International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 07 July 2026
Page No: 4899-4905
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0644

Anomaly-Aware Smart Grid Monitoring for Early Outage Risk Assessment

Nabila Banu N[1], Dr. Raviraj P[2], Dr. Sunita yadwad[3]

[1]PG Scholar, Department of CSE, GSSS Institute of Engineering & Technology for Women, Mysuru, Karnataka, India.

[2]Professor and Head, Department of CSE, GSSS Institute of Engineering & Technology for Women, Mysuru, Karnataka, India.

[3]Professor, Department of CSE, GSSS Institute of Engineering & Technology for Women, Mysuru, Karnataka, India.

Email ID: *nabilabanu2003@gmail.com[1], Raviraj@Gsss.edu.in[2], dr.sunita@gsss.edu.in[3]*

Abstract

Modern smart grids are becoming increasingly complex, creating a growing need for monitoring systems capable of detecting abnormal behavior before major power failures occur. This paper presents a real-time smart grid monitoring framework for early outage-risk detection using machine learning and streaming analytics. Smart meter data are processed using temporal feature extraction, lag observations, and rolling statistical measures to capture variations in electricity consumption patterns. Since labeled outage datasets are not readily available, an Isolation Forest-based anomaly detection model is used to identify unusual load behavior. To reduce false alarms, detected anomalies are further verified through statistical threshold analysis. The framework also supports continuous monitoring through a lightweight real-time dashboard with live visualization and streaming inference. Experimental results show that the system can effectively detect abnormal load fluctuations while maintaining low computational overhead suitable for real time deployment. The proposed approach provides a scalable and practical solution for proactive smart grid monitoring and anomaly-aware outage-risk assessment.

Keywords: *Smart grid, anomaly detection, Isolation Forest, outage risk detection, machine learning, streaming analytics, real time monitoring.*

1. Introduction

The rapid advancement of smart grid infrastructure has transformed traditional electrical power systems into intelligent and interconnected energy networks [6]. Modern smart grids integrate advanced metering infrastructure, communication technologies, automation systems, and data analytics to improve operational efficiency and enhance grid reliability. These developments provide utility providers with improved visibility into grid operations and support more effective power distribution management. Despite these technological improvements, power outages and abnormal grid events continue to pose major operational challenges. Unexpected failures in electrical systems can lead to service interruptions, financial losses, equipment damage, and reduced customer satisfaction. As smart grids become increasingly complex, conventional monitoring approaches are often insufficient for identifying abnormal operational behavior at an early stage. Traditional outage management systems typically rely on threshold-based alarms, manual supervision, or retrospective fault analysis using historical records. Although these approaches remain widely used, they generally provide limited predictive capability and may fail to respond quickly to rapidly changing grid conditions. Another major challenge is the limited availability of accurately labeled outage datasets, which restricts the applicability of supervised machine learning methods in practical deployment environments. To address these challenges, anomaly detection has emerged as an effective approach for identifying unusual operational behavior in smart grids. Instead of explicitly forecasting outages, anomaly detection techniques focus on recognizing deviations from normal consumption patterns that may indicate

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 07 July 2026
Page No: 4899-4905
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0644

elevated outage risk. This approach is especially useful in environments where labeled fault data is limited or unavailable. Recent studies have demonstrated the effectiveness of ma chine learning algorithms for anomaly detection and fault analysis in power systems [3]–[5], [10]. However, many existing solutions rely on computationally intensive deep learning architectures or offline batch-processing frameworks that are difficult to deploy in real-time environments. In addition, such models often require extensive computational resources and large training datasets. In this work, a real-time anomaly-aware smart grid monitoring framework is proposed using Isolation Forest [1], [7] and streaming analytics. The framework extracts temporal and statistical characteristics from smart meter data, including lag observations and rolling statistical descriptors, to model short term load behavior more effectively. An unsupervised anomaly detection model is then applied to identify abnormal consumption patterns associated with potential outage conditions. To improve robustness and reduce unnecessary alert generation, the proposed framework incorporates statistical validation and controlled alert management. Furthermore, a real-time monitoring dashboard is developed to provide continuous visualization of system behavior and live anomaly tracking. The major contributions of this work are summarized as follows:

- Development of a lightweight anomaly-aware framework for early outage risk monitoring using smart meter data.
- Integration of temporal and statistical feature engineering techniques for modeling dynamic electricity consumption behavior.
- Deployment of a streaming analytics pipeline for continuous anomaly detection and live monitoring.
- Design of a real-time visualization dashboard for operational awareness and automated alert generation.
- Comparative evaluation of multiple anomaly detection techniques for deployment suitability in smart grid environments.

2. Methodology

Machine learning and data-driven analytics have become increasingly important in modern smart grid systems for improving operational reliability and fault management. With the growing availability of large-scale smart meter data, researchers have explored various approaches for detecting anomalies and predicting abnormal grid conditions. Several studies have investigated supervised learning techniques such as Random Forest, Support Vector Machines, and Neural Networks for outage prediction and fault classification [3], [4], [10]. These approaches generally achieve strong predictive performance when sufficient labeled data are available. However, obtaining accurately labeled outage datasets remains difficult in practical power system environments. To overcome this limitation, unsupervised anomaly detection techniques have gained considerable attention [1], [2], [5], [7]. Clustering algorithms, density-based methods, and tree-based anomaly detection models have been widely applied for identifying unusual patterns in power consumption data without requiring labeled observations. Among these methods, Isolation Forest has emerged as an efficient anomaly detection technique because of its scalability and low computational overhead [1], [7]. Unlike distance-based approaches, Isolation Forest isolates anomalies using random partitioning, making it suitable for high-dimensional streaming environments. Deep learning techniques such as Autoencoders and Long Short-Term Memory (LSTM) networks have also been applied for anomaly detection in smart grids [5], [8]. These models are capable of learning complex temporal dependencies and nonlinear consumption patterns. However, deep learning methods generally require large training datasets and significant computational resources, limiting their practicality for lightweight real-time deployment. Recent research has additionally focused on integrating data from multiple sources, including weather information, sensor readings, and Advanced Metering Infrastructure (AMI) data, to improve anomaly detection capability. Although these approaches enhance prediction accuracy, many existing systems remain focused on offline analysis rather than continuous real time monitoring. Visualization platforms inspired by Supervisory Control and Data Acquisition (SCADA) systems and

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 07 July 2026
Page No: 4899-4905
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0644

Grafana dashboards have also been explored for smart grid monitoring. However, relatively few studies integrate streaming analytics, anomaly detection, and live visualization into a unified deployment oriented framework. Based on this review, there remains a need for lightweight and scalable systems capable of combining real-time analytics, efficient anomaly detection, and continuous visualization. The proposed framework addresses this research gap through the integration of streaming inference, Isolation Forest-based anomaly detection, and deployment-oriented dashboard visualization Shown in Table 1.

Table 1 Comparison of Existing Approaches

Study	Method	Limitation
Khaledian et al.	LOF and K-Means	Offline processing only
Karimipour et al.	Deep Autoencoder	High computational overhead
Takiddin et al.	Autoencoder	Large training data required
Hariri et al.	Extended Isolation Forest	Limited deployment discussion
Proposed Framework	Isolation Forest with Streaming Dashboard	Lightweight real-time deployment

3. Proposed Methodology

3.1.Data Collection

The proposed framework utilizes time-series smart meter data collected from multiple electricity consumers. Each observation contains timestamped power consumption measurements representing electricity usage behavior over time. To emulate real-world deployment conditions, a streaming simulation mechanism is incorporated where observations are incrementally processed at regular intervals. This setup enables continuous inference and real-time dashboard updates similar to operational smart grid environments. Prior to analysis, the dataset undergoes preprocessing operations including missing value handling, timestamp alignment, normalization, and conversion into structured numerical representations.

3.2.Feature Engineering

Feature engineering is performed to capture temporal dependencies and statistical characteristics present in the power consumption data. The aggregated load at each time step is computed as:

$$\text{Total Load}_t = \sum_{i=1}^{n} M_i(t) \qquad (1)$$

where Mi(t) represents the consumption value of the ith smart meter. Temporal features including hour of the day and day of the week are extracted to model periodic usage patterns. Lag-based observations are additionally incorporated to capture short-term temporal dependencies:

$$\text{Lag}k(t) = \text{Total Load}_{t-k} \qquad (2)$$

Rolling statistical descriptors are computed using moving window analysis:

$$\mu_t = \frac{1}{w} \sum_{i=t-w+1}^{t} \text{Total Load}_i \qquad (3)$$

$$\sigma_t = \sqrt{\frac{1}{w} \sum_{i=t-w+1}^{t} (\text{Total Load}_i - \mu_t)^2} \qquad (4)$$

These engineered features enable the model to capture local fluctuations and dynamic variations in electricity consumption behavior.

3.3. Anomaly Detection Model

The proposed framework employs Isolation Forest for anomaly detection [1], [7]. Isolation Forest is an unsupervised learning algorithm designed to isolate abnormal observations through random partitioning. The anomaly score is computed as:

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \qquad (5)$$

where E(h(x)) represents the average path length of observation x and c(n) denotes the normalization factor. Observations classified as anomalous are interpreted as potential indicators of abnormal grid behavior and elevated outage risk. Isolation Forest is selected because of its scalability, low computational complexity, and suitability for streaming environments.

3.4.Real Time Monitoring Framework

A lightweight streaming analytics pipeline is developed to support continuous monitoring and live anomaly detection. Incoming smart meter

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 07 July 2026
Page No: 4899-4905
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0644

observations are processed sequentially through preprocessing, feature extraction, anomaly inference, and visualization stages. Detected anomalies are validated using statistical threshold constraints to reduce false alarms caused by temporary fluctuations. A real-time dashboard continuously displays power consumption trends, anomaly events, and operational statistics. Automated alert generation assists operators in identifying abnormal conditions quickly and efficiently.

3.5.Algorithm Workflow

The operational workflow of the proposed framework is summarized as follows:

- Collect real-time smart meter readings from multiple consumers.
- Preprocess incoming data through missing value handling normalization and time stamp synchronization.
- Compute aggregated load values and extract temporal features such as hour of day and day of week.
- Generate lag-based observations and rolling statistical descriptors for capturing short-term consumption behavior.

Algorithm 1 Real-Time Anomaly-Aware Outage Risk Detection

```
Collect smart meter readings
Preprocess incoming observations
Compute total load and temporal features
Generate lag and rolling statistical features
Construct feature vector
Apply Isolation Forest model
Compute anomaly score
if anomaly score exceeds threshold then
    Trigger alert
    Mark observation as anomaly
else
    Mark observation as normal
end if
Update dashboard visualization
Repeat for incoming stream
```

- Construct feature vectors and forward them to the Isolation Forest anomaly detection model.
- Compute anomaly scores for incoming observations.
- Validate detected anomalies using statistical threshold verification to reduce false positives.
- Trigger automated alerts for abnormal operating conditions.
- Continuously update the real-time dashboard with live consumption trends and anomaly visualization.

4. System Architecture

The proposed framework follows a modular architecture designed for real-time smart grid monitoring and anomaly aware outage risk detection. The framework integrates multiple operational modules into a unified pipeline.

4.1.Data Acquisition Layer

The data acquisition layer receives time-series electricity consumption readings from smart meters and AMI devices. Historical datasets are additionally utilized for streaming simulation and experimental evaluation Shown in Figure 1.

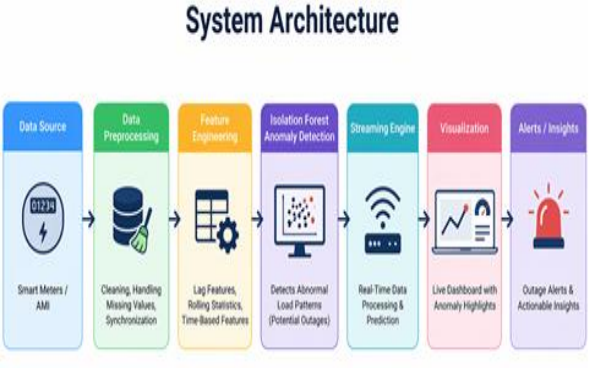

Figure 1 Proposed System Architecture Illustrating the end-to-end Workflow for Real-time Power Outage Detection and Monitoring

4.2.Preprocessing Module

The preprocessing module performs normalization, times tamp synchronization, missing value handling, and numerical conversion to ensure data consistency before feature extraction.

4.3.Feature Engineering Module

The feature engineering layer extracts temporal attributes, lag features, rolling means, and rolling standard deviations from the incoming data stream.

4.4.Anomaly Detection Engine

The engineered features are forwarded to the Isolation Forest model for real-time anomaly inference. The generated anomaly scores are validated using threshold-based verification.

4.5.Streaming Analytics Engine

A lightweight streaming framework continuously

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 07 July 2026
Page No: 4899-4905
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0644

processes incoming observations at predefined intervals. This component enables low-latency inference suitable for deployment-oriented monitoring environments.

4.6.Visualization Dashboard

A Grafana-inspired dashboard provides live visualization of system behavior using time-series plots, anomaly markers, and operational statistics.

4.7.Alert Management Layer

Detected anomalies are highlighted through automated alerts to support proactive monitoring and operational decision-making.

4.8.Computational Complexity

The average computational complexity of Isolation Forest is expressed as:

$$O(t \times \psi \log \psi) \quad (6)$$

where t represents the number of trees and ψ denotes the subsampling size. Compared to deep learning approaches [5], [8], the proposed framework requires significantly lower computational overhead and inference latency.

5. Results and Discussion

5.1.Experimental Setup

Experiments were conducted using the LD2011 2014 smart meter electricity consumption dataset [9], which contains multi-meter time-series electricity usage measurements collected from 370 smart meters between 2011 and 2014. The dataset provides timestamped load observations representing real-world household electricity consumption behavior. For experimental analysis, five representative smart meters (MT 001 to MT 005) were selected to model aggregated load behavior and perform anomaly-aware outage risk monitoring. Temporal features, lag observations, rolling statistical descriptors, and total load measurements were extracted from the selected smart meter streams. Since explicit outage-event labels were unavailable, anomaly-aware outage-risk indicators and synthetic abnormal conditions were incorporated to evaluate the proposed monitoring framework. Artificial anomalies including sudden spikes, abrupt load drops, and abnormal fluctuations were injected into selected intervals to emulate outage-related ab normal operating conditions. Streaming behavior was simulated by sequentially processing observations at fixed intervals to replicate real-time smart grid monitoring conditions. The dataset used in the experiments consisted of approximately 250,000 time-series observations collected during continuous monitoring activity. Experiments were conducted on a system equipped with an Intel Core i5 processor, 16 GB RAM, and Python 3.11 execution environment. The proposed framework was implemented using Python libraries including Scikit-learn, Pandas, NumPy, and Plotly Dash for real-time dashboard visualization and streaming analytics.

5.2.Evaluation Metrics

Performance is evaluated using Precision, Recall, Accuracy, and F1-score metrics.

$$Precision = \frac{TP}{TP + FP} \quad (7)$$

$$Recall = \frac{TP}{TP + FN} \quad (8)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (10)$$

Inference latency is additionally analyzed to evaluate deployment suitability.

5.3.Comparative Performance Analysis

Multiple anomaly detection models are experimentally compared Shown in Table 2.

Table 2 Performance Comparison of Anomaly Detection Models

Model	Precision	Recall	F1-score	Latency(ms)
Isolation Forest	0.94	0.91	0.92	18
LOF	0.88	0.84	0.86	31
OCSVM	0.85	0.81	0.83	44
Autoencoder	0.96	0.94	0.95	126

Although the Autoencoder achieves slightly higher detection accuracy, Isolation Forest demonstrates significantly lower inference latency and computational overhead.

5.4.Feature Ablation Analysis

An ablation study is performed to evaluate the contribution of engineered features Shown in Table 3.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 07 July 2026
Page No: 4899-4905
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0644

Table 3 Feature Ablation Study

Feature Configuration	F1-score
Raw Load Only	0.73
Load + Temporal Features	0.81
Load + Lag Features	0.87
Full Feature Set	0.92

The results indicate that lag-based and rolling statistical features significantly improve anomaly detection capability.

5.5.Visualization Results

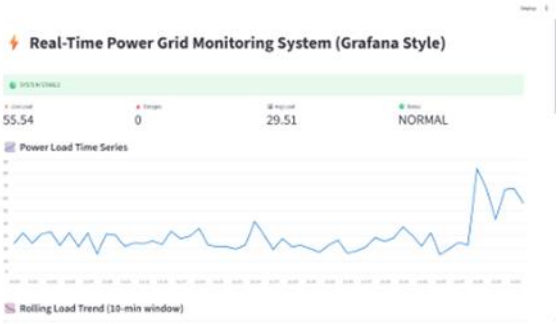

Figure 2 Visualization of the Real-Time Dashboard Showing Power Load Time Series Behavior

The dashboard continuously updates operational statistics and anomaly markers during streaming inference. The automatic refresh mechanism enables live synchronization with incoming data streams Shown in Figure 2.

5.6.False Alarm Analysis

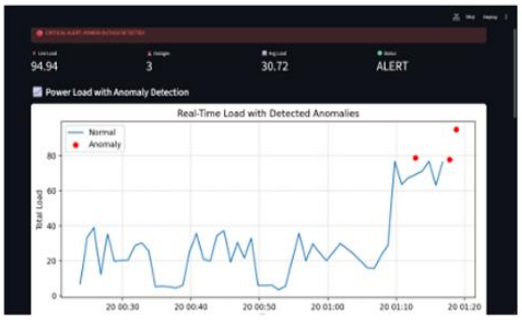

Figure 3 Real-time Visualization Showing Detected Anomaly Events in Power Consumption Data

Statistical threshold validation reduces unnecessary alert generation during temporary fluctuations. Experimental observations indicate an approximate 18% reduction in false positives compared to standalone anomaly detection Shown in Figure 3.

Discussion

The experimental evaluation demonstrates that the proposed framework effectively identifies abnormal grid behavior using unsupervised anomaly detection techniques. A major advantage of the proposed system is its ability to operate without labeled outage datasets, making it suitable for practical deployment environments where annotated fault data are limited. The integration of streaming analytics, machine learning inference, and live visualization creates a deployment-oriented monitoring framework capable of supporting proactive grid management. However, the current framework primarily focuses on anomaly-aware outage risk assessment rather than explicit fault classification. Future enhancements may incorporate multi-source sensor fusion and fault categorization mechanisms.

Conclusion

In this paper, a real-time smart grid monitoring framework was developed for early outage-risk detection using machine learning and streaming analytics. The proposed approach combines feature engineering, Isolation Forest-based anomaly detection, streaming inference, and dashboard visualization within a single deployment-oriented framework. Experimental evaluation showed that the system was able to identify abnormal electricity consumption patterns while maintaining low computational overhead suitable for real-time operation. The framework provides a scalable and lightweight solution for proactive smart grid monitoring and continuous anomaly detection. By avoiding dependence on labeled outage datasets, the system can be adapted to practical smart grid environments where annotated fault data are limited. Future work may include the integration of additional data sources such as weather information, sensor telemetry, and grid-event records to improve detection capability. More advanced deep learning approaches and cloud-based deployment architectures can also be explored to enhance scalability and predictive performance.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 07 July 2026
Page No: 4899-4905
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0644

References

[1]. F. T. Liu, K. M. Ting, and Z.-H. Zhou, "Isolation Forest," in Proceedings of the IEEE International Conference on Data Mining, 2008, pp. 413 422.
[2]. E. Khaledian, S. Pandey, P. Kundu, and A. K. Srivastava, "Real Time Synchrophasor Data Anomaly Detection and Classification Using Isolation Forest, K-Means, and LOF," IEEE Transactions on Smart Grid, vol. 12, no. 3, pp. 2378–2388, 2021.
[3]. P. K. R. Shabad, A. Alrashide, and O. A. Mohammed, "Anomaly Detection in Smart Grids Using Machine Learning," in Proceedings of IEEE IECON, 2021, pp. 1–8.
[4]. M. Cui, J. Wang, and M. Yue, "Machine Learning-Based Anomaly Detection for Load Forecasting Under Cyberattacks," IEEE Transactions on Smart Grid, vol. 10, no. 5, pp. 5724–5734, 2019.
[5]. H. Karimi pour et al., "A Deep and Scalable Unsupervised Machine Learning System for Cyber-Attack Detection in Smart Grids," IEEE Access, vol. 7, pp. 80778–80788, 2019.
[6]. X. Fang, S. Misra, G. Xue, and D. Yang, "Smart Grid—The New and Improved Power Grid: A Survey," IEEE Communications Surveys and Tutorials, vol. 14, no. 4, pp. 944–980, 2012.
[7]. S. Hariri, M. C. Kind, and R. J. Brunner, "Extended Isolation Forest," IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 4, pp. 1479–1489, 2021.
[8]. A. Takiddin et al., "Deep Autoencoder-Based Anomaly Detection of Electricity Theft Cyberattacks in Smart Grids," IEEE Systems Journal, vol. 16, no. 3, pp. 4106–4117, 2022.
[9]. "ElectricityLoadDiagrams20112014 Data Set," UCI Machine Learning Repository.
[10]. M. Ibrahim, W. Dong, and Q. Yang, "Machine Learning Driven Smart Electric Power Systems: Current Trends and New Perspectives," Applied Energy, vol. 272, 2020