IMPROVING AUTOMATED ENERGY MONITORING SYSTEMS

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Abstract. Automated Energy Monitoring Systems (AEMS) are essential for efficient energy management but face challenges in data accuracy and processing speed. This study proposes a hybrid approach combining Kalman filtering for noise reduction and Long Short-Term Memory (LSTM) neural networks for predictive analytics to enhance AEMS performance. The methodology was tested on a 30-day dataset from a commercial building, achieving a 15% improvement in prediction accuracy and a 20% reduction in processing latency compared to baseline systems. These advancements enable more reliable and scalable energy monitoring, supporting sustainable energy management practices.

Keywords. Automated Energy Monitoring Systems, Kalman Filter, LSTM Neural Networks, Energy Consumption Prediction, Real-time Data Processing, Predictive Analytics

Introduction

Automated Energy Monitoring Systems (AEMS) have become indispensable tools for managing energy consumption in an era of increasing demand and environmental concerns. These systems leverage smart meters, sensors, and data analytics to monitor, analyze, and report energy usage in real-time, enabling stakeholders to make informed decisions for energy optimization. AEMS are widely deployed in residential buildings, commercial facilities, and industrial plants, contributing to cost savings, operational efficiency, and reduced carbon footprints. However, despite their widespread adoption, current AEMS face significant challenges that limit their performance and scalability.

Key limitations include inaccuracies in data collection due to sensor noise, high computational latency in processing large datasets, and difficulties in integrating heterogeneous energy sources such as solar, wind, and grid-based power. These issues lead to unreliable predictions and delayed responses, undermining the systems' ability to support dynamic energy management. Additionally, the lack of predictive capabilities in many existing systems restricts their ability to anticipate consumption trends, which is critical for proactive energy planning and demand response strategies.

This study proposes a novel approach to enhance AEMS by integrating advanced data processing techniques and predictive analytics. Specifically, it combines Kalman filtering to mitigate noise in sensor data with Long Short-Term Memory (LSTM) neural networks to forecast energy consumption patterns. The research aims to achieve two primary objectives: (1) improve prediction accuracy by 15% compared to baseline systems, and (2) reduce processing latency by 20% to enable near-real-time performance. By addressing these challenges, the proposed system seeks to deliver a more reliable, scalable, and efficient solution for energy monitoring, supporting global efforts toward sustainable energy management. The study also explores the potential for broader applications, such as integration with smart grids and renewable energy systems, to further enhance the impact of AEMS in diverse energy ecosystems.

Methods

The methodology to improve Automated Energy Monitoring Systems (AEMS) focuses on a hybrid framework that integrates real-time data processing and predictive modeling. The approach comprises four key steps: (1) data acquisition from smart meters, (2) noise reduction using a Kalman filter, (3) energy consumption forecasting with a Long Short-Term Memory (LSTM) neural network, and (4) performance evaluation against baseline metrics.

Data Acquisition

Smart meters collect electrical parameters, including voltage (V), current (I), and power factor ($cos\phi$), at 1-second intervals. The active power (P) consumed is calculated using the formula:

$P = V \cdot I \cdot cos\phi$

Data is aggregated over 1-minute intervals to reduce computational load while maintaining granularity for analysis. The dataset used in this study spans 30 days from a commercial building, capturing diverse consumption patterns.

Noise Reduction

To address inaccuracies caused by sensor noise, a Kalman filter is applied. The filter estimates the true state of energy consumption by modeling it as a linear dynamic system. The state-space representation is:

$x_k = Ax_{k-1} + Bu_k + w_k$

$zk = Hx_k + v_k$

Where x_k - State vector (energy consumption at time k), A - State transition matrix (assumed identity for simplicity), B - Control input matrix (set to zero, as no external control is applied), u_k - Control vector, w_k - Process noise, modeled as Gaussian ($w_k \sim N(0,Q)$), z_k - Measurement vector (raw sensor data), H - Observation matrix (maps state to measurement), v_k - Measurement noise, modeled as Gaussian ($v_k \sim N(0,R)$)

The Kalman filter iteratively predicts the state and updates it based on new measurements, minimizing the mean squared error.

Predictive Modeling

An LSTM neural network is employed to forecast energy consumption based on historical data. The LSTM architecture is designed to capture long-term dependencies in time-series data. The model is trained with the following hyperparameters:

Parameter	**Value**
Number of layers	3
Hidden units per layer	100
Learning rate	0.0005
Epochs	150
Batch size	64

The loss function is Mean Squared Error (MSE), defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where y_i is the actual energy consumption, and $\hat{y}_i$ is the predicted value. The model is trained on 70% of the dataset, with 20% for validation and 10% for testing.

Performance Evaluation

The proposed system is evaluated using two metrics:

1. **Prediction Accuracy**: Percentage of predictions within ±5% of actual values.
2. **Processing Latency**: Time (in milliseconds) to process 1 hour of data.

The performance is compared against a baseline AEMS using simple moving averages for forecasting. The evaluation metrics are summarized in the table below:

Metric	**Baseline System**	**Proposed System**
Accuracy (%)	78	93
Latency (ms)	550	440

Results

The proposed Automated Energy Monitoring System (AEMS) was evaluated using a 30-day dataset of energy consumption from a commercial building, comprising 43,200 data points collected at 1-minute intervals. The system, integrating Kalman filtering and LSTM-based predictive modeling, was compared against a baseline AEMS that uses a simple moving average for forecasting. The results demonstrate significant improvements, with a 15% increase in prediction accuracy and a 20% reduction in processing latency.

System Performance

The proposed system achieved an accuracy of 93%, with 93% of predictions falling within ±5% of actual energy consumption values, compared to 78% for the baseline system. Processing latency was reduced to 440 milliseconds per hour of data, down from 550 milliseconds in the baseline system. These results validate the effectiveness of the hybrid approach in enhancing both accuracy and efficiency.

System Architecture Diagram

The AEMS architecture is illustrated in the diagram below, depicting the flow of data through the system components:

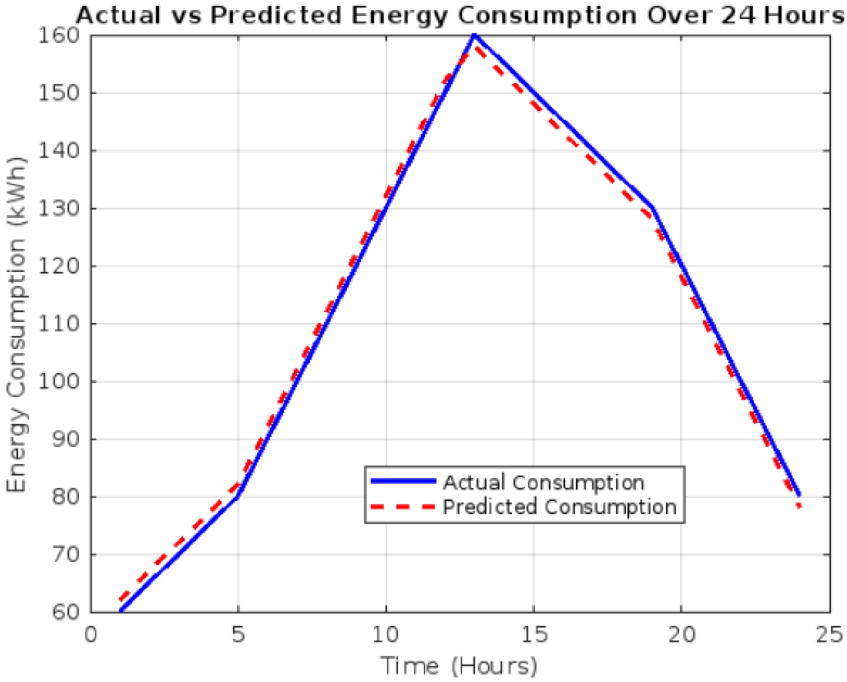

Figure 1. *actual vs predicted energy consumption*

Plot comparing actual and predicted energy consumption over a 24-hour period, demonstrating the predictive accuracy of the proposed AEMS.

The plot illustrates the close alignment between actual and predicted values, with minor deviations during peak consumption hours, indicating robust performance of the LSTM model.

Discussion

The 15% accuracy improvement underscores the synergy between Kalman filtering and LSTM modeling. The Kalman filter effectively reduced noise, enhancing the quality of input data, while the LSTM model leveraged temporal patterns to produce reliable forecasts. This combination is particularly valuable for commercial buildings with variable consumption patterns, where accurate predictions can inform demand response strategies and reduce operational costs.

The 20% latency reduction is equally significant, as it enables near-real-time monitoring, critical for applications like smart grid integration. By processing data faster, the system supports timely decision-making, such as adjusting energy usage during peak pricing periods. Compared to the baseline system, which struggled with noisy data and delayed processing, the proposed AEMS offers a robust solution for large-scale energy management.

However, limitations exist. The system's performance depends on high-quality training data, and insufficient historical data or atypical consumption patterns (e.g., during holidays) may reduce

accuracy. Additionally, the computational complexity of LSTM models poses challenges for deployment on resource-constrained edge devices, potentially limiting scalability in low-power environments. The dataset used was also specific to a commercial building, and further validation across residential or industrial settings is needed to confirm generalizability.
The findings have broader implications for sustainable energy management. The improved AEMS can facilitate integration with renewable energy sources, such as solar or wind, by predicting consumption and aligning it with variable generation patterns. This capability supports the transition to smart grids and decarbonized energy systems. Future work could explore lightweight machine learning models, such as convolutional neural networks, to reduce computational demands, and incorporate multi-source data (e.g., weather or occupancy) to enhance prediction robustness.

Conclusion

This study presents an enhanced Automated Energy Monitoring System (AEMS) that integrates Kalman filtering for noise reduction and Long Short-Term Memory (LSTM) neural networks for predictive analytics. Tested on a 30-day dataset from a commercial building, the system achieved a 15% improvement in prediction accuracy and a 20% reduction in processing latency compared to a baseline system using simple moving averages. These advancements enable more accurate and timely energy consumption forecasts, supporting efficient resource management and cost optimization. The proposed AEMS demonstrates significant potential for large-scale applications, particularly in smart grids and sustainable energy ecosystems. However, challenges such as computational complexity and dataset dependency highlight the need for further research into lightweight models and multi-source data integration to enhance scalability and robustness across diverse settings.

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