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Development of an LSTM-Based Power Monitoring and Prediction System for Campus Electrical Facilities Using ESP32 and PM2120

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Abstract

This study develops a data acquisition system for monitoring, detecting, and forecasting electrical energy consumption to support efficient energy management. Electrical parameters such as voltage, current, and power are measured using a PM2120 power meter via Modbus RTU RS485 and processed by an ESP32 microcontroller. The data are displayed in real-time through a Nextion Human-Machine Interface (HMI) and utilized as input for a Long Short-Term Memory (LSTM) model trained on historical consumption data. Safety features include LED indicators that activate when current reaches 80% of maximum capacity and a buzzer that signals threshold violations. Experimental results demonstrate high prediction accuracy, with RMSE values of 0.38 kW (5.32%) for phase R, 0.47 kW (7.55%) for phase S, and 0.28 kW (5.39%) for phase T. Transmission latency averages two to three seconds, while prediction computation is under 10 seconds. The system effectively reflects consumption trends, making it a reliable decision-support tool for enhancing energy efficiency in small- to medium-scale installations.

A. Introduction

The monitoring of electrical energy usage continues to increase in line with the growth of industry, households, and digital technologies. The demand for stable and efficient electricity drives the importance of smarter energy monitoring and management systems. However, one of the main challenges that often arises is the high power consumption and load imbalance across phases, which may lead to energy losses and equipment damage [1], [2]. Therefore, research on prediction and early detection of electrical conditions has become increasingly relevant to support energy efficiency and power system reliability.

In the context of three-phase power systems, the phenomenon of load imbalance has gained significant attention as it can cause overheating, reduced efficiency of electric motors, and shortened transformer lifespan [3]. Several studies have shown that real-time monitoring of three-phase current can serve as a primary indicator in assessing load balance conditions [4]. For this reason, monitoring three-phase current data is crucial to detect potential issues before they develop into serious system disturbances.

Artificial intelligence methods, particularly deep learning, have demonstrated promising results in time-series modeling for predicting electrical data [5]. Long Short-Term Memory (LSTM), as one of the Recurrent Neural Network (RNN) architectures, excels at overcoming the vanishing gradient problem and is capable of learning long-term dependencies in sequential data [6], [7]. Recent studies have highlighted the effectiveness of LSTM in predicting electrical load, energy consumption, and overall power system stability [8], [9]. This makes LSTM a highly potential approach for application in predicting electrical load balance.

Beyond prediction methods, the integration of microcontroller-based hardware such as ESP32 also plays an important role in supporting real-time electrical data acquisition. The ESP32 offers advantages such as wireless connectivity, Modbus RS485 communication support, and efficient data storage capabilities [10]. In several studies, the ESP32 has proven reliable for implementing Internet of Things (IoT)-based energy monitoring systems in both industrial and household sectors [11], [12]. Thus, the combination of ESP32 as a data acquisition device and LSTM as a predictive model can create an integrated and adaptive monitoring and prediction system.

Based on this background, this study aims to develop an LSTM-based electrical load balance prediction system using three-phase power data collected from a Power Meter. The prediction results are compared with actual values to evaluate the model's accuracy using the Root Mean Square Error (RMSE). Furthermore, the system provides load balance status and recommendations, which are displayed through a Human Machine Interface (HMI). With this approach, the study seeks to establish a monitoring and prediction system that supports energy efficiency efforts while improving the reliability of power systems [13], [14], [15].

B. Research Method

B.1. Research Flowchart

The research flowchart illustrates the main stages of the system, starting from data acquisition to the prediction process. In the initial stage, three-phase power data are obtained from the PM2120 power meter through Modbus RS485 communication and stored by the ESP32 on an SD card for further analysis in Python.

Subsequently, current detection is performed as part of the early warning system. The current data from each phase are compared with the system's maximum capacity. If one of the phases indicates a current value exceeding 80% of the maximum capacity, a pilot lamp is activated corresponding to the overloaded phase. In addition, a buzzer is triggered as the primary indicator, alerting the operator to immediately check field conditions. If this condition is not met, the system proceeds with normal operation without activating any warning devices.

The next stage involves data preprocessing, which includes cleaning, normalization, and windowing to prepare the prediction dataset. After preprocessing, the LSTM model is trained in Python using historical power data to predict future load balance patterns.

The prediction results are then evaluated using the Root Mean Square Error (RMSE) metric to determine the model's accuracy. Finally, the overall data information, load balance status, and corrective recommendations are displayed through the Nextion HMI, allowing operators to gain a real-time overview of the system's condition.

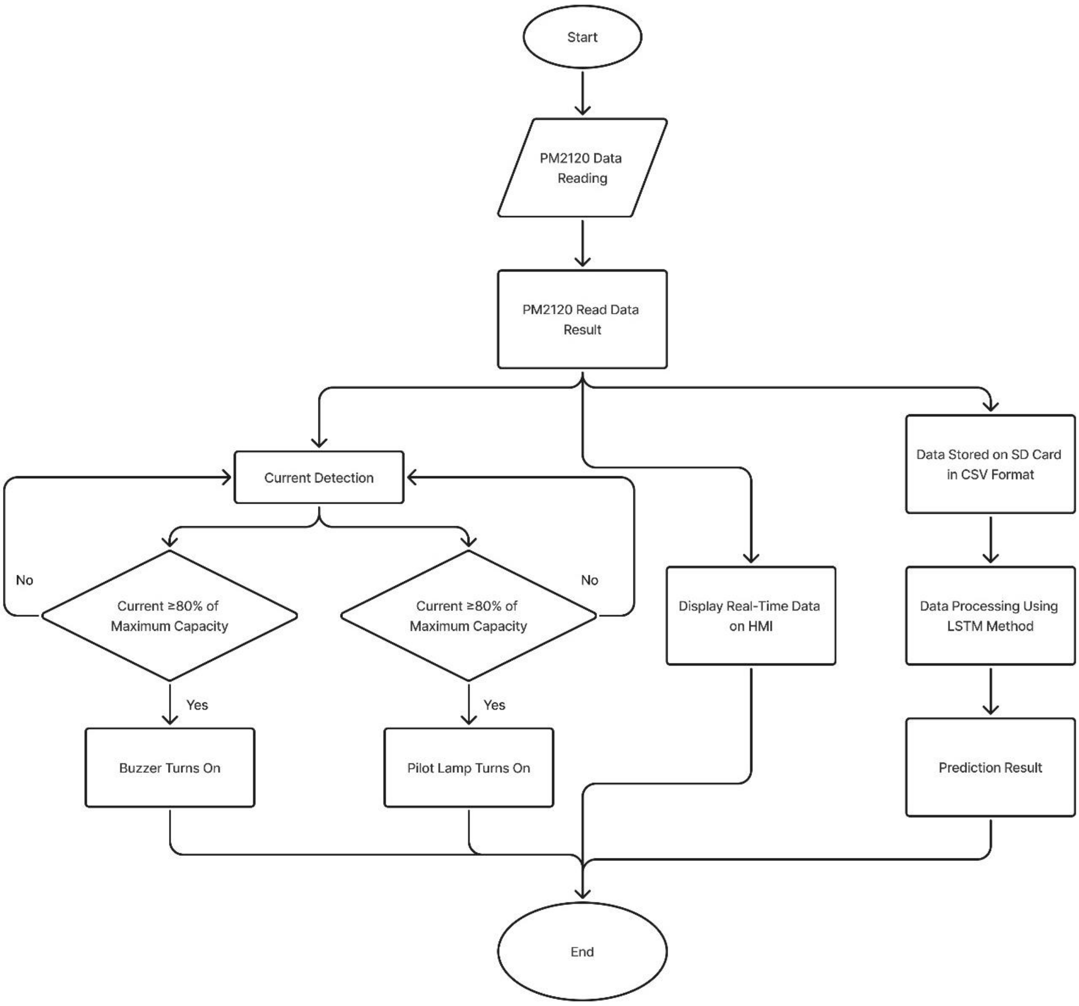

Figure 1. System Flowchart

B.2. Data Acquisition

Data acquisition was carried out by reading the three-phase power and current values from the PM2120 via Modbus RS485 communication. The ESP32 functions as the master device, transmitting queries and receiving responses from the PM2120. The collected data were stored on a microSD card at one-minute recording intervals throughout the measurement period. The use of the ESP32 as an acquisition device was selected due to its advantages in terms of connectivity, processing speed, and support for the Modbus protocol [10]–[13]. Furthermore, Modbus RTU over RS485 provides reliable long-distance data transmission with high noise immunity, which is particularly important for industrial and energy monitoring applications. The one-minute recording interval was determined to balance the granularity of monitoring with storage efficiency, enabling the capture of dynamic load variations while maintaining manageable dataset size for subsequent analysis. By integrating the ESP32 with the PM2120, the system not only ensures accurate and continuous data logging but also establishes a flexible platform for real-time monitoring and predictive modeling using machine learning techniques.

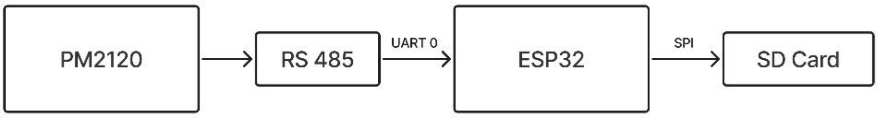

Figure 2. Data Acquisition Flowchart

B.3. Data Preprocessing

Before being used in the LSTM model training process, the acquired power data were subjected to several preprocessing stages to improve data quality and model performance. First, smoothing was applied using the rolling mean method to reduce short-term fluctuations or random noise, which is a common issue in power measurement data and may degrade forecasting accuracy. Second, normalization was performed using MinMaxScaler to rescale all values within the range [0,1], ensuring uniformity across input features and accelerating model convergence during training [6], [7]. This step is particularly important in neural network–based models, as unnormalized data may lead to slower training or biased weight updates. Finally, a windowing process was conducted by constructing sequential datasets, in which the previous 60 data points were used to predict the subsequent data point. This sliding window approach is widely adopted in time series forecasting because it allows the model to capture temporal dependencies and learn sequential patterns more effectively [1], [2].

Figure 3. Data Preprocessing Flowchart

B.4. LSTM Model

The architecture employed in this study consists of two LSTM layers, each comprising 50 units, followed by a Dense layer to generate the prediction output. The model was trained using the Adam optimizer with a learning rate of 0.0005 and Mean Squared Error (MSE) as the loss function [3]. To prevent overfitting, the Early Stopping technique was applied, which terminates the training process when the validation error does not improve over several consecutive epochs [5]. This approach ensures that the model remains generalizable and capable of producing accurate forecasts. The combination of stacked LSTM layers and a fully connected output layer enables the model to capture both short-term and long-term temporal dependencies in the data, while the selected optimization strategy balances convergence speed with stability.

Table 1. LSTM Model Parameters

Parameter	Value
Total sequence data	53864 data
Data training	43091 data
Data testing	10773 data
Sequence length	60 data
Number of LSTM layers	2
Neurons LSTM layer	50
Epoch	1
Batch size	32
Loss function	Mean Squared Error
Optimizer	Adam
Evaluation function	RMSE, Relative RMSE

B.5. Evaluation

Model evaluation was conducted by calculating the Root Mean Square Error (RMSE) on the test dataset. RMSE was chosen as the primary evaluation metric because it directly represents the magnitude of prediction error in the same unit as the original data, making it highly interpretable for practical applications. A smaller RMSE value indicates that the model achieves higher accuracy in forecasting [3], [4]. Moreover, RMSE is particularly suitable for continuous variables such as electrical load, where both underestimation and overestimation contribute equally to the error measurement. By adopting RMSE, the model’s performance can be objectively quantified and benchmarked against related studies in the field, ensuring a fair and standardized comparison of predictive accuracy.

Table 2. Accuracy Classification Based on RMSE

Criteria	Accuracy Category
RMSE < 10% of the average	High
RMSE >10% - ≤ 20%	Medium
RMSE > 20%	Low

B.6. HMI Integration

All data obtained from the PM2120, including inter-phase deviation values, load balance status (normal, warning, or unbalanced), and corresponding recommendations, are displayed in real-time on the Nextion HMI. The interface was designed to be simple yet informative, ensuring ease of interpretation by users with varying technical backgrounds. The integration of the HMI transforms the system into not only a predictive tool but also an interactive monitoring platform that supports rapid decision-making in the field [11], [16]. Furthermore, by combining visualization with automated status indicators, the system enhances situational awareness and reduces the risk of misinterpretation, which is critical for maintaining electrical reliability and safety in small- to medium-scale installations.

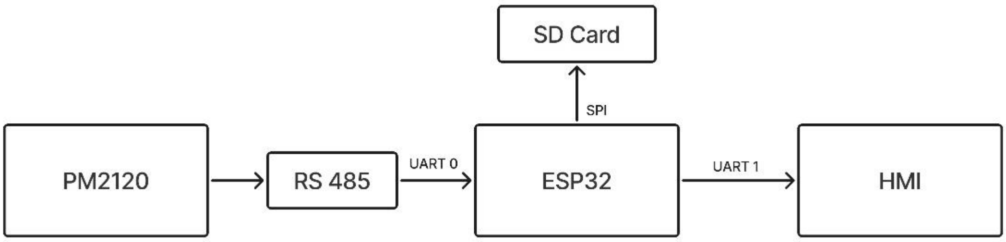

Figure 4. HMI Integration Flowchart

C. Result and Discussion

C.1. Power Prediction Results

The actual power data and prediction results for the three phases (R, S, T) are presented in graphical form. The plots indicate that the LSTM predictions closely follow the pattern of the actual data, with relatively minor deviations. This demonstrates that the model successfully learned the historical load consumption patterns and was able to generate predictions that approximate real-world conditions.

Figure 5. Prediction vs Actual Graph Using LSTM Model for Phase R

Figure 5 illustrates the comparison between actual data and LSTM prediction results for the Active Power of phase R during the testing period. The graph is divided into three main sections:

1. Training Data (dark green): The initial portion of the plot represents the actual data used for training the LSTM model. This section clearly shows recurring load consumption patterns at specific intervals, which formed the basis for the model to recognize trends and electrical load characteristics.
2. Actual Data (testing – blue): This section displays the actual measurements from the testing period, which were not included during the training phase. These data serve as the benchmark for evaluating the generalization ability of the model.
3. Predicted Data (dashed orange): This section represents the LSTM model's predictions of active power values for phase R during the testing period. The predicted curve demonstrates a strong alignment with the actual data, effectively capturing fluctuations as well as on/off load tendencies.

The obtained RMSE of 0.38 confirms that the model achieved satisfactory performance, with relatively low average prediction errors compared to actual values. These results highlight that the LSTM model was able to accurately learn and forecast power consumption patterns based on historical data, thereby validating its effectiveness for short-term load prediction tasks.

Figure 6. Prediction vs Actual Graph Using LSTM Model for Phase S

Figure 6 presents the comparison between actual data and the LSTM model's prediction results for the Active Power of phase S during the testing period. The graph is divided into three main sections:

1. Training Data (dark green): The initial part of the graph represents the actual data used for training the LSTM model. This section exhibits recurring load consumption patterns at specific intervals, which served as the foundation for the model to recognize temporal trends and electrical load characteristics.
2. Actual Data (testing – blue): This section shows the actual measurement data from the testing period, which were not included during model training. These data provide an independent benchmark to assess the generalization capability of the model.

3. Predicted Data (dashed orange): This section illustrates the LSTM model's predictions of active power values for phase S throughout the testing period. The predicted curve closely follows the actual data, effectively capturing both fluctuations and on/off load tendencies.

The RMSE value of 0.47 indicates that the model achieved satisfactory predictive performance, with relatively low average error compared to the actual values. These findings confirm that the LSTM model successfully learned the historical power consumption patterns and was able to provide accurate predictions for phase S active power during the evaluation period.

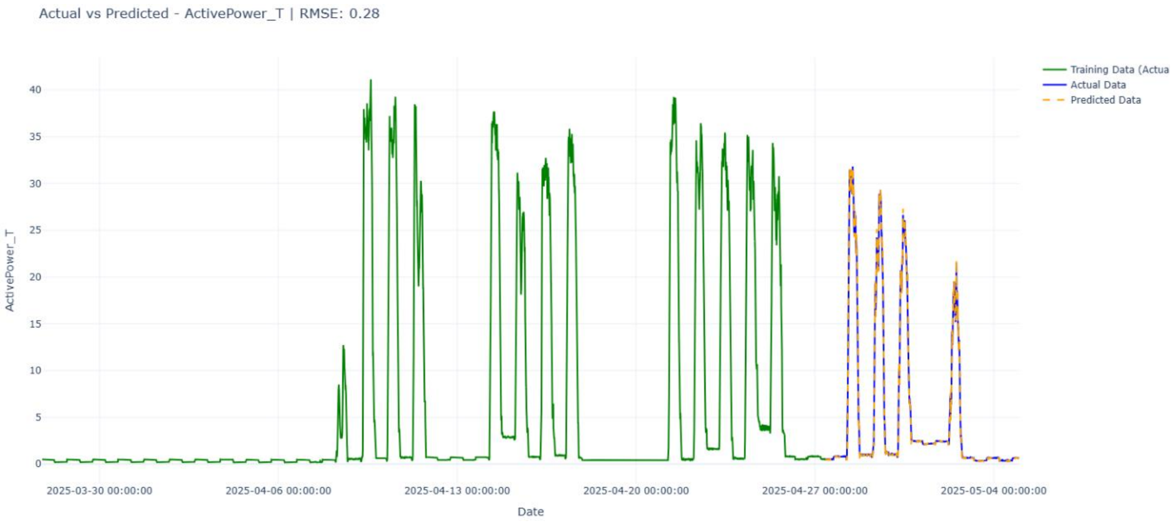

Figure 7, Prediction vs Actual Graph Using LSTM Model for Phase T

Figure 7 presents the comparison between actual data and the LSTM model's prediction results for the Active Power of phase T during the testing period. The graph consists of three main components:

1. Training Data (dark green): The initial section of the plot represents the actual data used for training the LSTM model. This portion reveals cyclic and recurring power consumption patterns, reflecting the typical load characteristics of phase T. These patterns served as the foundation for the model to learn and understand the dynamics of the electrical load.
2. Actual Data (testing – blue): This section corresponds to the actual measurement data from the testing period, which were not included in the training process. These data act as a benchmark for assessing the model's ability to accurately predict unseen data.
3. Predicted Data (dashed orange): This section displays the LSTM model's predictions of active power values for phase T. The predicted curve demonstrates a strong alignment with the actual data, effectively capturing both the trends and fluctuations, as well as the on/off switching behavior of the load.

The obtained RMSE of 0.28 indicates that the model achieved a high level of accuracy in predicting the active power of phase T, with a relatively small average deviation between the actual and predicted values. This result further confirms that the LSTM approach is effective for modeling energy consumption patterns based on historical data.

C.2. Model Evaluation

The evaluation was conducted by calculating the RMSE value for each phase. The results indicate that the model achieved relatively low RMSE values, which are consistent with the standards of Short-Term Load Forecasting (STLF) [3], [4], [9]. This finding demonstrates that the applied LSTM architecture is sufficiently effective in modeling the time series data of three-phase power consumption. The low RMSE values across all phases confirm the model's robustness and its ability to generalize well to unseen data, thereby validating its applicability for practical load forecasting tasks in real-world scenarios.

Table 3 Evaluation of Electrical Power Prediction Phase Using LSTM

Phase	RMSE (kW)	Actual Average (kW)	Relative RMSE (%)	Accuration Category
R	0.38	7.16	5.32	High
S	0.47	6.25	7.55	High
T	0.28	5.16	5.39	High

C.3. Load Balance Analysis

To evaluate load balance conditions, the EN50160 standard was adopted as a reference framework. The deviation of active power among the three phases was computed and categorized into three conditions: normal (<2%), warning (2–10%), and unbalanced (>10%) [17], [18], [19].The analysis revealed that the majority of the data fell within the normal condition, while several intervals exhibited warning-level deviations. These findings highlight the critical role of predictive modeling in early detection of load imbalance, which is particularly relevant in multi-phase electrical distribution systems where imbalance can lead to increased losses, overheating, and reduced equipment lifespan. By integrating predictive analytics based on LSTM, the system provides not only short-term load forecasting but also a proactive mechanism to identify and mitigate potential imbalance conditions before they escalate.

C.4. HMI Display

The Nextion HMI interface is designed to present real-time power data for each phase, the status of load balance, and corresponding operational recommendations. For instance, when the deviation of power among phases exceeds the 10% threshold, the system automatically displays the status "Unbalanced" accompanied by a recommendation to redistribute loads across phases. This visualization framework enhances user situational awareness by providing an intuitive yet technically accurate representation of the electrical system condition. Consequently, operators can identify anomalies at an early stage and implement corrective actions promptly, thereby minimizing risks of inefficiency, equipment stress, or potential system failures.

Figure 8. Reading Tests and Technical Recommendations on the HMI

D. Conclusion

This study successfully developed an electrical data acquisition system using the PM2120 power meter connected to an ESP32 via Modbus RTU RS485, with historical data stored on a microSD card and real-time visualization displayed on the Nextion HMI [10], [12], [16]. The LSTM-based predictive model demonstrated reliable performance, achieving RMSE values of 0.38 kW (5.32%) for phase R, 0.47 kW (7.55%) for phase S, and 0.28 kW (5.39%) for phase T, indicating that the predicted values closely follow the actual data and effectively capture consumption trends [1]–[4], [6], [8].

In addition, the system integrates an early warning mechanism consisting of pilot lamps and a buzzer that are activated when the current approaches or exceeds the threshold (≥80% of capacity). This feature proved effective as a preventive notification against overload risks, consistent with previous studies on ESP32- and Modbus-based protection and monitoring systems [12], [16].

Overall, the proposed system fulfills the research objectives by successfully acquiring data from the PM2120, delivering high-accuracy load prediction, and providing early warnings against hazardous operating conditions [7], [9]. These contributions highlight the system's potential as a practical solution for real-time monitoring and predictive energy management, particularly in small- to medium-scale electrical installations.

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