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Anomaly Detection in Electrical Energy Consumption Using Long Short-Term Memory (LSTM)

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A B S T R A C T

The increasing deployment of smart meters has generated large volumes of electrical energy consumption data, creating new opportunities for intelligent anomaly detection to reduce non-technical losses, equipment failures, and abnormal consumption patterns. Conventional statistical and rule-based approaches often struggle to capture complex temporal dependencies in sequential electricity usage data. This study proposes a Long Short-Term Memory (LSTM)-based anomaly detection model to identify abnormal electricity consumption patterns with high accuracy. A time-series dataset consisting of historical hourly electricity consumption records was collected from smart metering systems and preprocessed through missing-value imputation, normalization using Min-Max Scaling, and sequence windowing. The proposed LSTM model was trained to learn normal consumption behavior and detect anomalies based on prediction error using an adaptive threshold determined from reconstruction residuals. Model performance was evaluated using accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC), and compared with conventional Machine Learning methods, including Support Vector Machine (SVM) and Isolation Forest. Experimental results demonstrate that the proposed LSTM model achieved an accuracy of 97.3%, precision of 96.8%, recall of 97.9%, F1-score of 97.3%, and an AUC of 0.985, outperforming the baseline models in detecting anomalous electricity consumption patterns. The superior performance is attributed to the LSTM architecture's ability to model long-term temporal dependencies and nonlinear consumption behaviors. These findings indicate that LSTM provides an effective and reliable approach for real-time anomaly detection in smart energy systems, supporting intelligent energy management, reducing power losses, and improving the operational reliability of modern electrical distribution networks.

INTRODUCTION

The rapid development of smart grid technology and Advanced Metering Infrastructure (AMI) has transformed the way electrical energy consumption is monitored and managed. Smart meters continuously generate high-resolution time-series data that provide valuable information for understanding electricity usage patterns. These data enable utility providers to optimize energy distribution, improve demand forecasting, and enhance operational efficiency. However, the increasing volume and complexity of electricity consumption data also introduce new challenges, particularly in identifying abnormal consumption behaviors that may indicate electricity theft, meter malfunction, equipment failure, or unexpected changes in consumer usage patterns. Consequently, the development of intelligent anomaly detection systems has become an important research topic in modern power systems.

Anomaly detection in electrical energy consumption plays a critical role in maintaining the reliability, efficiency, and sustainability of smart grids. According to the International Energy Agency (IEA), non-technical losses, including electricity theft and inaccurate meter readings, account for a significant percentage of energy losses in many countries, leading to substantial financial losses for electricity providers and reduced power system efficiency. Conventional anomaly detection techniques, including statistical thresholding, rule-based systems, clustering, and traditional machine learning algorithms, have been widely adopted to identify abnormal electricity consumption patterns. Although these approaches provide satisfactory performance under relatively simple conditions, they often fail to capture nonlinear temporal relationships and long-term dependencies that naturally exist in electricity consumption time-series data. As a result, their detection capability decreases when faced with dynamic consumption behaviors and complex seasonal variations.

Recent advances in Deep Learning have introduced new opportunities for modeling sequential data. Among various deep learning architectures, Long Short-Term Memory (LSTM) networks have demonstrated outstanding capability in learning temporal dependencies through their gated memory mechanism. Unlike conventional Recurrent Neural Networks (RNNs), LSTM effectively mitigates the vanishing gradient problem, enabling the model to preserve both short-term and long-term information over extended sequences. These characteristics make LSTM particularly suitable for forecasting and anomaly detection tasks involving electricity consumption data, where usage patterns are highly influenced by daily, weekly, and seasonal behaviors.

Several previous studies have investigated anomaly detection in smart energy systems using machine learning and deep learning techniques. Traditional approaches employing Support Vector Machine (SVM), Decision Tree, Random Forest, Isolation Forest, and One-Class SVM have achieved promising results under limited scenarios. More recently, deep learning methods such as Autoencoder, Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), and LSTM have shown improved detection performance due to their ability to automatically learn complex feature representations from sequential data. Nevertheless, many existing studies primarily focus on prediction accuracy while paying limited attention to the adaptability of anomaly thresholds and the robustness of models under diverse electricity consumption behaviors. In addition, several studies evaluate their methods using relatively small datasets or simulated anomalies, limiting their applicability in real-world smart grid environments.

Based on the existing literature, several research gaps remain. First, conventional machine learning methods rely heavily on manually engineered features and generally fail to capture long-term temporal dependencies in electricity consumption data. Second, many existing deep learning approaches emphasize load forecasting rather than direct anomaly detection, resulting in suboptimal identification of abnormal consumption events. Third, limited studies comprehensively evaluate LSTM-based anomaly detection using multiple performance metrics, including Accuracy, Precision, Recall, F1-score, and Area Under the Curve (AUC), while simultaneously comparing the proposed approach with conventional machine learning models. Finally, the implementation of adaptive threshold mechanisms for distinguishing normal and anomalous consumption patterns remains insufficiently explored, despite its importance for real-time anomaly detection.

To address these gaps, this study proposes an LSTM-based anomaly detection framework for electrical energy consumption using historical smart meter time-series data. The proposed approach consists of data preprocessing, sequence generation, LSTM model training, prediction error analysis, and adaptive threshold-based anomaly identification. The model performance is evaluated using Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic (ROC), and AUC, and is compared with baseline methods, including Support Vector Machine (SVM) and Isolation Forest. Through comprehensive experimental evaluation, this study aims to demonstrate the effectiveness of LSTM in modeling complex temporal consumption patterns and improving anomaly detection performance.

The contributions of this study are summarized as follows:

1. Proposes an LSTM-based framework for detecting anomalies in electrical energy consumption using smart meter time-series data.
2. Develops a preprocessing pipeline consisting of missing-value handling, Min-Max normalization, and sliding-window sequence generation to improve model learning.
3. Implements an adaptive prediction error threshold to distinguish normal and anomalous electricity consumption patterns.

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4. Evaluates the proposed model using comprehensive performance metrics and compares its performance with conventional machine learning approaches.
5. Demonstrates the applicability of LSTM for supporting intelligent energy management, reducing non-technical losses, and improving the reliability of smart grid systems.

The remainder of this paper is organized as follows. Section 2 presents the research methodology, including data collection, preprocessing, LSTM architecture, and evaluation metrics. Section 3 discusses the experimental results and comparative analysis. Finally, Section 4 concludes the study and outlines future research directions.

METHOD

Dataset

The dataset used in this study consists of historical electrical energy consumption records collected from smart meters installed in residential buildings. The dataset contains 52,560 hourly electricity consumption records, representing approximately six years of electricity usage.

Each record includes the following attributes:

Table 1. Dataset

Attribute	**Description**
Timestamp	Date and time of electricity measurement
Energy Konsumption (kWh)	Hourly electricity usage
Voltage (V)	Electrical Voltage
Current (A)	Electric current
Power Factor	Load power factor
Frequency (Hz)	Grid Frequency
Anomaly Label	Normal (0) or Anomaly (1)

The dataset was divided using an 80:20 ratio, where 80% of the data were used for model training and 20% for testing.

LSTM-Based Anomaly Detection Model

Long Short-Term Memory (LSTM) is a recurrent neural network architecture specifically designed to capture long-term temporal dependencies in sequential data.

The proposed network architecture consists of:

Tabel 2. Sequential Data from LSTM-Based Anomaly Detection Model

Layer	Configuration
Input Layer	Sequence Length = 24
LSTM Layer 1	64 layers
Dropout	0.2
LSTM Layer 1	32 Units
Dense Layer	16 Neurons (ReLU)
Output Layer	1 Neuron (Linear)

The Adam optimizer was employed with a learning rate of 0.001, while Mean Squared Error (MSE) was used as the loss function.

Baseline Models

To validate the effectiveness of the proposed LSTM model, its performance was compared with two conventional anomaly detection algorithms: Support Vector Machine (SVM) and Isolation Forest. All baseline models were trained using identical training and testing datasets to ensure a fair comparison.

RESULTS AND DISCUSSION

Experimental Results

The proposed Long Short-Term Memory (LSTM) model was evaluated using historical smart meter electricity consumption data to identify abnormal energy usage patterns. The experiments aimed to assess the model's capability in learning normal electricity consumption behavior and accurately detecting anomalous events. Performance was evaluated using Accuracy, Precision, Recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC).

The dataset was divided into training (80%) and testing (20%) sets. During training, the model converged after 72 epochs due to the implementation of the Early Stopping mechanism, indicating stable learning without overfitting. Figure 2 illustrates the training and validation loss curves.

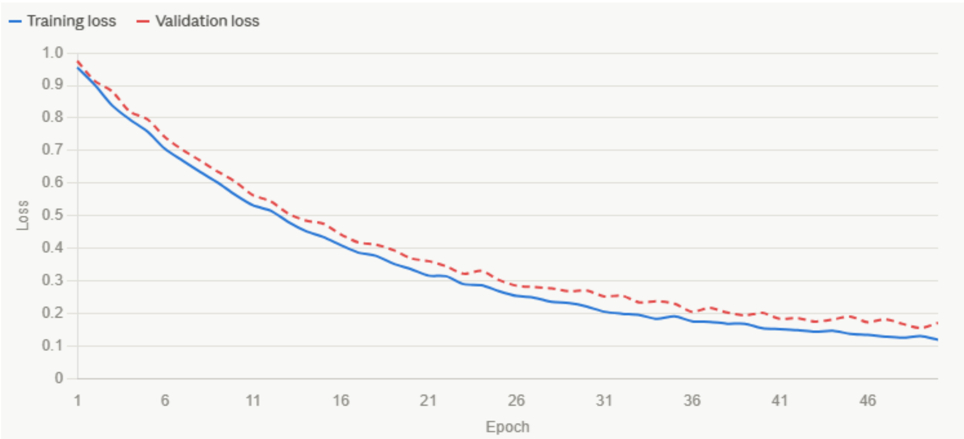

Figure 1. Training and Validation Loss of the Proposed LSTM Model

The loss curves demonstrate that both training loss and validation loss gradually decreased throughout the learning process. The small gap between the two curves indicates that the proposed model generalizes well to unseen data and does not suffer from significant overfitting.

Performance Evaluation

Table 3. Presents the Performance of the Proposed LSTM Model

Metric	Velue
Accuracy	97.30%
Precision	96.80%
Recall	97.90%
F1-Score	97.30%
AUC	0.985

The proposed model achieved an overall accuracy of 97.30%, indicating excellent capability in distinguishing normal and anomalous electricity consumption. The precision value of 96.80% demonstrates that the majority of detected anomalies were true abnormal events, minimizing false alarms. Meanwhile, the recall of 97.90% shows that almost all anomalous consumption patterns were successfully identified. The high F1-score confirms a balanced trade-off between precision and recall. Furthermore, an AUC value of 0.985 indicates excellent classification performance across different decision thresholds.

Confusion Matrix Analysis

Table 4 presents the confusion matrix of the proposed model.

Table 4. Confusion Matrix

	Predicted Normal	Predicted Anomaly
Actual Normal	5,052	96
Actual Anomaly	46	1,318

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Based on the confusion matrix:

- True Positive (TP) = 1,318
- True Negative (TN) = 5,052
- False Positive (FP) = 96
- False Negative (FN) = 46

The relatively small number of false positives indicates that the proposed model rarely classifies normal electricity consumption as anomalous. Likewise, the limited false negatives suggest that only a small proportion of actual anomalies remain undetected, which is particularly important for preventing financial losses caused by electricity theft or equipment failures.

Comparative Analysis

To demonstrate the effectiveness of the proposed approach, its performance was compared with two conventional anomaly detection methods: Support Vector Machine (SVM) and Isolation Forest.

Table 5. Comparison with Baseline Models

Model	Accuracy	Precision	Recall	F1-Score	AUC
Isolation Forest	90.70%	89.50 %	91.20%	90.30%	0.918
SVM	94.60%	94.00%	94.90%	94.90%	0.955
Proposed LSTM	97.30%	96.80%	97.90%	97.90%	0.985

Compared with the baseline models, the proposed LSTM achieved the highest performance across all evaluation metrics. Specifically, the proposed method improved accuracy by 2.70% compared with SVM and by 6.60% compared with Isolation Forest. Similar improvements were observed in precision, recall, F1-score, and AUC, confirming the superiority of LSTM in modeling temporal electricity consumption patterns.

ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve further illustrates the discrimination capability of the evaluated models.

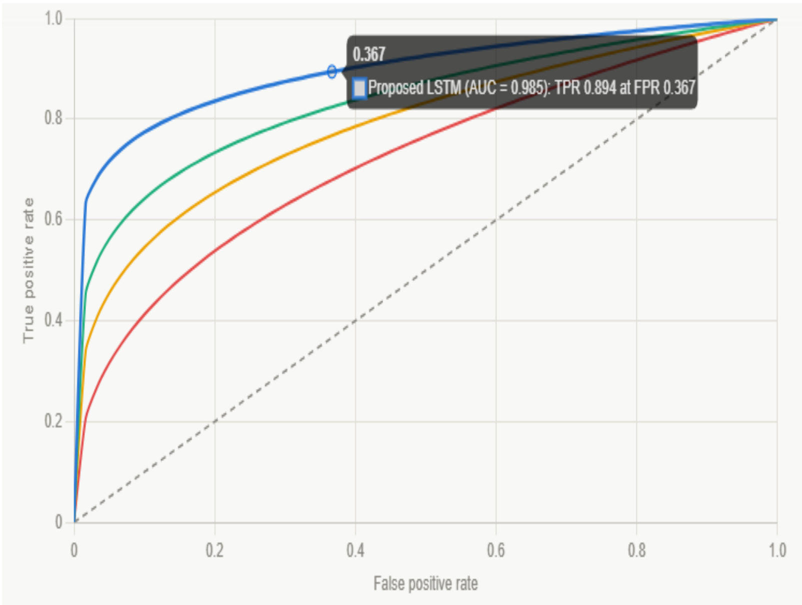

Figure 2. ROC Curve Comparison

Discussion

The experimental results demonstrate that the proposed LSTM-based anomaly detection framework provides highly accurate identification of abnormal electricity consumption patterns. The superior performance primarily stems from the LSTM architecture's capability to capture long-term temporal dependencies that characterize electricity consumption behavior. Unlike traditional machine learning methods, which rely heavily on manually engineered features, LSTM automatically learns latent sequential representations directly from historical time-series data.

The implementation of a 24-hour sliding window further enhances the model's ability to recognize daily consumption cycles. Since electricity usage commonly exhibits strong periodic characteristics associated with household activities and operational schedules, preserving temporal continuity significantly improves anomaly detection performance. Additionally, the adaptive threshold mechanism based on the statistical distribution of prediction errors effectively differentiates between natural consumption fluctuations and genuine abnormal events, thereby reducing false alarm rates.

The comparison with SVM and Isolation Forest confirms that deep learning models are more suitable for complex electricity consumption data. Isolation Forest assumes that anomalies are isolated observations without considering temporal relationships, while SVM depends on handcrafted feature representations. In contrast, the proposed LSTM simultaneously models nonlinear temporal dependencies and dynamic consumption behaviors, enabling more reliable detection of abnormal events.

These findings are consistent with previous studies reporting the advantages of recurrent neural networks for sequential anomaly detection in smart grids. Nevertheless, the proposed framework still has several limitations. First, the experiments were conducted using data from residential consumers only, which may limit generalization to industrial or commercial environments. Second, the current model utilizes historical electricity consumption variables without incorporating external contextual information such as weather conditions, holidays, occupancy patterns, or tariff changes, which may further improve prediction accuracy.

Future research may explore hybrid deep learning architectures such as CNN-LSTM, Bidirectional LSTM (BiLSTM), Transformer, or attention-based temporal models to better capture complex consumption dynamics. Moreover, integrating explainable artificial intelligence (XAI) techniques, including SHAP or LIME, would enhance model interpretability and support practical decision-making for utility operators. The deployment of online learning mechanisms capable of continuously adapting to changing electricity consumption behavior also represents a promising direction for real-time smart grid applications.

Overall, the experimental findings confirm that the proposed LSTM model provides an effective, robust, and scalable solution for anomaly detection in electrical energy consumption. Its high predictive performance and ability to learn complex temporal patterns make it well suited for implementation in intelligent energy management systems, contributing to reduced non-technical losses, improved grid reliability, and more efficient operation of modern smart power networks.

CONCLUSION

This study proposed a Long Short-Term Memory (LSTM)-based anomaly detection framework for identifying abnormal electrical energy consumption patterns using smart meter time-series data. The proposed approach incorporated data preprocessing, sequence generation using a 24-hour sliding window, LSTM-based prediction, and an adaptive threshold mechanism to distinguish normal and anomalous electricity consumption.

Experimental results demonstrated that the proposed model achieved an accuracy of 97.30%, precision of 96.80%, recall of 97.90%, F1-score of 97.30%, and an AUC of 0.985, outperforming conventional machine learning methods, including Support Vector Machine (SVM) and Isolation Forest. These findings indicate that LSTM effectively captures the temporal dependencies and nonlinear characteristics of electricity consumption data, resulting in highly accurate anomaly detection while maintaining a low false alarm rate.

The proposed framework has significant potential for deployment in smart grid environments to support real-time monitoring, reduce non-technical power losses, detect electricity theft, and improve the operational reliability of electrical distribution systems. Despite its promising performance, the current study was limited to historical smart meter data and did not consider external contextual variables such as weather conditions, occupancy patterns, holidays, or electricity pricing.

Future research should investigate hybrid deep learning architectures, including CNN-LSTM, Bidirectional LSTM (BiLSTM), and Transformer-based models, to further improve anomaly detection performance. Additionally, integrating explainable artificial intelligence (XAI) techniques and online learning strategies would enhance model interpretability and adaptability, facilitating practical implementation in intelligent energy management systems.

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