

REAL-TIME SMART MCB BASED ON NODE-RED FOR PROTECTION AND ENERGY PREDICTION USING LSTM

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ABSTRACT

Keywords:

Raspberry Pi 3B
PZEM-004T sensor
5V relay module
LY2N relay
overcurrent protection
undervoltage protection,
LSTM-based energy
consumption prediction.

A household electrical protection system based on the Raspberry Pi 3B was developed to prevent damage to electrical appliances caused by overcurrent and undervoltage faults. Conventional Miniature Circuit Breakers (MCBs) can protect against overcurrent faults but cannot protect against undervoltage, cannot be remotely controlled, and require manual resetting after tripping. Therefore, this study proposes a smart MCB system that provides overcurrent and undervoltage protection, real-time monitoring, Telegram Bot notifications, and one-day-ahead electrical energy consumption prediction using the Long Short-Term Memory (LSTM) method. The proposed system uses a Raspberry Pi 3B as the main controller, a PZEM-004T sensor to measure electrical parameters, a 5 V relay module to drive an LY2N relay, and the LY2N relay to disconnect or reconnect the load. The PZEM-004T sensor achieved average measurement errors of 0.60% for voltage, 7.29% for current, and 0.87% for active power. The overcurrent protection test showed that the system followed an inverse-time characteristic, where the tripping time became shorter as the multiplier increased. For undervoltage protection, the average tripping times were 2.00 s at 180 V and 2.86 s at 198 V. The LSTM model was trained using 13,041 monitoring data samples and achieved an MAE of 0.000572 kWh, an RMSE of 0.001408 kWh, and an R^2 score of 67.18%. The average prediction error was 7.58%, with a prediction accuracy of 92.42%. The proposed system successfully performed overcurrent and undervoltage protection, real-time monitoring, and one-day-ahead electrical energy consumption prediction.

INTRODUCTION

Along with technological advancements and the increasing use of electronic devices, the need for household electrical systems that are safe, efficient, and flexible continues to increase. Disturbances such as overcurrent, short circuits, undervoltage, and overvoltage can cause damage to electronic equipment and electrical installations (Nursalim et al., 2022). A Miniature Circuit Breaker (MCB) is used as a protection system against overcurrent faults. However, conventional MCBs have limitations because they cannot provide undervoltage protection, do not support remote control, and require manual reconnection after a trip occurs (Nursalim et al., 2022), (Sumerta Yasa, 2025c). In addition to protection, electrical energy consumption is generally monitored using a kilowatt-hour (kWh) meter. The limitations of the kWh meter in displaying electrical parameters have encouraged the implementation of the Internet of Things (IoT) for real-time monitoring (Hermanto & Agustini, 2022). Several studies have developed IoT-based protection and monitoring systems. Nursalim et al (2022) designed an IoT-based protection and monitoring system for overcurrent and overvoltage with Telegram notifications, while Severiche-Maury et al (2025) developed a Long Short-Term Memory (LSTM) model for household energy consumption prediction. However, the integration of overcurrent and undervoltage protection, IoT-based monitoring, and energy consumption prediction using the Long Short-Term Memory (LSTM) method into a single system has not been widely developed. Based on these limitations, this study

proposes a Real-Time Smart MCB Based on Node-RED for Protection and Prediction Using the LSTM Method. The system integrates overcurrent and undervoltage protection, real-time monitoring of electrical parameters, notifications through Telegram and an LCD, as well as one-day-ahead electrical energy consumption prediction using the Long Short-Term Memory (LSTM) method. The prediction feature provides information on energy consumption as a basis for managing electricity usage more efficiently and helps reduce the potential for simultaneous load usage that may trigger the operation of the protection system.

The main contributions of this work are:

1. The Smart MCB system supports household electricity management and user awareness of energy consumption.
2. The system provides overcurrent and undervoltage protection, monitoring, and one-day-ahead energy prediction.
3. In the future, this system will support the energy transition, improve energy efficiency, and optimize load management.

RESEARCH METHOD

A. Research Design / Experimental Setup

The method used in this study is experimental using a quantitative approach for measurement and analysis. The research stages include hardware design, software development, monitoring data collection, LSTM model training, system integration, and system performance testing. The testing evaluates the accuracy of the PZEM-004T sensor, the performance of the protection system against overcurrent and undervoltage faults, real-time monitoring of electrical parameters, and the performance of the LSTM model in predicting electrical energy consumption based on the collected monitoring data.

B. System Architecture

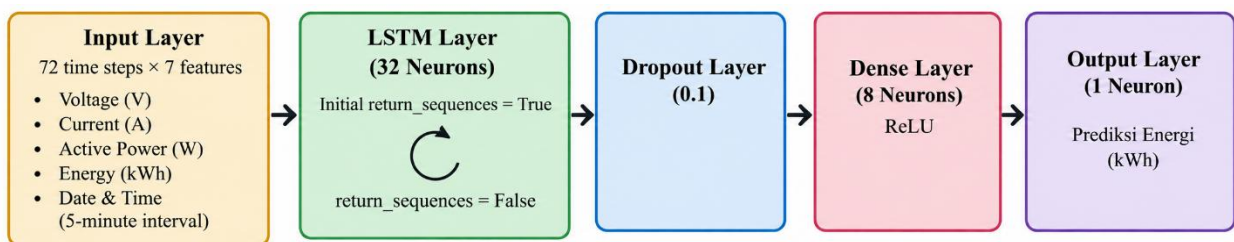


Figure 1. LSTM Model Architecture

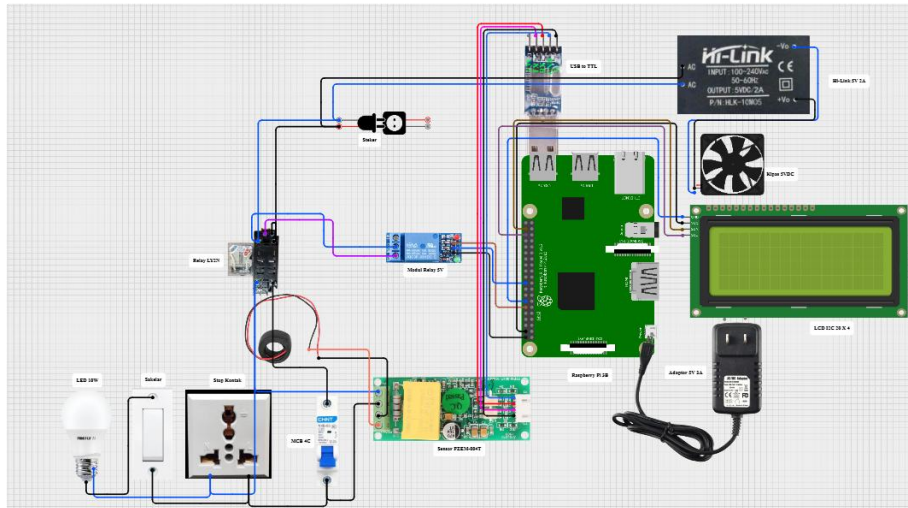


Figure 2. System Diagram

C. Protection System Design

The Smart MCB system is designed to provide protection against overcurrent and undervoltage faults. Overcurrent protection uses the standard inverse characteristic based on the IEC 60255 standard, where the relay operating time is calculated using the following inverse-time equation (Palevi et al., 2022b).

$$t = \frac{0.14 - TMS}{\left(\frac{I}{I_n}\right)^1 - 1} \dots \dots \dots (1)$$

Where:

t = relay operating time (s)

TMS = Time Multiplier Setting

I = measured current from the sensor

I_n = rated current

Undervoltage protection uses the definite-time characteristic with a fixed time delay to prevent unnecessary tripping due to momentary voltage drops.

D. LSTM Prediction Model

The monitoring data are first normalized using the min-max normalization method as follows (Raharjo et al., 2022), (Sianturi et al., 2023).

$$X' = \frac{X - X_{Min}}{X_{Max} - X_{Min}} \dots \dots \dots (2)$$

Where:

X' = normalized data

X = original data

X_{Min} = minimum data value

X_{Max} = maximum data value

Next, the time-series data are generated using the sliding window method with a look-back of 72 data points to produce input-target pairs. The dataset is then divided into 70% training data and 30% testing data. After the prediction process, the model output is restored to its original scale using the denormalization process (Sianturi et al., 2023).

$$X = X' (X_{Max} - X_{Min}) + X_{Min} \dots \dots \dots (3)$$

Where:

X = denormalized data

X' = normalized data

X_{Min} = minimum data value

X_{Max} = maximum data value

E. Flowchart

1. Hardware System Flowchart

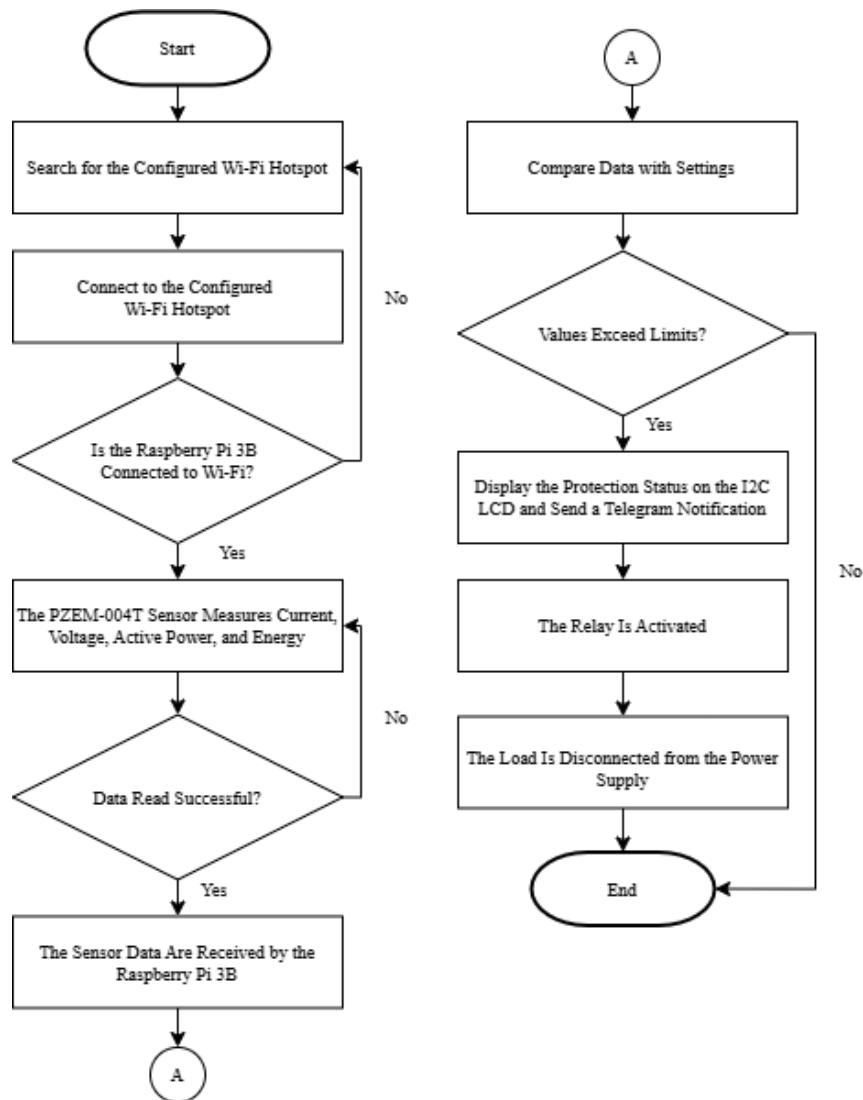


Figure 3. Hardware System Flowchart

2. Software System Flowchart

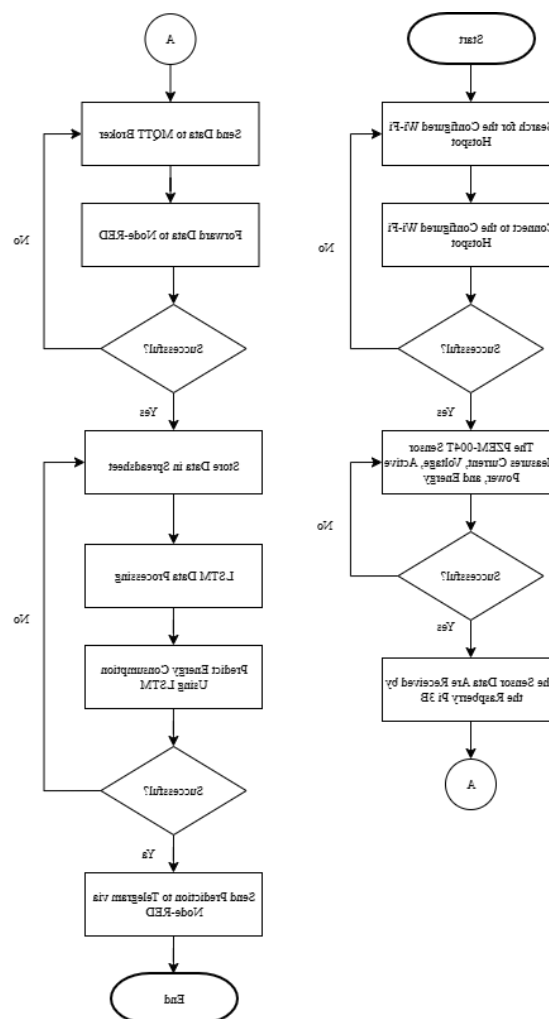


Figure 4. Software System Flowchart

RESULTS AND DISCUSSION

A. PZEM-004T Sensor Testing

The PZEM-004T sensor was tested to evaluate its accuracy in measuring electrical parameters. The test was conducted by comparing the measurements obtained from the measuring instrument with the sensor readings.

Table 1. Accuracy Test Results of the PZEM-004T Sensor

No	Test Load	Voltage (V)			Current(A)			Active Power (W)		
		Measuring Instrumen	PZEM 004T Sensor	Error %	Measuring Instrumen	PZEM 004T Sensor	Error %	Measuring Instrumen	PZEM 004T Sensor	Error %
1	Fan	241,8	243,2	0,58	0,147	0,16	8,84	39,3	39,5	0,51
2	Fan	242,5	243,9	0,58	0,158	0,17	7,59	42,3	42,5	0,47
3	Fan	242,7	244	0,53	0,139	0,15	7,91	36,8	36,8	0

4	Rice cooker	238,9	240,4	0,62	0,974	0,98	0,62	233,9	235,8	0,81
5	Rice cooker	239	240,8	0,75	0,997	0,98	1,70	233,9	236,3	1,03
6	LED Lamp	243,4	244,8	0,57	0,041	0,05	21,95	12,9	12,6	2,33
7	LED Lamp	242,9	244,1	0,49	0,034	0,04	15	10,5	10,4	0,95
8	Iron	238,8	240,3	0,63	1,781	1,73	2,86	412,1	415,4	0,81
9	Iron	239,3	240,9	0,66	1,790	1,73	3,35	412,9	416,9	0,97
10	Iron	239	240,4	0,58	1,786	1,73	3,13	411,9	415,4	0,85
Average				0,60			7,29			0,87

Based on the test results, the average measurement errors of the PZEM-004T sensor for voltage, current, and active power were 0.60%, 7.29%, and 0.87%, respectively. The current measurement error was relatively higher at low current loads (0.03–0.05 A) but decreased as the load current increased. These results indicate that the PZEM-004T sensor provides good accuracy for voltage and active power measurements and achieves higher current measurement accuracy at larger load currents.

B. Overcurrent Protection Testing

The overcurrent protection system was tested to evaluate the performance of the Smart MCB in disconnecting the circuit when the current exceeded the 2 A rated current.

Table 2. Overcurrent Protection Test Results

No	Test	Multiplier (I/In)	Current(A)	Status	Calculated Delay(s)	Trip Time (s)	Time Difference (s)
1	Test 1	1,55	3,10	Trip	31,69	32,43	0,74
2	Test 2		3,10	Trip	31,69	32,22	0,53
3	Test 3		3,11	Trip	31,64	31,18	0,46
Average Trip Time					31,67	31,94	0,27
4	Test 1	1,85	3,71	Trip	22,53	22,87	0,34
5	Test 2		3,71	Trip	22,54	22,60	0,06
6	Test 3		3,71	Trip	22,47	22,86	0,39
Average Trip Time					22,51	22,78	0,26
7	Test 1	2,02	4,03	Trip	19,86	19,93	0,07
8	Test 2		4,04	Trip	19,77	19,93	0,16
9	Test 3		4,04	Trip	19,80	19,86	0,06
Average Trip Time					19,81	19,91	0,10

Based on Table 2., the average actual trip times were 31.94 s, 22.78 s, and 19.91 s, respectively. These results indicate that a higher current multiplier results in a shorter trip time, demonstrating that the protection characteristic follows the standard inverse curve in accordance with IEC 60255. The differences between the calculated delay and the actual trip time were relatively small, at 0.27 s, 0.26 s, and 0.10 s, respectively. These differences were influenced by the sensor sampling interval, the processing time of the Raspberry Pi 3B, and the relay operating time.

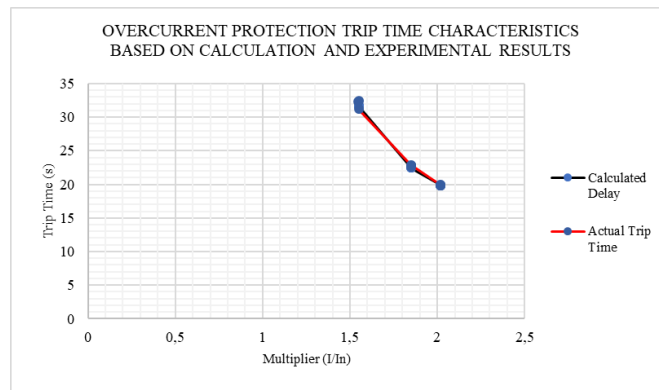


Figure 5. Overcurrent Trip Time Characteristic

Figure 5. shows the trip time characteristic of the Smart MCB based on the calculated and experimental results. The actual trip time follows the standard inverse characteristic, where the trip time decreases as the current multiplier increases.

C. Undervoltage Protection Testing

This test was conducted to evaluate the response of the Smart MCB under undervoltage conditions. The voltage was reduced to three set points: 200 V, 198 V, and 180 V.

Table 3. Undervoltage Protection Test Results

No	Test	Voltage Set (V)	Set Delay (s)	Voltage (V)	Status	Trip Time (s)	Time Difference (s)
1	Test 1	180	2	177,9	Trip	2	0
2	Test 2			173,8	Trip	2	0
3	Test 3			175,8	Trip	2	0
Average Trip Time						2	0
6	Test 1	198	2	197,2	Trip	2,86	0,86
7	Test 2		2	195,8	Trip	2,86	0,86
8	Test 3			194,5	Trip	2,86	0,86
Average Trip Time						2,86	0,86
9	Test 1	200	-	201	No Trip	-	-
10	Test 2			201	No Trip	-	-

11	Test 3	200	-	201	No Trip	-	-
Average Trip Time						-	-

Based on Table 3., the system successfully disconnected the load at the 180 V and 198 V set points, with average trip times of 2.00 s and 2.86 s, respectively. At 200 V, the system did not trip because the voltage was still within the normal operating range according to the PLN standard. These results indicate that the system operates according to the predefined set points.

D. LSTM Model Performance

The LSTM model was evaluated to assess its ability to predict one-day-ahead electrical energy consumption. The model was trained using 13,041 monitoring data points, with 70% of the dataset used for training and 30% for testing. The model architecture consisted of a single LSTM layer with 32 neurons, a dropout rate of 0.1, and the Adam optimizer with a learning rate of 0.001. The training process was performed with 30, 50, and 100 epochs, while Early Stopping and ReduceLROnPlateau were applied to improve model stability. The model performance was evaluated using the training loss and validation loss curves, as well as the MAE, RMSE, and R² Score metrics.

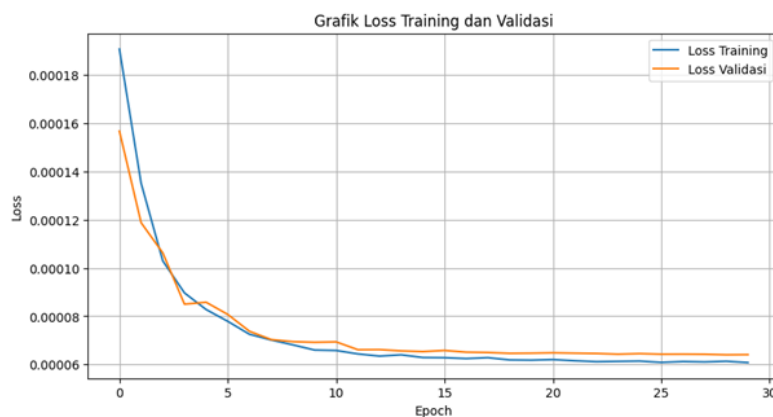


Figure 6. Training and Validation Loss Curves for the 30 Models

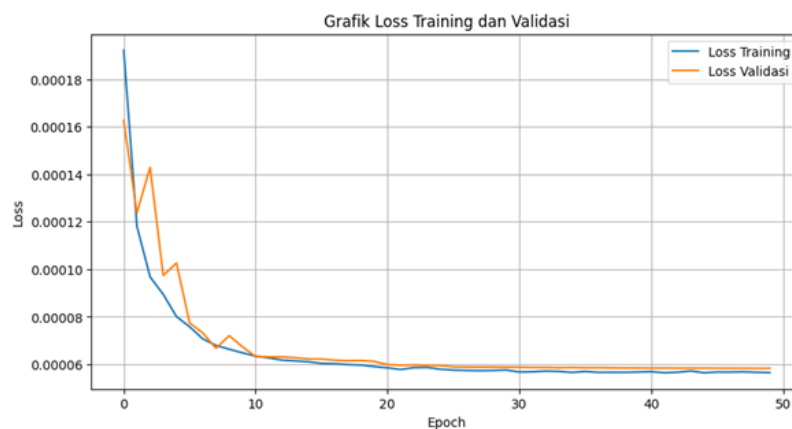


Figure 7. Training and Validation Loss Curves for the 50 Epoch Models

Figure 6. and 7. shows the training and validation loss curves of the LSTM model. Both curves decrease and then converge, indicating that the model successfully learns the data patterns without significant overfitting.

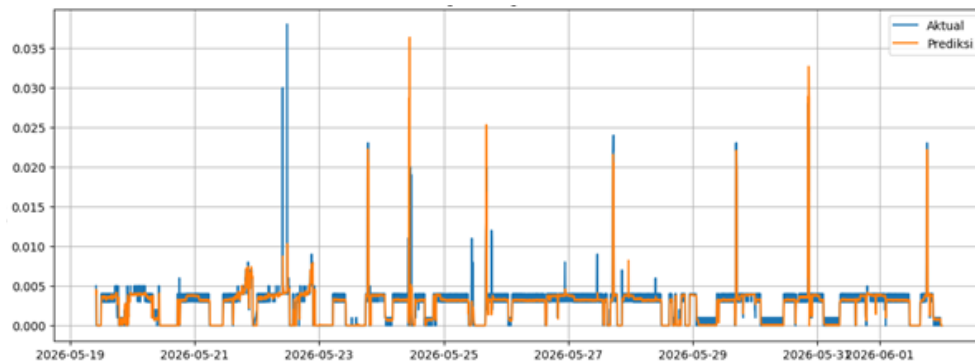


Figure 8. Comparison of Actual and Predicted Energy Consumption for the 30 Models

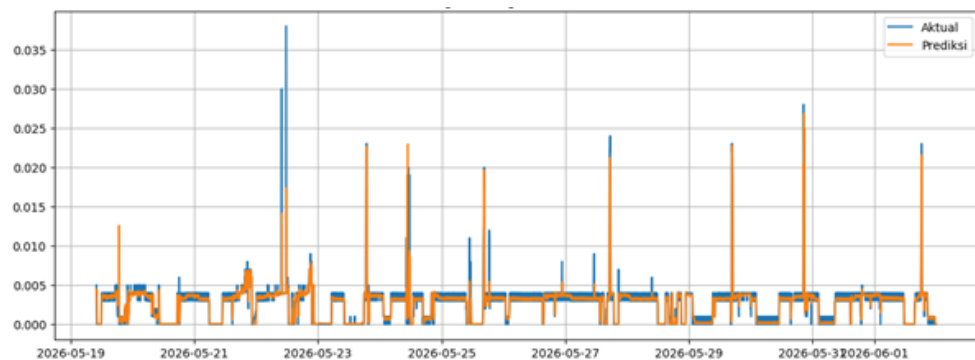


Figure 9. Comparison of Actual and Predicted Energy Consumption for the 30 and 50 Epoch Models

Figure 8. and 9. shows that the LSTM predictions are able to follow the actual energy consumption pattern, although differences remain at several points with high energy consumption peaks.

Table 4. Performance Evaluation of the LSTM Model

No	Epoch	MAE (kWh)	RMSE (kWh)	R ²
1.	30	0,000572	0,001408	67,18%
2.	50	0,00519	0,001483	63,08%

Based on Table 4., the 30-epoch model achieved the best performance, with an MAE of 0.000572 kWh, an RMSE of 0.001408 kWh, and an R² Score of 67.18%. Therefore, this model was selected as the final model because it provides the best balance between accuracy and generalization.

CONCLUSION

This study successfully developed a Raspberry Pi 3B-based Smart MCB capable of providing overcurrent and undervoltage protection, real-time monitoring of electrical parameters, and electrical energy consumption prediction using the Long Short-Term

Memory (LSTM) method. The PZEM-004T sensor achieved average measurement errors of 0.60%, 7.29%, and 0.87% for voltage, current, and active power, respectively. The experimental results showed that the protection system follows the standard inverse characteristic for overcurrent faults and is capable of detecting undervoltage conditions according to the predefined set points. The LSTM model achieved an MAE of 0.000572 kWh, an RMSE of 0.001408 kWh, an R² Score of 67.18%, and a prediction accuracy of 92.42%, demonstrating that the proposed system effectively supports household electrical protection, real-time monitoring, and energy consumption prediction.

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