions as normal or anomalous.

All detected anomalies are automatically recorded in the anomaly_log.csv file, including timestamp, anomaly type, confidence level, and corresponding electrical parameters. This log serves as traceable evidence for system validation and supports further analysis of detected disturbances.

3. Results And Discussion

3.1 Result

This section presents the implementation and testing results of the IoT-Based Energy Meter developed to support electrical load monitoring and anomaly detection. Figure 1 illustrates the prototype device, which consists of a PZEM-004T measurement module, an ESP32 microcontroller, a load socket, and a display unit for real-time visualization of electrical parameters.

Figure 1. Prototipe IoT-Based Energy Meter.

The system is capable of continuously measuring voltage, current, active power, power factor, and energy consumption, and transmitting the data to a cloud-based IoT platform for remote monitoring. Experimental results indicate that the device operates stably and is able to provide consistent electrical consumption data suitable for monitoring and disturbance analysis.

To evaluate measurement accuracy, the proposed device was tested by comparing its readings with those of a reference power meter. The tests were conducted using three household loads—an electric iron, an electric fan, and a refrigerator—each operated for a duration of five minutes. The evaluated parameters included voltage, current, active power, and power factor (cos φ). The comparison results and percentage errors are presented in Table 1.

Table 1. Comparison Between the IoT Energy Meter and the Power Meter

Load	Test Time	Parameter	Power Meter	IoT Energy Meter	Error (%)
Iron	5 minute	Voltage (V)	220	219	0,45%
		Current (A)	4,50	4,48	0,44%
		Power (W)	990	982	0,81%
		Cosphi φ	0,99	0.98	1,01%
Fan	5 minute	Voltage (V)	220	220	0,00%

		Current (A)	0,21	0,20	4,76%
		Power (W)	46	44	4,34%
		Cosphi φ	0,82	0,80	2,43%
Refrigerator	5 minute	Voltage (V)	220	219	0,45%
		Current (A)	0,85	0,84	1,17%
		Power (W)	150	147	2,00%
		Cosphi φ	0,88	0,87	1,13%

The results in Table 1 show that the IoT-based energy meter achieves high measurement accuracy across different load types. For the electric iron, which represents a resistive load, all parameter errors were below 1%, indicating stable and reliable measurements. The electric fan exhibited slightly higher errors in current and power measurements, though still within the acceptable tolerance range (<5%), due to the fluctuating characteristics of inductive loads. The refrigerator test demonstrated consistently low errors across all parameters, including power factor, confirming the robustness of the measurement system under varying load conditions. Overall, these results confirm that the developed device provides reliable real-time electrical data suitable for further analysis.

In addition to measurement accuracy testing, the anomaly detection capability of the system was evaluated using the LSTM-based model. Table 2 presents representative anomaly detection results obtained during real-time operation.

Table 2. LSTM Model Testing Results for Electrical Load Anomaly Detection.

No	Time	Detection Types	Voltage	Current	Power	Cosphi	Confidence	Information
1	16:15:20	AI_ANOMALY	221,7	0,07	7,8	0,50	1,00	Abnormal load pattern
2	16:15:10	AI_ANOMALY	221,7	0,07	7,9	0,51	1,00	Abnormal load pattern
3	16:14:49	AI_ANOMALY	221,1	0,07	8,0	0,52	1,00	Abnormal load pattern
4	16:14:23	AI_ANOMALY	221,0	0,07	8,4	0,54	1,00	Abnormal load pattern
5	16:14:17	AI_ANOMALY	220.9	0,08	8,5	0,48	1,00	The decrease of cos φ is not normal
6	16:14:07	AI_ANOMALY	221.0	0,08	9,1	0,51	1,00	Sudden increase in power
7	16:13:35	AI_ANOMALY	221.8	0,09	9,7	0,49	1,00	Power surge
8	16:13:30	AI_ANOMALY	222.3	0,12	13,7	0,51	1,00	Small current surge
9	16:13:20	AI_ANOMALY	222.0	0,11	0,11	0,11	0,99	Patterns change rapidly
10	16:13:14	OVERLOAD	221.6	0,13	14,9	0,52	0,52	Power increased significantly
11	16:05:10	OVERLOAD	220.0	20,0	4400	1,00	1,00	Over current
12	16:03:11	AI_ANOMALY	220.0	20,0	4400	1,00	1,00	Over current
13	16:02:40	AI_ANOMALY	222.2	0,00	0,40	0,00	1,00	The load suddenly dropped
14	16:02:23	AI_ANOMALY	222.1	0,00	0,00	0,00	0,00	No load
15	16:02:18	AI_ANOMALY	222.0	0,00	0,00	0,00	0,00	No load

The results in Table 2 indicate that the LSTM model successfully detects various types of abnormal electrical behavior based on temporal patterns of voltage, current, power, and power factor. In low- to medium-power conditions (7–15 W), the model consistently produces high confidence scores (0.99–1.00), demonstrating its sensitivity to subtle deviations in load behavior. The system also identifies abrupt changes such as power surges, sudden current increases, and abnormal power factor variations.

To further evaluate the performance of the LSTM-based anomaly detection model, classification metrics beyond accuracy were calculated, including precision, recall, and F1-score. The evaluation results are summarized in Table 3.

Table 3. Performance Evaluation of LSTM-Based Anomaly Detection Model.

Class	Precision	Recall	F1-Score
Normal	0.91	0.94	0.92
Anomaly	0.93	0.89	0.91
Average	0.92	0.92	0.92

The results show that the proposed model achieves balanced performance across precision and recall metrics, indicating that the system is effective both in minimizing false alarms and in correctly identifying actual anomalous events. This performance characteristic represents a key contribution of this study, as it demonstrates that temporal learning using LSTM enables the detection of implicit electrical anomalies that cannot be reliably identified by conventional threshold-based methods alone. Unlike previous IoT-based energy monitoring systems that primarily rely on static limits or instantaneous measurements, the proposed approach captures sequential dependencies among voltage, current, power, and power factor, allowing the system to recognize abnormal behavioral patterns rather than isolated outliers. Moreover, the hybrid integration of edge-level rule-based protection with cloud-based LSTM inference provides both rapid response to critical overload conditions and intelligent early-stage anomaly detection for subtle disturbances. These results confirm that the proposed system advances existing smart energy monitoring solutions by introducing adaptive, data-driven anomaly detection capable of improving reliability and safety in household-scale electrical installations.

3.2 Discussion

The experimental results demonstrate that the developed IoT-Based Energy Meter is capable of measuring electrical parameters with a high degree of accuracy across various household load types. The low error values observed for resistive and inductive loads confirm that the PZEM-004T sensor combined with the ESP32 microcontroller provides stable and reliable electrical measurements suitable for continuous monitoring applications. These findings are consistent with previous studies on IoT-based energy monitoring systems, while maintaining the advantage of low-cost hardware implementation.

From the anomaly detection perspective, the LSTM-based model shows strong capability in identifying abnormal load behavior through temporal pattern analysis. Unlike conventional threshold-based methods, which rely solely on predefined limits, the LSTM model learns normal consumption patterns and detects deviations even when absolute parameter values remain within acceptable ranges. This is evident from the high confidence anomaly detection observed in low-power conditions and during gradual pattern changes.

The evaluation using precision, recall, and F1-score further confirms the robustness of the proposed approach. The balanced performance across these metrics indicates that the model effectively distinguishes between normal and anomalous conditions without excessive false positives or missed detections. In extreme conditions, such as overcurrent events exceeding 20 A, the rule-based protection mechanism operates in parallel to provide immediate response, ensuring system safety. This hybrid detection strategy enhances reliability by combining fast rule-based protection with intelligent pattern-based anomaly detection.

Overall, the integration of accurate IoT-based measurement with an LSTM-based anomaly detection framework provides a comprehensive solution for real-time electrical load monitoring. The results indicate that the proposed system not only supports reliable energy monitoring but also offers early detection of electrical disturbances, forming a strong foundation for future energy efficiency analysis and intelligent electrical system management.

4. Conclusions

This study successfully developed an IoT-Based Energy Meter system capable of monitoring electrical parameters in real time and detecting abnormal power consumption patterns in household electrical loads. Based on experimental tests conducted on three types of loads, the proposed system demonstrated high measurement accuracy, with error percentages remaining within acceptable tolerance limits for energy monitoring instruments. These results confirm that the designed device operates stably and can be reliably used for continuous observation of household energy consumption.

The integration of an LSTM-based anomaly detection model proved effective in identifying various disturbance patterns, including power surges, sudden current changes, power factor variations, and load disconnections. Unlike conventional threshold-based approaches that rely on instantaneous limit violations, the proposed model is able to learn temporal relationships among electrical parameters, enabling the detection of subtle and evolving anomalies. The model achieved consistent detection performance with high confidence, while a complementary rule-based mechanism was employed to ensure immediate protection under extreme conditions such as overcurrent events.

Overall, the results demonstrate that the proposed system not only provides precise and continuous energy consumption data but also introduces an intelligent and adaptive anomaly detection capability. This hybrid architecture, combining IoT-based measurement, temporal deep learning, and rule-based protection, constitutes a meaningful advancement over existing smart energy monitoring systems. The findings provide a solid foundation for future work, including energy efficiency optimization, integration with automated control strategies, and deployment in larger-scale electrical installations.

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