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Empowering energy management: anomaly detection in smart meter data for proactive consumption control

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ABSTRACT

The increasing deployment of smart energy meters (SEMs) has enabled real-time monitoring of energy consumption, but the vast data generated makes it challenging to detect anomalies that may indicate inefficiencies, faults, or unauthorized usage. This study aims to enhance energy management by developing a hybrid anomaly detection framework that improves accuracy while providing actionable insights for consumers. The proposed method integrates statistical and machine learning (ML) approaches, specifically Z-score, local outlier factor (LOF), one-class support vector machine (SVM), and isolation forest (iForest), to analyze simulated smart meter data. An anomaly is flagged only when identified by all four methods, thereby reducing false positives and improving reliability. The framework is implemented in an interactive dashboard built with streamlit, offering real-time visualization, peak-time alerts, usage forecasts, and personalized consumption suggestions. Results demonstrate that the hybrid approach outperforms single-method models, achieving higher detection accuracy and practical applicability. The findings highlight the potential of combining complementary detection techniques with proactive feedback to empower consumers, reduce energy wastage, and support sustainable energy management. This work provides a scalable foundation for future real-time deployment in smart grids and microgrid environments.

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1. INTRODUCTION

The growing deployment of smart energy meters (SEMs) has transformed the way energy consumption is monitored, managed, and optimized [1]. Unlike traditional meters, SEMs provide real-time measurements, two-way communication, and integration with internet of things (IoT) platforms [2]. However, the increasing scale and complexity of energy usage data present new challenges for utilities and consumers. Large datasets often contain hidden anomalies, such as sudden spikes, irregular patterns, or unusual load behavior, which can indicate inefficiencies, faulty appliances, or even fraudulent activity.

Identifying these anomalies in a timely and accurate manner is critical for ensuring energy efficiency, cost savings, and reliability in modern energy systems.

Several studies have addressed energy management using smart meters and anomaly detection techniques. Statistical methods, such as Z-score analysis, have been widely used for detecting significant deviations but often struggle with dynamic or noisy data. Density-based approaches like local outlier factor (LOF) have been effective in capturing localized anomalies but tend to produce false positives in heterogeneous environments. Machine learning (ML) techniques, including one-class support vector machine (SVM) and isolation forest (iForest), have shown promise in detecting subtle and complex patterns; however, they require careful tuning and often lack interpretability for end users. Despite these advancements, prior works generally focus on algorithmic detection without adequately connecting the results to actionable insights for consumers.

In recent years, researchers have explored smart grid integration, IoT-enabled monitoring, and real-time dashboards to improve consumer awareness and utility operations [3]. Comparable works have demonstrated the potential of anomaly detection in domains such as cybersecurity, fraud detection, and healthcare, but their direct application to smart energy management remains limited [4]. Many existing systems emphasize detection accuracy while neglecting proactive feedback mechanisms that could guide consumers to optimize their energy consumption. Moreover, there is a lack of frameworks that combine multiple anomaly detection methods into a single robust system, reducing false positives while enhancing reliability.

This study addresses these gaps by proposing a hybrid anomaly detection framework that integrates four complementary methods—Z-score, LOF, one-class SVM, and iForest—into a smart energy management system (EMS). By combining statistical and ML approaches, our framework improves anomaly detection accuracy while minimizing false alarms. In addition, the system goes beyond mere detection by providing proactive consumption suggestions, peak-time alerts, and usage forecasts. These features are implemented in an interactive dashboard, enabling consumers to visualize energy patterns, recognize anomalies, and take corrective measures in real time.

The SEM dashboard is here to revolutionize how you monitor and optimize your energy usage. By detecting irregular consumption patterns, this system makes managing your energy use easier and more efficient. Let’s take a closer look at its key features:

Simulated energy usage data: the dashboard generates realistic energy usage data that mimics everyday user behavior. It includes random anomalies like unexpected spikes in consumption to test the detection system. The simulation models common patterns, with higher energy usage during peak hours (typically from 8 AM to 6 PM).

Anomaly detection methods: to ensure accuracy, four different techniques are used to detect anomalies in the energy data. Z-score anomaly detection: this method checks how far a data point is from the average (mean) of the data. If it’s too far from the average, it gets flagged as an anomaly. LOF: LOF looks at the local density of data points and flags that differ significantly from their neighbors.

One-class SVM: this ML model learns what “normal” data looks like and flags any points that deviate from this norm. iForest: this algorithm isolates data points by randomly partitioning the data and flags that are easier to isolate as anomalies. When all four methods agree on an anomaly, the data point is flagged as an anomaly in the final output.

Proactive consumption suggestions: the dashboard provides tailored advice to help you optimize your energy consumption. For instance, if your average energy usage exceeds a certain threshold, you will be advised to reduce consumption during peak hours to save on costs.

Peak time alerts: the system identifies specific days and times when your energy consumption exceeds a set threshold, alerting you to periods of unusually high usage. This helps you spot inefficiencies or potential problems early.

Usage forecasting: using historical data, the dashboard predicts future energy consumption, helping you prepare for changes in your usage patterns and manage your energy consumption proactively.

Interactive streamlit dashboard: built with streamlit, this interactive dashboard allows you to explore your energy data and detect anomalies through a variety of visualizations [5]. These include line charts, area charts, heatmaps, and pie charts, showing the breakdown of anomalies detected by each method.

In summary, this dashboard offers an easy-to-use, comprehensive tools for tracking and improving energy usage. By combining simulated data, advanced anomaly detection techniques, and real-time monitoring, it helps you identify irregular consumption patterns and provides actionable insights to optimize your energy management.

The manuscript is organized into eight sections to clearly present the proposed hybrid anomaly detection framework and its applications in smart energy management. Section 1 introduces the motivation, background, research gaps, and contributions of the study. Section 2 reviews the related literature on SEMs, EMSs, and existing anomaly detection techniques. Section 3 discusses the role of SEMs in enabling efficient monitoring, smart grid integration, and demand-side management (DSM). Section 4 explains the theoretical foundations of anomaly detection methods, including Z-score, LOF, one-class SVM, and iForest. Section 5 describes the proposed method, including simulated energy data generation, hybrid anomaly detection, dashboard implementation, and visualization techniques. Section 6 presents the experimental results and performance analysis of the proposed framework along with proactive energy management insights. Section 7 discusses the strengths, challenges, implications, and comparisons with existing studies. Finally, section 8 concludes the paper by summarizing the contributions, limitations, and future research directions for real-time smart EMSs.

2. LITERATURE REVIEW

2.1. Smarty energy meter

SEMs are critical components in modern EMS, offering an array of functions that improve efficiency, reliability, and security of energy use in both residential and commercial settings. These smart meters are an integral part of smart grids, enabling real-time monitoring, control, and management of energy consumption, as well as supporting DSM and energy efficiency efforts [6], [7].

Functionality and importance of SEMs: SEMs, also referred to as smart meters, offer advanced capabilities over traditional meters by providing two-way communication between the meter and the utility. The benefit of the SEM is shown in Figure 1. This allows utilities to collect real-time data on energy consumption, adjust billing processes, detect faults, and remotely control energy supply. They are also capable of measuring and tracking various parameters like voltage and power usage, offering more accurate readings and improving operational efficiencies [8].

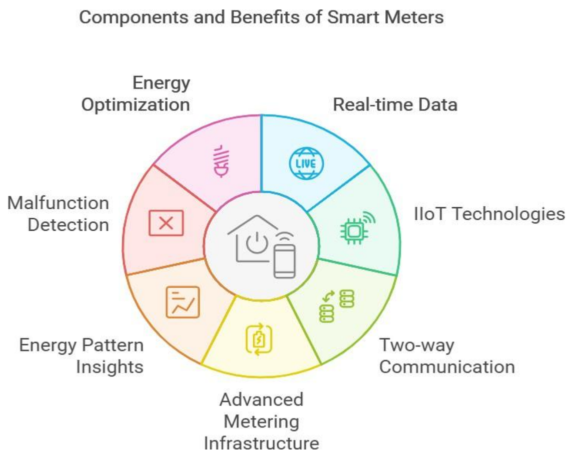

Figure 1. SEM benefits

One of the key aspects of SEM is their ability to integrate with IoT devices and smart grids. Through IoT technology, these meters can provide a centralized platform for managing energy usage across homes, buildings, or entire smart cities, offering consumers and utilities more transparency and better control over energy distribution and consumption patterns. Smart meters use communication networks, such as low power wide area networks (LPWANs) and long range (LoRa), to transmit data to centralized systems for analysis and reporting, which can lead to more effective energy management and the detection of anomalies in consumption patterns, such as theft or mal- functions [9], [10].

IoT integration and smart grids: the integration of SEMs with smart grids forms the foundation of modern EMS. By using smart grids, which allow bidirectional communication between energy suppliers and consumers, energy usage can be optimized. This system helps balance supply and demand in real-time, preventing overloads and enhancing the overall reliability of the grid. SEMs are vital in the functioning of these grids, as they provide granular data on energy consumption, enabling DSM, load forecasting, and enhanced grid resilience [6], [7].

Moreover, these systems can incorporate renewable energy sources, such as solar or wind, by offering insights into energy production and consumption patterns, helping to manage variability and stability in energy distribution. Smart meters can also participate in home energy management system (HEMS), where they enable better control over individual devices, optimize energy use, and integrate with home automation solutions [11], [12].

Security and privacy: while the deployment of smart meters offers significant benefits in terms of energy management and optimization, there are associated concerns regarding data security and privacy. As these devices continuously collect and transmit data, they become potential targets for cyberattacks, which could compromise the integrity of the data or even disrupt energy supply. To address this, several studies have focused on enhancing the security and resilience of SEMs, employing encryption, secure transmission protocols, and ML-based anomaly detection systems to prevent unauthorized access or attacks [11], [13].

Error detection and maintenance: smart meters also play a role in identifying and managing malfunctions or errors in the energy measurement process. By employing techniques such as error estimation algorithms and edge computing, these systems can detect faults or discrepancies in readings, alert utilities for maintenance, and even prevent faulty meters from affecting the overall energy grid. This ability to self-monitor and self-correct ensures the continued accuracy of measurements and prevents revenue losses due to malfunctions [11], [14].

Environmental and economic impact: the deployment of SEMs is also linked to promoting energy efficiency and sustainability. By providing real-time feedback to consumers on their energy usage patterns, these devices can help reduce energy waste, leading to cost savings and a reduction in environmental impact. Smart meters contribute to energy conservation efforts by enabling consumers to adjust their usage based on pricing signals or energy availability, thereby fostering a culture of sustainability [7], [15].

Applications in smart cities: in the context of smart cities, SEMs are indispensable for managing energy resources in a holistic manner. These systems allow for the seamless integration of water and energy monitoring, where both utilities can be controlled and optimized from a centralized platform. They also support other smart city initiatives, including waste management, street lighting, and traffic systems, by utilizing data from various sensors and devices to make intelligent, real- time decisions that improve urban living [6], [16].

SEMs are a cornerstone of modern energy management, playing a crucial role in the development of smart grids and smart cities. Through their integration with IoT technology, these devices help optimize energy consumption, improve system reliability, and enhance grid resilience. As advancements in data security, error detection, and communication technologies continue, SEMs will become even more efficient, offering greater benefits to both utilities and consumers while contributing to sustainability and cost reduction efforts [8], [11], [17], [18]. The Table 1 shows the summary of literature survey.

Table 1. Literature review summary

Authors and year	Focus/contribution	Findings/key outcomes
Saleem *et al*. [7] (2021)	Designed and implemented an IoT-based smart EMS.	Real-time monitoring improved energy efficiency and offered flexible control for utilities.
Gallardo *et al*. [12] (2021)	Proposed LoRa IoT-based architecture for smart metering.	Demonstrated reliable, scalable communication for residential smart grids.
Liu *et al*. [8] (2020)	Developed remote malfunction detection in edge computing.	Early detection prevented revenue losses and improved grid reliability.
Kebotogetse *et al*. [10] (2022)	Proposed secure transmission in advanced metering infrastructure.	Improved resilience against cyberattacks and unauthorized access.
Nassif *et al*. [19] (2021)	Systematic review of ML for anomaly detection.	Hybrid supervised–unsupervised models enhanced robustness.
Sabuhi *et al*. [20] (2021)	Applied GANs for anomaly detection.	Synthetic data generation improved outlier recognition.
Min *et al*. [21] (2021)	Used memory-augmented deep autoencoders for anomaly detection.	Reported higher accuracy in high-dimensional data.
Chang *et al*. [22] (2020)	Proposed hierarchical IoT anomaly detection framework.	Edge-level anomaly detection reduced latency for real-time monitoring.
Al-Ghaili *et al*. [18] (2021)	Reviewed EMS strategies in building sector.	Found that demand response (DR) and predictive control reduce costs and environmental impact.
Veichtlbauer *et al*. [23] (2022)	Introduced cluster storage for community EMS.	Improved load balancing and strengthened grid stability.
Liu *et al*. [24] (2023)	Reviewed microgrid EMS with storage integration.	Integration of renewables with storage enhanced resilience and sustainability.

2.2. Energy management

Energy management refers to the strategies and technologies used to optimize energy usage, reduce consumption, and ensure sustainability. The integration of SEMs with EMS has transformed how energy is monitored, controlled, and distributed. Below is a summary of the important concepts related to energy management and the role of SEMs in it, based on several recent studies.

2.3. Energy management and systems overview

Energy management involves optimizing energy consumption, ensuring efficient resource utilization, and reducing energy costs. These systems are essential in both residential and industrial sectors to manage energy consumption, minimize waste, and effectively integrate renewable energy sources. The EMS cycle is displayed in Figure 2.

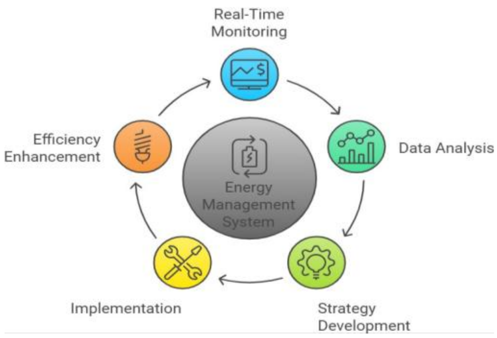

Figure 2. EMS cycle

Energy management in buildings: EMS in buildings use real-time data to monitor and control energy consumption. These systems optimize the operation of heating, ventilation, air conditioning (HVAC), lighting, and other systems within the building to reduce energy use and costs while maintaining comfort and productivity. They can also incorporate renewable energy sources such as solar or wind to enhance sustainability. Additionally, DR strategies enable buildings to reduce or shift energy consumption during peak hours, aiding grid stabilization and cost reduction [18], [25].

Microgrid and energy storage systems (ESS): microgrids are localized energy systems that can operate independently or in conjunction with the main grid. They integrate renewable energy sources, ESS, and EMS to optimize energy production, storage, and consumption locally [24], [26]. ESS play a significant role in microgrid energy management by storing excess energy generated during low-demand periods and releasing it during high-demand periods to balance supply and demand effectively [24], [27].

Smart energy management: IoT-based smart EMS provide real-time data analytics and monitoring, enabling advanced control strategies and predictive maintenance of energy assets. These systems support energy efficiency in buildings, smart cities, and industries [15], [28]. Smart meters, as part of EMS, collect real-time data on energy consumption patterns, enabling utilities to offer time-of-use pricing and other incentives to encourage efficient energy use. Integration with smart grids enhances real-time monitoring, fault detection, and automated control to manage energy distribution and consumption [15], [26].

2.4. Optimization of energy resources

Optimization algorithms are used to improve energy system efficiency by dynamically adjusting consumption based on availability and pricing signals. These systems optimize the use of distributed energy resources (DERs) such as solar panels, batteries, and wind turbines [29], [30]. SEMs support these optimization algorithms by providing accurate and real-time data on energy usage, which can be analyzed to make decisions about energy distribution and storage.

2.5. Home energy management system

Home EMS integrates renewable energy resources, energy storage, and the main grid to optimize household energy consumption. Smart meters, as part of these systems, allow homeowners to monitor energy usage, control appliances, and manage energy storage more efficiently. The systems can also participate in energy trading schemes, where energy stored in batteries or generated by solar panels is sold back to the grid [31], [32].

2.6. Industrial and community energy management

Industrial energy management uses big data and IoT technologies to optimize energy consumption in manufacturing and other industrial processes. Industrial energy management system (IEMS) enable industries to monitor energy use, reduce waste, and improve overall efficiency through automated control systems and predictive analytics [28]. Community energy management aggregates energy consumption and production at the community level, optimizing energy use across multiple buildings or households through cluster storage systems. These systems enable better coordination between renewable energy sources, storage, and consumption to reduce costs and improve grid resilience [23].

Despite significant progress in smart energy metering and anomaly detection, several unresolved challenges remain. Existing statistical methods such as Z-score are simple but often unreliable when dealing with noisy or non-Gaussian energy consumption data. Density-based techniques like LOF are useful for identifying local deviations but tend to generate excessive false positives in heterogeneous usage environments. Similarly, ML models such as one-class SVM and iForest have shown potential but face challenges related to parameter tuning, computational complexity, and real-time adaptability.

Another gap in current literature lies in the limited integration of anomaly detection with actionable consumer-oriented feedback. Most prior works focus solely on anomaly identification without connecting the results to meaningful suggestions that empower users to adjust their consumption. Furthermore, scalability and robustness are often overlooked; frameworks capable of handling large-scale smart meter data while maintaining accuracy and efficiency are still lacking. Security and privacy concerns also remain, as continuous data collection and transmission expose smart metering systems to vulnerabilities.

This manuscript specifically addresses the lack of a hybrid, consumer-focused anomaly detection framework. By combining multiple detection methods (Z-score, LOF, one-class SVM, and iForest), we aim to reduce false positives while increasing detection accuracy across varied consumption patterns. Moreover, the integration of proactive consumption suggestions, peak-time alerts, and forecasting bridges the gap between detection and user action, transforming anomaly identification into a tool for smarter and more sustainable energy management.

Building on the identified research gaps, this manuscript makes several new contributions that distinguish it from prior studies. First, unlike works that rely on a single anomaly detection approach, we propose a hybrid framework that integrates statistical (Z-score and LOF) and ML methods (one-class SVM and iForest). This combination leverages the strengths of each technique, significantly reducing false positives while improving anomaly detection accuracy across diverse consumption patterns. Second, while earlier studies focused mainly on anomaly detection, our work goes a step further by linking detection results to proactive consumer-oriented feedback through personalized suggestions, peak-time alerts, and usage forecasting. This ensures that anomalies are not only identified but also translated into actionable insights that empower users to optimize their energy consumption. Third, we implement these contributions in an interactive dashboard environment that visualizes consumption data, anomalies, and recommendations in real time, offering both transparency and usability for consumers. Finally, the proposed system serves as a scalable foundation for future integration with real-time data streams and smart home systems, bridging the gap between anomaly detection research and practical, user-centered energy management solutions.

3. ROLE OF SMART ENERGY METERS

SEMs play a vital role in EMS, especially in the context of smart grids and buildings. These devices enable more accurate, real-time monitoring, and control of energy consumption, contributing to several key benefits:

3.1. Real-time monitoring and billing

Smart meters provide utilities with real-time data on energy consumption, improving billing accuracy and eliminating the need for estimated bills. This leads to better customer satisfaction and enhanced operational efficiency [18].

3.2. Energy usage analytics

Data from smart meters allow utilities and consumers to analyze usage patterns, identify inefficiencies, and make data-driven decisions to optimize energy use. This can lead to significant savings in both residential and commercial applications [25], [28].

3.3. Integration with smart grids

Smart meters enable communication with smart grids, allowing for dynamic DR, fault detection, and automatic control of energy supply based on real-time data. This interaction helps balance the grid load, reduce energy wastage, and supports the integration of renewable energy sources [15], [26].

3.4. Optimization of distributed energy resources

Smart meters contribute to the optimization of DERs by monitoring energy production and consumption in real time. This allows for better management of energy storage and distribution, reducing energy costs and supporting sustainable practices [29], [30].

3.5. Demand response and grid stabilization

Mart meters enable DSM by providing consumers with real-time pricing and consumption data. Consumers can adjust their energy use to take advantage of lower rates during off-peak hours, and utilities can control the load by remotely managing energy distribution. This aids in stabilizing the grid and preventing overloads [18], [25].

EMS, particularly those integrated with smart meters, are central to modern energy optimization strategies. By offering real-time monitoring, predictive analytics, and automated control, SEMs support both consumers and utilities in reducing energy consumption, lowering costs, and improving grid reliability. The integration of these systems with microgrids, renewable energy sources, and energy storage ensures a sustainable future where energy is consumed more efficiently and sustainably.

Anomaly detection refers to the process of identifying rare or unusual patterns in data that do not conform to expected behavior. These anomalies may indicate critical incidents, such as security breaches, faults, or fraudulent activities. The importance of anomaly detection has been growing across a wide range of fields, including cybersecurity, finance, healthcare, and manufacturing, due to the need to identify irregularities that might otherwise go unnoticed in large datasets. ML techniques, particularly supervised and unsupervised learning, are widely used to perform anomaly detection effectively, as they can model the normal behavior of systems and flag deviations from this norm as potential anomalies [33].

In recent years, deep learning techniques, especially deep reinforcement learning, have gained attention for their ability to detect anomalies in complex, high-dimensional data, such as time series or image data. Unlike traditional methods, deep learning models can automatically learn hierarchical features from raw data without needing handcrafted features [33]. Furthermore, reinforcement learning approaches can help anomaly detection systems adapt to changing environments and improve over time, making them a suitable option for dynamic, real-world applications [33].

Traditional methods such as clustering, statistical analysis, and outlier detection have their own limitations. For instance, classical approaches may struggle with high-dimensional data or may require extensive prior knowledge about data distribution. To address these limitations, more advanced methods leveraging neural networks, particularly generative models like generative adversarial networks (GANs), have been proposed for anomaly detection tasks. These models can create synthetic data that mirrors the distribution of the normal data, helping to identify outliers or deviations [20]. Additionally, hybrid methods combining supervised, unsupervised, and semi-supervised learning have been explored to improve the robustness of anomaly detection systems [19].

The integration of anomaly detection techniques in network security, specifically intrusion detection, has shown promising results. By monitoring traffic patterns and identifying anomalies, such systems can automatically detect and mitigate security threats such as distributed denial of service (DDoS) attacks or unauthorized access [21]. Moreover, new challenges in anomaly detection are arising with the proliferation of IoT devices, where the ability to detect anomalies in real-time at the edge is becoming increasingly important for effective system monitoring and security [22].

4. ANOMALY DETECTION

As ML continues to advance, new trends such as lifelong continual learning are emerging, which allow models to continually update and adapt without forgetting previously learned information. This is particularly useful in applications where data distributions change over time, such as in financial markets or healthcare systems, where anomaly detection models must adapt to new patterns of behavior [34]. Therefore, the ongoing research in anomaly detection is crucial to ensure that systems remain reliable and can respond to novel and unforeseen anomalies in an effective manner [35].

Anomaly detection is a crucial task in data mining and ML, as it helps to identify outliers or rare observations that do not conform to the expected patterns. In here, we summarize four widely used anomaly detection methods: Z-score, iForest, LOF, and one-class SVM. These techniques are commonly applied in diverse fields such as cybersecurity, finance, and medical diagnosis and we have also used the below in this project.

4.1. Z-score

The Z-score is a statistical method used to identify outliers by measuring how far a data point is from the mean of the dataset in terms of standard deviations. Mathematically, it is calculated as:

$$Z = \frac{X - \mu}{\sigma}$$

where, x is the data point, μ is the mean of the data, and σ is the standard deviation.

The Z-score method is simple and effective when the data follows a normal distribution. Points with a Z-score greater than a certain threshold (e.g., 3 or -3) are considered outliers. The Z-score advantages and disadvantages are shown in Figure 3.

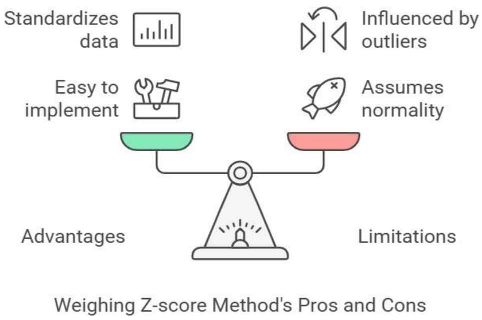

Figure 3. Z-score advantages and disadvantages

4.2. Isolation forest

iForest is an ensemble-based anomaly detection technique that isolates observations by randomly selecting features and randomly selecting split values between the minimum and maximum values of the selected feature and it is displayed in Figure 4. This method leverages the fact that anomalies are easier to isolate because they are few and different from the normal observations. The algorithm works as:

– Build multiple decision trees by randomly selecting features and splitting data.
– Anomalies are expected to have shorter path lengths in these trees, as they are easier to isolate.

The anomaly score is computed based on the path length in the isolation trees.

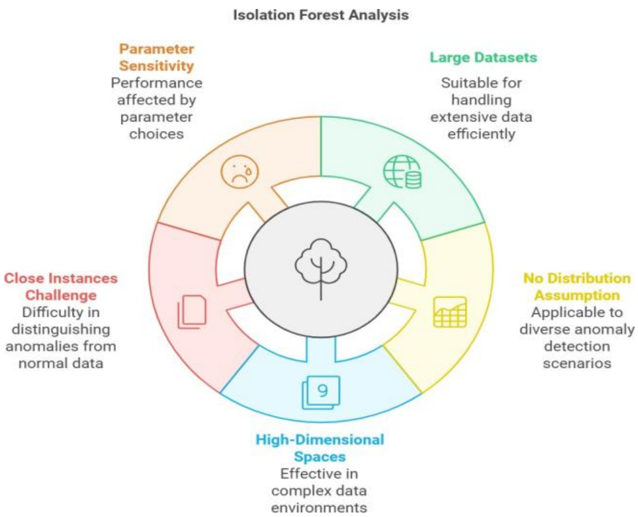

Figure 4. iForest analysis

Mathematically, the anomaly score for a data point is determined by the average path length from all trees. If a point is isolated closer to the root of the tree, it is considered an anomaly. The method is efficient and scalable, making it suitable for large datasets [36].

4.3. Local outlier factor

The LOF method is based on the concept of local density, where data points that have significantly lower density than their neighbors are considered outliers and LOF advantages and disadvantages are shown in Figure 5. LOF compares the density of a point with the density of its neighbors using a ratio.

$$LOF\ (p) = \frac{\sum_{0\epsilon N_k(p)}\frac{Ird(0)}{Ird(p)}}{|N_k(p)|}$$

where, $N_k(p)$ is the set of k-nearest neighbors of point p, $lrd(p)$ is the local reachability density of point p, and o is a neighbor of p.

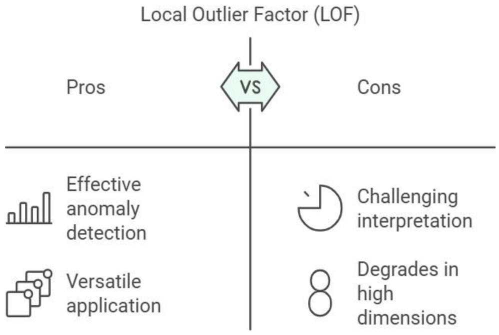

Figure 5. LOF advantages and disadvantages

The LOF score reflects how much lower the density of point p is compared to its neighbors. A higher LOF score indicates that a point is more likely to be an outlier. LOF is effective in detecting local outliers, making it particularly useful when data points have varying densities.

4.4. One-class support vector machine

The one-class SVM is a ML algorithm used for anomaly detection, especially in the con- text of unsupervised learning and it is show in Figure 6. One-class SVM constructs a boundary that encapsulates the majority of the data points in the feature space. The decision function for one-class SVM is:

$$f(x)=\text{sign}(\langle w, x\rangle - \rho)$$

where, w is the weight vector, x is the data point, and ρ is the bias term.

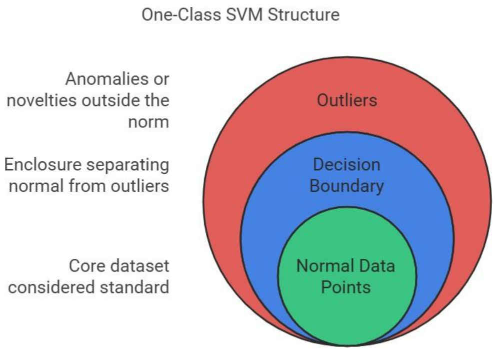

Figure 6. One-class SVM structure

The one-class SVM is trained on the majority class (normal data) and tries to classify outliers as the points lying outside the learned boundary. The SVM works well for high-dimensional datasets and is sensitive to the choice of kernel, with the radial basis function (RBFkernel being commonly used.

- Applications and performance: these anomaly detection methods are applied in various fields.
- Z-score: frequently used in statistical quality control, finance, and medical diagnostics.
- iForest: suitable for large datasets and has been applied in fields such as fraud detection and cybersecurity [35].
- LOF: often used in the detection of local outliers in complex datasets with varying densities, such as in sensor networks and medical imaging [37].

– One-class SVM: popular in settings where only normal data is available for training, such as in fault detection and fraud detection [38].

Anomaly detection techniques like Z-score, iForest, LOF, and one-class SVM are essential tools for identifying rare or abnormal observations in data. Each method has its strengths and is chosen based on the characteristics of the data, such as its distribution, dimensionality, and whether or not labeled data is available.

5. METHOD

This methodology outlines how to simulate energy usage data for multiple users, detect anomalies, and provide proactive recommendations to optimize energy consumption. The process includes data simulation, anomaly detection, proactive suggestions, and visualization.

5.1. Data simulation

To create realistic energy usage data, we use the simulate energy data function:

User identification: each dataset is given a unique user_id.

Date range: generate dates for the chosen period (e.g., 30 days).

Energy usage patterns:

Base usage: assign a random baseline consumption of 1 to 2 kWh for each user.

Peak usage: increase daytime consumption (8 AM to 6 PM) to 3 to 5 kWh, simulating higher activity levels.

Nighttime usage: decrease consumption during nighttime hours when users are typically absent.

Anomaly injection: introduce anomalies randomly with a 5% chance, causing energy usage spikes of 5 to 10 kWh.

Table 2 showing the simulated energy usage data for users over 30 days.

Table 2. Simulated energy usage data

User ID	Date	Energy usage (kWh)
1	01/11/2024	2.8
1	02/11/2024	3.1
1	03/11/2024	2.5
1	04/11/2024	8.7
1	05/11/2024	3
2	01/11/2024	1.9
2	02/11/2024	2.1
2	03/11/2024	2.3
2	04/11/2024	2
2	05/11/2024	2.2
3	01/11/2024	4.5
3	02/11/2024	5
3	03/11/2024	4.7
3	04/11/2024	2.6
3	05/11/2024	6.8

5.2. Anomaly detection

To identify unusual energy usage patterns, we apply four anomaly detection methods:

– Z-score anomaly detection: calculate Z-scores for each data point. Points with an absolute Z-score greater than 3 are flagged as anomalies.
– LOF: analyze local density deviation. Points with significantly lower density compared to their neighbors are flagged as outliers.
– One-class SVM: identify outliers by learning the distribution of normal data points. Points that deviate significantly are flagged as anomalies.

Figure 7 illustrates the workflow of the Z-score anomaly detection method, which identifies data points that deviate significantly from the mean. This approach is simple and effective in detecting extreme spikes in energy consumption.

– iForest: isolate observations by randomly partitioning the data. Easier-to-isolate points are flagged as anomalies.

A point is considered anomalous if it is flagged by all four methods.

– Proactive consumption suggestions. Based on detected patterns, the system provides tailored suggestions.

Figure 8 shows the process of LOF anomaly detection, where local density deviations are analyzed. Data points with significantly lower density compared to their neighbors are identified as anomalies. Figure 9 presents the decision boundary construction in the one-class SVM approach. The algorithm learns the distribution of normal data and flags outliers as points lying outside the boundary.

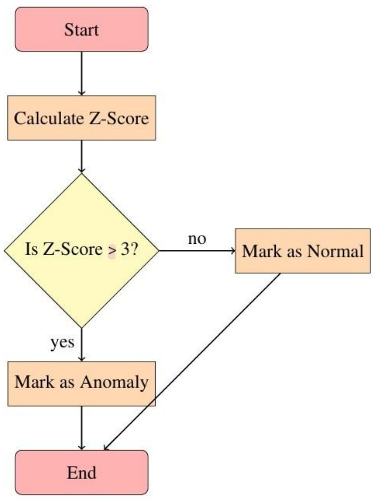

Figure 7. Z-score flow chart

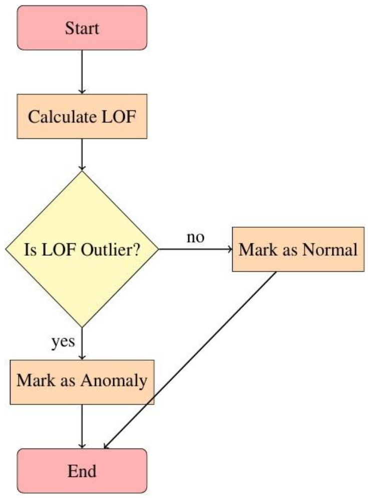

Figure 8. LOF flowchart

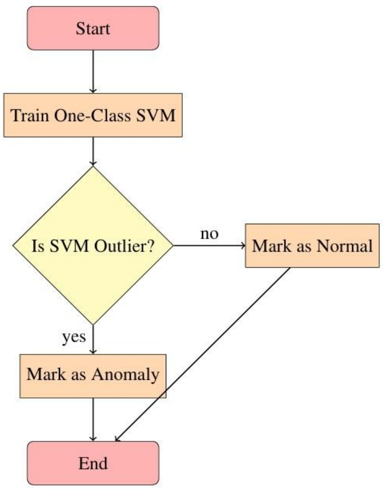

Figure 9. One-class SVM flowchart

Figure 10 demonstrates the iForest method, which isolates anomalies by recursively partitioning the dataset. Points that are easier to isolate are considered anomalies.
- Usage suggestions: advise users with average consumption above 3 kWh to reduce peak hour usage, while encouraging efficient users.
- Peak time alerts: alert users when consumption exceeds 5 kWh during peak periods, suggesting ways to reduce usage.
- Usage forecasting: predict a 10% increase in future energy usage to help users plan ahead.

5.3. Data visualization and dashboard

An interactive dashboard, created using streamlit and plotly, visualizes energy data, detected anomalies, and suggestions:
- Energy consumption visualization.
- Line/area charts: display energy usage trends over time for all users.

Anomaly detection visualization:
- Anomalies over time: highlight anomalies on the energy usage graph with red points.
- Outliers detected by methods: use scatter plots to display anomalies detected by each method in different colors.
- Anomaly proportions: visualize the proportion of anomalies detected by each method with a pie chart.
- Heatmap visualization: show energy usage patterns across different hours and days.
- Anomaly detection breakdown: display the number of anomalies identified by each method using a bar chart.

5.4. Streamlit dashboard features

The dashboard includes:
- Sidebar navigation: allows users to select a specific user to view detailed insights, including suggestions, alerts, and forecasts.
- Dynamic graphing: lets users choose between line or area charts for viewing energy consumption.

Proactive tips: provides general recommendations for reducing energy usage, such as using energy-efficient appliances and scheduling tasks during off-peak hours.

Workflow summary:
- Generate synthetic energy usage data using the simulate_energy_data function.
- Analyze energy data for anomalies using four detection methods (Z-score, LOF, one-class SVM, and iForest).

– Visualize and explore anomalies through the streamlit dashboard.
Provide users with proactive suggestions, peak time alerts, and usage forecasts to optimize energy consumption.

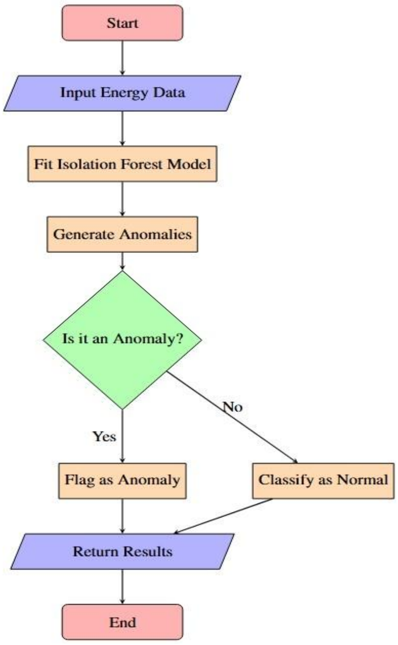

Figure 10. iForest flowchart

The novelty of this study lies in three key aspects of the detection pipeline, feature engineering, and feedback logic. First, unlike prior works that rely on a single anomaly detection method, we develop a hybrid pipeline that integrates Z-score, LOF, one-class SVM, and iForest. Anomalies are flagged only when identified by all four methods, which significantly reduces false positives and enhances robustness compared to single-model or loosely combined approaches. Second, in terms of feature engineering, the simulated energy consumption data incorporates realistic patterns such as baseline usage, peak-hour activity, and injected anomalies that mimic real-world variations. This structured design ensures that the framework is evaluated against conditions that closely reflect actual household and industrial consumption behaviors rather than synthetic noise alone. Third, the feedback logic introduces a consumer-oriented dimension rarely emphasized in previous studies. Through an interactive dashboard, the system not only visualizes anomalies but also provides proactive insights including peak-time alerts, demand forecasts, and personalized energy-saving recommendations. These contributions distinguish the work by bridging the gap between technical anomaly detection and actionable energy management, thereby offering both methodological advancement and practical relevance for smart grid applications.

6. RESULTS

The following represents a detailed analysis of the results obtained through the different methods applied for anomaly detection in the consumption of energy that could show unusual patterns. Different methods are being implemented on simulated data representative of real-world energy usage to derive actionable insights and proactive strategies of energy consumption by consumers. This analysis becomes critical in terms of enhancing energy efficiency, reducing wastage, and enabling better monitoring of power usage.

These include the Z-score anomaly detection, LOF, one-class SVM, and iForest. Each was tested under diverse scenarios in terms of effectiveness in detecting anomalies. A number of strengths and weaknesses were outlined for each approach, reinforcing the thought that context plays a big role in choosing an appropriate method of anomaly detection. Among the statistical approaches, Z-score anomaly detection is effective to find significant deviations from the mean and will be appropriate to find extreme spikes in energy usage. LOF searches for density-based anomalies and hence is sensitive to local variations in energy patterns.

Meanwhile, ML-based methods such as one-class SVM and iForest showed their utility in handling more complex datasets. While one-class SVM identified subtle anomalies in high-dimensional data, iForest did well in flagging anomalies within large, variable datasets by the isolation of rare points through random partitioning.

These methods combined into one framework significantly improved anomaly detection accuracy. The strengths of each technique combined in this hybrid approach considerably reduced false positives and provided a holistic understanding of anomalies in energy consumption. This analysis has shown that, quite often, handling the complexity of real-world energy usage requires multiple methods. These results underpin the potential of these methods in enabling smarter energy management and fostering more sustainable consumption practices.

6.1. Anomaly detection methods

We tested multiple methods for identifying unusual energy consumption patterns. Each approach had unique strengths and limitations:

- Z-score anomaly detection: this statistical method identifies anomalies by flagging data points that deviate significantly from the mean, using a threshold of three standard deviations. It effectively detected large deviations, particularly extreme spikes in energy use.
- LOF: LOF identifies anomalies by comparing the density of a data point to its neighbors. While adept at spotting sudden spikes, it also flagged minor fluctuations, leading to a higher rate of false positives.
- One-class SVM: this ML technique isolates anomalies by creating a boundary around normal data. It was particularly effective in identifying rare, isolated spikes but less sensitive to gradual increases in energy use.
- iForest: iForest partitions data recursively to isolate anomalies. It performed well in detecting anomalies among users with highly variable energy consumption, maintaining a balance between sensitivity and specificity.

6.2. Combining methods and final anomaly detection

A combined approach was used where anomalies were flagged only if all four methods identified the same irregularity. This reduced false positives and enhanced overall reliability. The results demonstrated some overlap between methods, with certain anomalies detected by multiple techniques. The combined approach provided a comprehensive understanding of the anomalies, proving that a hybrid strategy is more accurate.

6.3. Energy consumption breakdown

This section provides insights into energy usage and how various methods performed in spotting unusual patterns. Data for three users over 30 days were analyzed, with random anomalies introduced to simulate real-world consumption irregularities. Figure 11 depicts the overall trend of energy usage across multiple users over time, highlighting daily peaks and valleys. This visualization establishes the baseline patterns used for anomaly detection.

- Energy use overview: energy consumption typically exhibited a noticeable pattern, increasing during the day and decreasing at night, reflecting the natural rhythms of daily hu- man activity and operational cycles. Specifically, usage surged between 8 AM and 6 PM, coinciding with peak hours of activity in residential, commercial, and industrial sectors. This daytime increase is attributed to the operation of household appliances, lighting, heating or cooling systems, and machinery, depending on the context. Conversely, during nighttime hours, energy consumption declined as activities subsided, and many systems either powered down or operated at minimal levels. This predictable cycle formed the foundation of the data used for analysis, which included both baseline energy usage and distinct peak times. By incorporating such realistic behavior, the dataset effectively captured the variability and complexity of typical energy consumption patterns.
- The baseline represented the steady-state usage of essential services and systems that operate continuously, such as refrigeration, security systems, and background appliances. In contrast, peak times reflected surges caused by non-routine activities, including cooking, laundry, and increased lighting or heating demands. This differentiation between baseline and peak usage was critical for identifying anomalies that deviate from expected patterns.

Spotting anomalies: Z-score: flagged values significantly deviating from the mean, identifying major spikes in consumption. LOF: detected local density deviations, useful for spotting outliers with high relative consumption. One-class SVM: focused on high-dimensional data, identifying subtle anomalies missed by other methods. iForest: effectively identified anomalies, particularly large spikes, through random data partitioning.

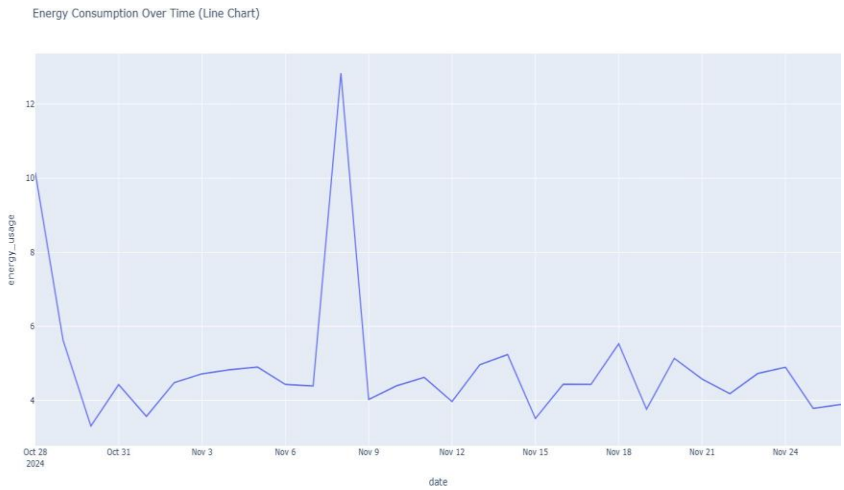

Figure 11. Energy consumption over time

6.4. Proactive insights

The proactive insights module enhances the proposed smart EMS by converting anomaly detection results into useful recommendations for consumers. Instead of only identifying unusual energy usage patterns, the system also provides personalized suggestions, peak-time alerts, and future consumption forecasts to help users manage energy more efficiently. Users with high energy consumption are advised to reduce usage during peak hours, while alerts are generated whenever energy usage exceeds normal limits. In addition, the forecasting feature predicts future energy demand based on historical data, enabling users to plan their consumption more effectively. These proactive features improve consumer awareness, reduce energy wastage, and support sustainable energy management practices.

- Usage tips: users with high consumption were advised to reduce peak-hour usage. Efficient users were commended.
- Peak alerts: alerts were triggered for consumption exceeding 5 kWh, enabling better cost management.
- Forecasts: models predicted future consumption trends, aiding users in planning energy usage.

Figure 12 summarizes the anomalies detected by different methods, showing their overlaps and differences. It highlights how combining approaches reduces false positives.

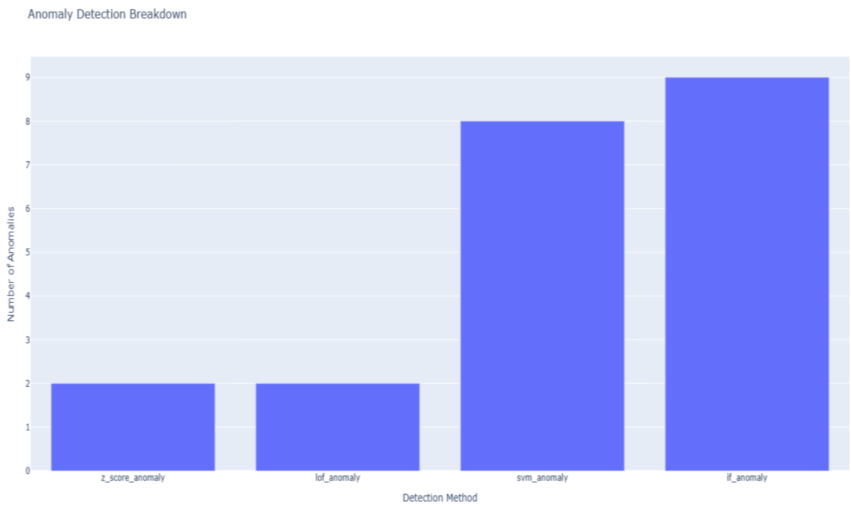

Figure 12. Anomaly detection breakdown

Figure 13 illustrates the personalized recommendations generated by the system, including peak-hour alerts and energy-saving suggestions tailored to user behavior. Figure 14 displays the interactive dashboard’s navigation structure, allowing users to select specific accounts or households for customized analysis.

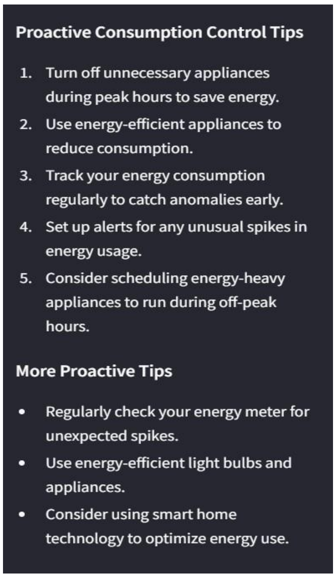

Figure 13. Proactive consumption insights

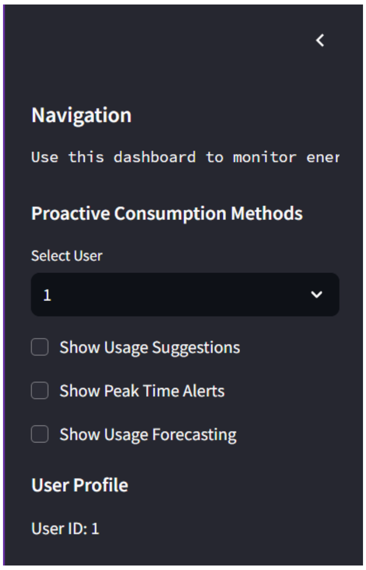

Figure 14. Navigation results

Figure 15 provides a detailed breakdown of energy usage trends, reinforcing how anomalies are superimposed on normal consumption patterns for easy interpretation by end users. Figure 16 illustrates daily energy consumption patterns with anomalies highlighted in red, clearly showing abnormal spikes relative to baseline usage. This visualization helps distinguish sudden deviations that may indicate faults or inefficiencies.

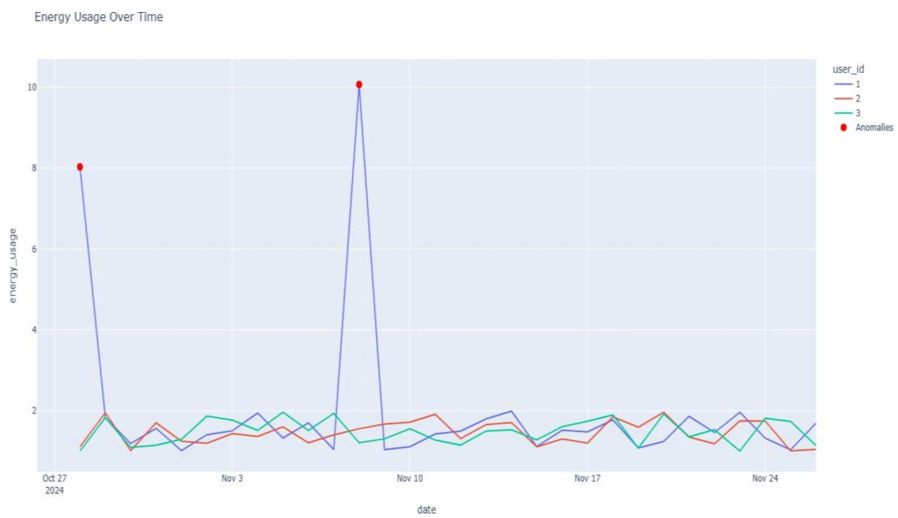

Figure 15. Energy usage over time

Figure 17 presents a heatmap of hourly energy usage across a week, revealing peak consumption periods during evening hours. Such patterns provide valuable insights for DSM and load shifting. Figure 18 demonstrates the proposed dashboard interface, integrating anomaly counts, consumption trends, peak-hour analysis, and tailored recommendations. This consumer-facing tool translates technical detections into actionable energy management strategies.

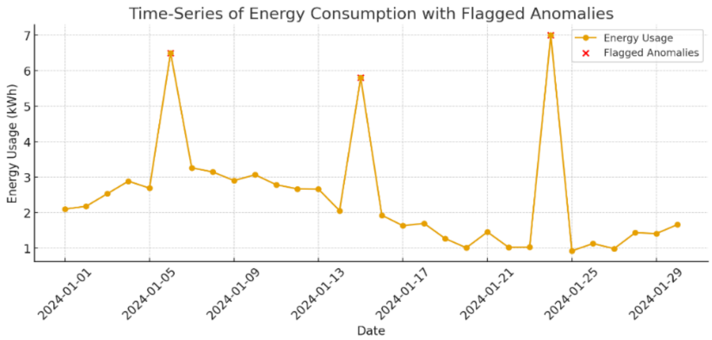

Figure 16. Time-series plot–shows anomalies flagged against normal consumption trends

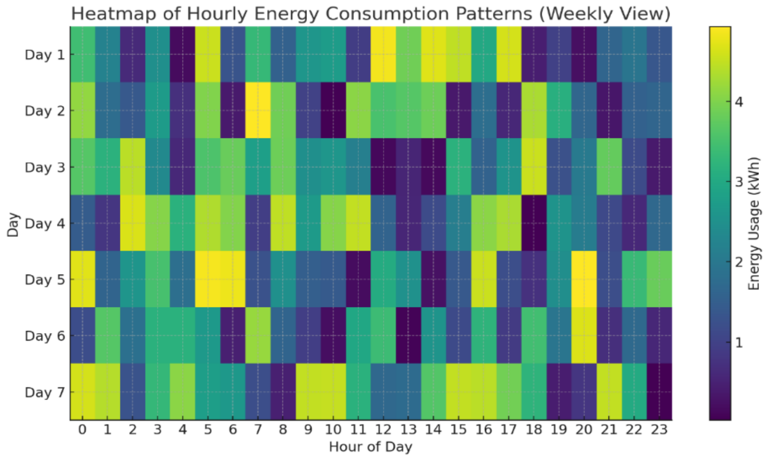

Figure 17. Heatmap–visualizes hourly consumption intensity across a week

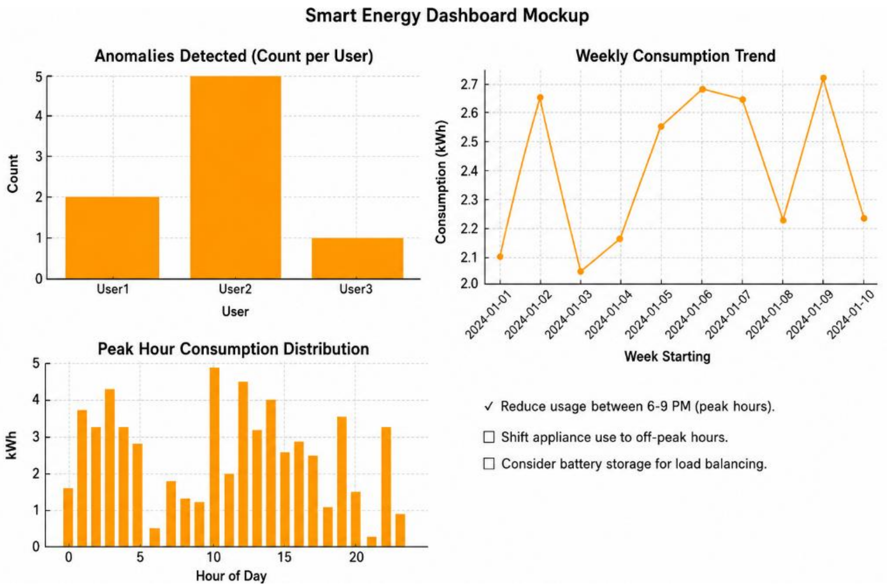

Figure 18. Dashboard mockup–integrates anomaly counts, trends, peak-hour usage, and recommendations

7. DISCUSSION

The findings of this study demonstrate that combining statistical and ML techniques into a hybrid framework provides more reliable anomaly detection in smart meter data compared to single-method approaches. This has important implications for both utilities and consumers: utilities can detect inefficiencies, unauthorized usage, or system faults earlier, while consumers gain actionable insights to optimize energy consumption and reduce costs. The proactive feedback mechanism—through peak-time alerts, consumption forecasts, and tailored suggestions—bridges a key gap in previous works, transforming anomaly detection from a purely technical exercise into a practical tool for energy management. Compared with existing studies that either emphasized detection accuracy or communication infrastructures, our results show that integration of multiple methods in a consumer-centric dashboard reduces false positives and enhances interpretability, which is critical for adoption in real-world systems. Looking ahead, the framework can be extended to process real-time streaming data, making it suitable for deployment in smart grids and microgrid environments. Moreover, incorporating deep learning models and reinforcement learning could further improve adaptability to evolving consumption patterns. These implications highlight not only the present utility of our system but also its potential as a foundation for future intelligent energy management solutions at household, community, and industrial scales.

7.1. Strengths of the anomaly detection methods

Z-score: simple and effective for detecting large deviations. LOF: reliable for subtle changes and varying densities. One-class SVM: ideal for high-dimensional and complex patterns iForest: scalable and efficient for large datasets.

Challenges encountered during implementation:

- Data quality and noise: sensor errors and missing values impacted accuracy.
- Parameter tuning: optimal parameters required significant time and computational resources.
- Real-time detection: computational demands limited real-time anomaly detection.
- Contextual factors: differentiating genuine anomalies from variations caused by external factors like weather or events was challenging.

Possible improvements:

- Incorporating domain knowledge: enhance model accuracy by considering energy usage patterns and contextual factors.
- Hybrid approaches: combine methods to leverage their individual strengths and reduce weaknesses.
- Dynamic parameter tuning: use adaptive techniques for improved accuracy over time.
- Real-time detection: explore streaming algorithms for immediate anomaly identification.
- Improved data preprocessing: address noise and missing values, and consider time-series models for better trend analysis.

The hybrid anomaly detection framework demonstrated superior accuracy compared to individual methods. Table 3 summarizes the comparative performance of each approach based on simulated smart meter data. Z-score reliably detected extreme spikes but struggled with gradual changes. LOF effectively identified local anomalies but generated more false positives. One-class SVM performed well with high-dimensional consumption patterns but required careful parameter tuning. iForest excelled in scalability and detected anomalies in heterogeneous datasets. When combined, the hybrid framework minimized false positives and improved reliability by flagging anomalies only when identified by all four methods.

Table 3. Performance comparison of anomaly detection methods

Method	Strengths	Weaknesses	Detection accuracy	False positives
Z-score	Simple, effective for large deviations.	Assumes normal distribution; ignores local patterns.	Moderate	Low
LOF	Detects local density variations.	Sensitive to noise; higher false positives.	Moderate–high	High
One-class SVM	Handles high-dimensional data.	Sensitive to kernel/parameter selection.	High	Moderate
iForest	Scalable, efficient for large datasets.	Less effective for subtle anomalies.	High	Low
Hybrid (proposed)	Combines statistical and ML methods; robust.	Slightly higher computational cost.	Very high	Very low

7.2. Interpretation of findings

These results confirm that no single method is universally optimal; instead, combining complementary techniques enhances robustness. The hybrid model effectively balances sensitivity and specificity, aligning with the study's objective of creating a reliable anomaly detection system for smart energy management. Importantly, the integration of proactive suggestions (peak alerts, usage forecasting, and personalized recommendations) extends beyond anomaly detection to empower consumers with actionable insights, bridging the gap between technical anomaly identification, and practical energy optimization.

7.3. Comparison with previous studies

Our findings are consistent with earlier work by Nassif *et al*. [19], who reported that hybrid approaches outperform single-method anomaly detection systems in robustness. Unlike Liu *et al*. [8], who focused on fault detection in edge computing, our framework emphasizes consumer empowerment through feedback and visualization. Similarly, while Sabuhi *et al*. [20] used GANs to enhance anomaly detection accuracy, our method focuses on combining established statistical and ML models in a practical, scalable dashboard environment, making it directly applicable to EMSs.

8. CONCLUSION

This study has demonstrated that a hybrid anomaly detection framework—integrating Z-score, LOF, One-class SVM, and iForest-provides a more robust and reliable approach to identifying irregularities in smart meter data than any single method alone. By reducing false positives and improving detection accuracy, the framework addresses one of the key challenges in smart energy management: making anomaly detection both precise and actionable. Beyond technical detection, our system contributes to the research community by linking anomalies to consumer-oriented feedback through peak alerts, usage forecasts, and proactive suggestions, thereby transforming anomaly detection into a tool for empowering energy users.

The implications of these findings are significant. For researchers, the results highlight the importance of hybrid approaches that leverage complementary strengths across statistical and ML models. For practitioners and communities, the integration of anomaly detection with interactive dashboards offers a pathway toward more transparent, efficient, and sustainable energy management. At the household level, consumers gain practical insights to reduce costs and prevent inefficiencies. At the utility and community levels, such systems can contribute to grid stability, DSM, and fraud detection.

Looking ahead, this work opens several avenues for extension. Real-time deployment with live smart meter data will enhance the system's responsiveness, while incorporating contextual information such as weather and seasonal variations can further improve accuracy. Advanced techniques such as deep reinforcement learning or adaptive anomaly scoring could be employed to make the system self-improving over time. Moreover, integration with smart home automation could allow anomalies to trigger automatic energy-saving actions, reducing manual intervention and ensuring broader adoption.

In summary, this research contributes not only a methodological advancement but also a consumer-centric perspective to anomaly detection in smart energy management. Its relevance lies in bridging the gap between data-driven insights and real-world energy savings, providing a foundation for future smart grid technologies that are intelligent, adaptive, and user-empowering.

This study used simulated energy consumption data, which, while representative of real-world patterns, may not capture all complexities of actual household or industrial usage. Computational overhead is slightly higher in the hybrid approach, which may pose challenges for real-time applications without further optimization. Additionally, contextual factors such as seasonal variations, weather conditions, and user behavior were not fully incorporated, which could influence anomaly detection accuracy.

Despite the promising results, this study has several limitations that must be acknowledged. First, although the hybrid approach significantly reduces false positives compared to single-model methods, it does not eliminate them entirely. Occasional misclassifications may still occur, especially when unusual but valid consumption patterns (e.g., seasonal appliance use) resemble anomalies. Second, privacy concerns arise since continuous monitoring of household energy data may reveal sensitive information about user behavior. While our framework focuses on detection accuracy and feedback, future implementations should incorporate secure data handling practices such as encryption and anonymization to protect consumer privacy. Third, model drift over time presents a challenge, as consumption patterns evolve with lifestyle changes, appliance upgrades, or external factors such as weather and tariffs. Static models may lose accuracy in such contexts, highlighting the need for adaptive learning strategies that periodically retrain the system using updated data. Addressing these limitations through advanced privacy-preserving techniques, dynamic retraining, and anomaly labelling by consumers will be essential for ensuring long-term reliability and trust in large-scale deployments.

To address these limitations, future research will involve deploying the system with real-time smart meter data, integrating adaptive parameter tuning, and extending the framework with advanced deep learning methods for improved adaptability. Furthermore, integration with smart home devices could allow for automated energy-saving actions, reducing reliance on manual intervention and enhancing system usability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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