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Multi-Model Energy Consumption Anomaly Detection Using Reconstruction-Based Deep Learning And Time-Series Analysis

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Abstract: The work introduces a smart energy-related consumption system that aims to detect deviations in the pattern and develop a better comprehension of how to use time-series data. This system takes advantage of a multi-perspective analytical perspective to identify both minimal and remarkable consumption patterns deviations whilst being flexible under different data circumstances. The combination of reconstruction-based learning and statistical analysis successfully separates regular operation patterns and abnormal fluctuations in the framework. Also, forecast technologies are included to determine the future consumption trends and enhance accuracy in prediction. The modular design allows effective data processing, application deployment, and easy visualization via interactive interface. Experimental testing shows that there is better consistency and interpretability of detection than as a single model. The proposed solution gives a scalable and real-world energy monitoring application a reliable base to enable proactive decision-making, resource optimization, and enhanced awareness of the working environment in dynamic environments.

***Index Terms* -** Energy Monitoring, Anomaly Detection, Time-Series Analysis, Consumption Patterns, Predictive Analytics, Intelligent Systems, Data Visualization…

I. INTRODUCTION

Rapid urbanization and industrialization have significantly increased global energy consumption, making energy management an important issue in modern society. Smart meters and Internet of Things (IoT) devices continuously generate large amounts of time-series energy data for intelligent monitoring and analysis. However, the high volume and complexity of this data make it difficult to identify abnormal energy consumption patterns. Detecting anomalies is important for system stability, preventing energy theft, identifying equipment faults, and improving resource utilization in smart grids and buildings.

Traditional statistical methods mainly use fixed thresholds and rule-based techniques for anomaly detection. These methods are not effective for detecting complex and nonlinear anomalies in real-world energy data. Since energy consumption depends on seasonal changes, user behavior, and environmental conditions, machine learning and deep learning methods are more suitable because they can automatically learn complex patterns and improve detection accuracy.

Reconstruction-based learning methods further improve anomaly detection by learning normal consumption patterns and identifying anomalies through reconstruction errors. When abnormal data is given to the model, higher reconstruction errors indicate possible anomalies. These methods are highly effective for time-series applications because they preserve temporal relationships. Probabilistic models also help in detecting high-confidence anomalies by analyzing uncertainty in the data.

Time-series forecasting is also important for understanding future energy consumption patterns and supporting proactive decision-making. Forecasting helps organizations predict demand, optimize resource allocation, and reduce operational costs. Modern forecasting methods analyze trends, seasonality, and external factors to generate reliable predictions.

Combining multiple analytical methods improves the robustness and reliability of anomaly detection systems. Single-model methods may fail to detect different types of anomalies or may be sensitive to noise. Multi-model approaches can identify both major and subtle anomalies more effectively and provide better understanding of energy consumption behavior in real-world environments.

Intelligent monitoring systems must support scalability, efficiency, and easy user access. Visualization tools help users understand energy trends and anomalies easily. Energy consumption patterns also change over time, so continuous learning and model updates are important for maintaining system performance.

The increasing focus on sustainability and energy efficiency has created a demand for smart monitoring systems. Anomaly detection helps reduce energy waste, lower carbon emissions, and improve efficiency. However, challenges such as noisy data, missing values, and false alarms still exist.This study proposes a unified framework using reconstruction-based learning and time-series forecasting for energy anomaly detection. The system improves detection accuracy, interpretability, and scalability for real-world energy monitoring applications.

II. PROPOSED METHODOLOGY

The proposed methodology follows a structured pipeline that includes data processing, anomaly detection, forecasting, and visualization. The modular framework is scalable, flexible, and efficient for handling time-series energy data. It combines statistical analysis, reconstruction-based learning, and predictive modeling to identify patterns and detect anomalies effectively.

2.1 Data Collection and Preprocessing:Energy consumption data is collected from smart meters and sensor systems. Preprocessing techniques such as data cleaning, interpolation, and normalization are used to handle missing values and noise. The data is organized into uniform intervals, and additional features are generated to improve model performance.

2.2 Baseline Anomaly Detection using Isolation Forest:Isolation Forest is used to detect global anomalies in energy consumption data. The model identifies abnormal data points through random decision trees and provides baseline anomaly scores for further analysis.

2.3 Reconstruction-Based Detection using Autoencoder:Autoencoder detects moderate anomalies by learning normal energy consumption patterns and reconstructing the input data. High reconstruction errors indicate abnormal behavior and help identify subtle anomalies.

2.4 Probabilistic Anomaly Detection using Variational Autoencoder:Variational Autoencoder (VAE) learns probabilistic representations of energy data to detect complex and high-confidence anomalies. It improves robustness by analyzing uncertainty and variability in consumption patterns.

2.5 Time-Series Forecasting and Performance Evaluation:Time-series forecasting is used to predict future energy consumption trends by analyzing trend and seasonal patterns in the data. The forecasting model is trained using historical energy data and evaluated using performance metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to measure prediction accuracy. Comparing predicted and actual values also helps identify anomalies and validate system performance.

2.6 System Integration and Visualization:All models are integrated into a unified system with an interactive dashboard for real-time analysis. The visualization platform displays energy trends, anomaly scores, and forecasting results using graphical representations. The modular architecture supports scalability and easy deployment in different application environments.

III. DATA PREPROCESSING

Data preprocessing is an important step because the quality of input data directly affects the performance of anomaly detection and forecasting models. Energy consumption data collected from smart meters, IoT devices, and sensor-based monitoring systems in smart buildings and energy management environments may contain missing values, noise, duplicate entries, inconsistent records, and abnormal values due to sensor errors or transmission issues.

To improve data quality and reliability, preprocessing techniques such as data cleaning, interpolation, normalization, and feature engineering are applied. Missing values are handled using suitable imputation methods to maintain continuous time-series information, while noisy and inconsistent data are filtered to improve analysis accuracy.

Normalization is performed to scale the data uniformly for efficient and stable model training. The processed data is then organized into fixed time intervals, and additional features such as rolling statistics, moving averages, and time markers are generated to improve pattern analysis, anomaly detection capability, and forecasting accuracy.

IV. MODEL TRAINING

The model training phase focuses on learning normal energy consumption behavior and identifying anomalies effectively. Different models are trained using the preprocessed time-series energy data to improve the accuracy and reliability of anomaly detection and forecasting.

A. ARIMA

AutoRegressive Integrated Moving Average is a statistical time-series forecasting model used to predict future energy consumption trends based on historical data. The model analyzes temporal dependencies, trends, and patterns in the time-series dataset to generate accurate forecasts. ARIMA combines autoregression, differencing, and moving average techniques to handle non-stationary data and improve prediction accuracy. It is effective for identifying linear patterns and forecasting short-term energy usage behavior.

B.PROPHET

Forecasting model developed for analyzing time-series data with strong seasonal and trend patterns. The model automatically handles daily, weekly, and yearly seasonality along with trend changes in the data. Prophet is highly effective for energy consumption forecasting because it can manage missing values, sudden changes, and large datasets efficiently. The model generates reliable long-term forecasts and helps in understanding future energy demand patterns.

C.K-MEANS CLUSTERING

Unsupervised machine learning algorithm used to group similar energy consumption patterns into clusters. The model divides the dataset into multiple clusters based on the similarity between data points and cluster centroids. Energy usage data that significantly differs from the cluster patterns is treated as a potential anomaly. K-Means Clustering helps identify hidden consumption behaviors, analyze usage trends, and improve anomaly detection performance.

D. ISOLATION FOREST

It is used as a baseline anomaly detection model to identify global outliers and major deviations in energy consumption patterns. The model works by constructing multiple random decision trees and isolating abnormal data points that differ significantly from normal observations. This helps in detecting sudden spikes or unusual energy usage patterns at an early stage.

E. AUTOENCODER (AE)

Trained to learn normal data representations and detect moderate anomalies using reconstruction errors. The model compresses the input data into a lower-dimensional latent space and reconstructs it back to its original form. During training, the Autoencoder learns the normal structure and behavior of the energy consumption data. When abnormal data is provided, the reconstruction error becomes high because the model cannot accurately reproduce unseen or unusual patterns. This method is effective for identifying subtle anomalies that may not be detected by traditional statistical methods.

F. VARIATION AUTOENCODER (VAE)

Further improves anomaly detection by learning probabilistic representations and identifying high-confidence anomalies. Unlike a standard Autoencoder, VAE learns the probability distribution of the input data in the latent space, allowing the model to capture uncertainty and variability in energy consumption patterns. This probabilistic learning approach helps detect complex and less frequent anomalies more accurately while improving system robustness and reliability.

V. RESULT AND DISCUSSIONS

The experimental evaluation of the energy consumption anomaly detection framework shows that the system effectively identifies abnormal energy usage patterns and analyzes time-series behavior using multiple analytical models. The combination of statistical methods, reconstruction-based learning, clustering techniques, and forecasting models improves the overall accuracy and reliability of anomaly detection. The framework successfully detects both major and subtle anomalies in energy consumption data while maintaining better interpretability and system performance compared to single-model approaches.

The forecasting performance of the system was analyzed using Prophet and ARIMA models. The Prophet RMSE results show variations across different folds of the dataset, indicating differences in energy consumption complexity and seasonal behavior. Lower RMSE and MAE values indicate accurate prediction and better alignment between actual and predicted energy consumption values, while higher values represent irregular consumption patterns. These results show that the forecasting models effectively capture trend and seasonal variations in the time-series data.

The anomaly detection performance was evaluated using Isolation Forest, K-Means Clustering, Autoencoder (AE), and Variational Autoencoder (VAE). Isolation Forest effectively detected global outliers and sudden deviations in energy consumption patterns. K-Means Clustering grouped similar consumption behaviors and identified abnormal clusters. Autoencoder detected moderate anomalies using reconstruction errors, while Variational Autoencoder improved detection performance by learning probabilistic latent representations and identifying high-confidence anomalies.

The comparison between actual and predicted energy consumption values showed strong alignment between forecasting outputs and real consumption trends. Differences between predicted and actual values helped identify abnormal events and validate anomaly detection results. The integration of forecasting and anomaly detection improved the ability of the framework to detect irregular energy usage patterns more accurately.

The Streamlit visualization dashboard provided an interactive platform for monitoring energy consumption trends, anomaly scores, and forecasting results. Graphical visualizations such as time-series plots and anomaly indicators improved interpretability and supported easier decision-making. The modular architecture of the framework also improved scalability and allowed easy integration of different analytical models for real-world energy monitoring applications.

VI. CONCLUSION

The work proposed a thorough framework on how to detect energy consumption anomaly involving the use of multi-level methods of analysis and time-series analytics in a single framework. The solution increases the possibility of detecting various anomaly patterns, and the effectiveness of the entire monitoring is also more reliable and interpretable. However, the system supports improved cognition on a consumption behaviour and allows making sound decisions in the dynamic environments by integrating the complementary views of detection with the forecasting abilities.

The modular design can be readily scaled and applicable in various practical use cases in the real world and thus can be utilized in intelligent energy management system. Subsequent development can be directed to the integration of adaptive learning processes to deal with changing consumption patterns and enhance long performance. Moreover, the outside contextual factors included in the integration, like weather and occupancy data, might be even more helpful in increasing the accuracy. The ability to explore real-time deployment, enhanced visualization systems, and enhanced interpretability systems can also reinforce the efficiency and user ability of this system.

REFERENCES

[1] A. N. Khan et al., "Dynamic Temporal Analysis and Modeling of Residential Lighting Consumption for Energy Efficiency and Sustainability," *IEEE Access*, vol. 12, pp. 154365–154380, 2024, doi: 10.1109/ACCESS.2024.3467337.

[2] I. S. M. Isa, T. E. H. El-Gorashi, M. O. I. Musa and J. M. H. Elmirghani, "Resilient Energy Efficient IoT Infrastructure With Server and Network Protection for Healthcare Monitoring Applications," *IEEE Access*, vol. 12, pp. 48910–48940, 2024, doi: 10.1109/ACCESS.2024.3352024.

[3] L. W. Tokam, S. K. Apeke and S. S. Ouro-Djobo, "Hybrid HDBSCAN-FHMM Approach for Energy Disaggregation in Non-Intrusive Load Monitoring (NILM) Systems," *IEEE Access*, vol. 13, pp. 89685–89703, 2025, doi: 10.1109/ACCESS.2025.3570930.

[4] E. Biçici, "A Cloud Monitor to Reduce Energy Consumption With Constrained Optimization of Server Loads," *IEEE Access*, vol. 12, pp. 25265–25277, 2024, doi: 10.1109/ACCESS.2024.3365674.

[5] S. Dash, "Green AI: Enhancing Sustainability and Energy Efficiency in AI-Integrated Enterprise Systems," *IEEE Access*, vol. 13, pp. 21216–21228, 2025, doi: 10.1109/ACCESS.2025.3532838.

[6] U. G. Shinde et al., "Task-Specific Energy Profiling for Microcontroller Selection in Energy-Autonomous Wireless Sensor Nodes," *IEEE Sensors Journal*, vol. 25, no. 21, pp. 40609–40622, Nov. 2025, doi: 10.1109/JSEN.2025.3609827.

[7] B. M. Beena, P. Cheluvasai Ranga, A. Vinitha Chowdary, R. Gamidi, M. Hemasri and T. Muppala, "Green Video Transcoding in Cloud Environments Using Kubernetes: A Framework With Dynamic Renewable Energy Allocation and Priority Scheduling," *IEEE Access*, vol. 13, pp. 116362–116390, 2025, doi: 10.1109/ACCESS.2025.3585615.

[8]T. B. de Sousa and R. D. A. L. Rabelo, "Smart Metering Enabled by the Internet of Things for Monitoring Residential Energy Consumption and Power Quality," *IEEE Access*, vol. 13, pp. 186872–186886, 2025, doi: 10.1109/ACCESS.2025.3627191.