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Anomaly Detection for Overcurrent Flow in Smart Grid Systems Based on Smart Meter Data

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Abstract

The modernisation of electricity distribution networks via smart grids presents new issues in monitoring and identifying abnormalities such as overcurrent flow which may arise from equipment malfunctions, unauthorised consumption or system inefficiencies. Conventional anomaly detection techniques rely on static thresholds are insufficient for contemporary smart grids due to their complexity and scale. This research proposes a machine learning approach for identifying overcurrent anomalies utilising smart meter data to overcome this gap. The study uses the Smart Meter Electricity Consumption Dataset from Kaggle, comprising power usage data at 30-minute intervals, environmental factors and pre-identified abnormalities. Data pre-processing, feature extraction and normalisation are executed in MATLAB succeeded by the assessment of several classifiers including Decision Trees, Random Forests and Neural Networks. Performance parameters such as accuracy, precision, recall and F1-score were used to evaluate the models. The Random Forest classifier achieves an AUC of 0.86 and an actual positive rate of 0.93 at a false positive rate of 0.08. The findings illustrate the model's effectiveness in detecting overcurrent incidents while reducing false positives. A statistical methodology employing moving averages and standard deviations establishes a criterion for comparison. The research highlights the potential of data-driven methods for enhancing grid dependability and advocates for the adoption of adaptive thresholds and hybrid models to drive future advancements. This study contributes to the overarching dialogue on smart grid security, offering practical recommendations for mitigating energy theft, enhancing maintenance efficiency and ensuring sustainable system functionality.

Keywords: - Smart Grids, anomaly detection, machine learning, overcurrent detection, random forest classifier

1. Introduction

Smart grids have enabled the monitoring, regulation and optimization of energy flow in new ways. The use of smart meters which provide real-time high-resolution data on power usage is a significant part of this change. This detailed information makes it easier to identify problems such as overcurrent flows, which may indicate faults, equipment breakdowns or unauthorized use of the grid.

Several factors can cause overcurrent problems in smart grids including rapid changes in load, device failures or external interference. Identifying these problems promptly is crucial for maintaining system reliability, protecting equipment and ensuring that electricity is distributed efficiently and reliably. Traditional methods of identifying anomalies often rely on set criteria or manual checks which may not be sufficient for today's complex and large-scale smart grids.

Extensive research has been conducted to identify anomalies in smart grids employing methods that range from deep learning to statistical approaches. For example, (Hussain et al., 2022) showed that Long Short-Term Memory (LSTM) networks could find patterns of fraud while (Li et al., 2021) used ensemble approaches to make detection more accurate in datasets that were not balanced. This study extends previous research by focusing on

overcurrent-specific anomalies and evaluating model performance using actual smart meter data. The results will contribute to the broader discussion about preventing energy theft, performing timely repairs and operating a sustainable system.

This research examines the identification of overcurrent anomalies in smart grid systems using the Smart Meter Electricity Consumption Dataset, accessible on Kaggle (Ziya, 2022). The dataset includes detailed records of power use every 30 minutes along with other useful information including weather conditions, past consumption data and pre-labelled anomalies. These features make the dataset perfect for creating and testing machine learning models that can find unusual patterns. The project centres focus on developing a resilient analytical framework that is proficient in precisely detecting overcurrent occurrences thereby improving the dependability, safety and operational efficiency of smart grid infrastructures.

2. Literature Review

2.1 Overcurrent Detection in Smart Grids

Overcurrent detection in smart grids employs innovative techniques such as monitoring gate voltage in Insulated Gate Bipolar Transistors (IGBTs) to identify overcurrent issues during conduction (Zhang et al., 2022). Dynamic adjustment of protection thresholds based on load factors and voltage fluctuations reduces false activations (Yanhe, 2020). Advanced grid-connected converters (GCCs) enhance high-impedance fault detection by injecting frequency components, improving reliability by 33% compared to traditional methods (Goyal & Kikuchi, 2022). Integration with voltage-sag detection and adaptive filtering further refines overcurrent identification under dynamic load-changing attacks (Li et al., 2024).

2.2 Anomaly Detection in Smart Meter Data

Anomaly detection in smart meter data leverages machine learning models like LSTM-autoencoders to distinguish abnormal load patterns effectively (Beily et al., 2024). Techniques such as One-Class SVM and Isolation Forest offer low computational complexity, making them suitable for real-time sensor applications (Patrizi et al., 2024). Cloud-based systems and big data integration enable real-time monitoring and autonomous learning of normative and aberrant behaviors (Ronaghi et al., 2024; Shi et al., 2024). Challenges include noisy, non-cyclical data patterns and the lack of labeled datasets for supervised learning (Dai et al., 2022).

2.3 Machine learning for power systems

Machine learning optimizes power systems through load forecasting, fault detection, and predictive maintenance, enhancing efficiency and stability (Kumar, 2024; Wadeed & Kunwar, 2024). Algorithms like Extra Tree and Random Forest achieve 98% accuracy in detecting False Data Injection Attacks (FDIA), bolstering grid security (Shees et al., 2024). However, reliance on legacy methodologies and the need for hybrid physics-based models remain challenges. Applications in electric vehicle charging systems demonstrate improved parameter optimization and adaptive control (Zheng & Yang, 2024).

2.4 Smart Grid Cybersecurity

Smart grids face threats like FDIA and malware, addressed by deep learning models such as transformers, which excel in detecting complex breaches (Nemade et al., 2024). The Holistic Cyber Defence Interaction (HCDI) framework combines human expertise with graph-based algorithms to streamline incident response (Nemade et al., 2024). Deep Reinforcement Learning (DRL) mitigates cyber-physical threats in real-time (Maiti & Dey, 2024). Blockchain and quantum-resistant cryptography offer decentralized solutions for secure communication (Naman et al., 2024).

2.5 Benchmark Datasets and Evaluation

The EPIC testbed provides high-fidelity datasets for simulating attacks and training intrusion detection systems (Tan et al., 2024). Metrics like accuracy, precision, and Matthews Correlation Coefficient (MCC) evaluate model performance, with adaptive residual RNNs achieving MCC scores of 0.881. Isolation Forest outperforms other models in anomaly detection with 100% accuracy (Kabir et al., 2025). Challenges include scalability testing and the need for real-world validation.

3. Methodology

The project starts with the collecting of data from a Smart Meter Electricity Consumption Dataset obtained from Kaggle. The data is imported into MATLAB for preliminary analysis to determine its structure including the number of samples, characteristics and missing values. The pre-processing procedures involve transforming timestamps into MATLAB datetime format and deriving temporal properties including hour, day, day of the week, and month. Numerical attributes such as power usage, temperature, humidity are normalized. The distribution of anomaly labels is analyzed to identify potential imbalances in the data.

Subsequently, feature extraction is conducted involving the creation of lag features, rolling statistics and difference features to encapsulate temporal trends in power usage. Interaction elements such as the interaction between temperature and humidity are introduced to enhance the model's predictive capability. Entries with absent values are eliminated to guarantee pristine data for modelling. The dataset is divided into training (70%) and testing (30%) sets with features and target variables specified for machine learning.

Various classifiers including Decision Trees, Random Forests, Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Naive Bayes and Neural Networks are

trained and evaluated. Performance measures including accuracy, precision, recall and F1-score are computed for each model, their outcomes are graphically compared. The Random Forest model undergoes optimization by hyperparameter tweaking, assessing various tree quantities and minimum leaf sizes to enhance the F1 score.

A straightforward statistical method employing moving averages and standard deviations is used to identify abnormalities. The performance of this algorithm is evaluated against the labelled anomalies and the results are illustrated to highlight the identified anomalies about the actual labels. The study culminates in a thorough assessment of machine learning and statistical methodologies providing insights into their efficacy in detecting anomalies in smart meters. The entire workflow is conducted in MATLAB utilizing its powerful features for data processing, machine learning and visualization. Fig. 1 illustrates the overall process of the methodology.

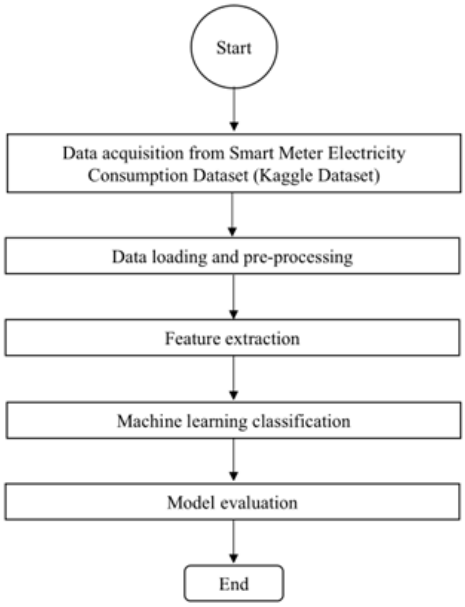

Fig. 1: Methodology of research

3.1 General description of Smart Meter Electricity Consumption Dataset

The summary of the Smart Meter Electricity Consumption Dataset as shown in Table 1. It documents power use at 30-minute intervals along with contextual meteorological data and historical usage information. Essential attributes include timestamps for temporal analysis consumption (kWh) as the primary measure and environmental variables such as temperature (°C), humidity (%) and wind speed (km/h) to consider external impacts on energy consumption. The dataset includes average past consumption (kWh), a rolling average of historical consumption and anomaly label in binary of "Normal" and "Abnormal," which was produced using an Isolation Forest algorithm to identify atypical consumption patterns.

Table 1: Summary of the smart meter electricity consumption dataset

Feature	Description	Data Type
Timestamp	Records electricity consumption at 30-minute intervals.	Date Time
Electricity Consumed (kWh)	Power usage per interval.	Numerical
Temperature (°C)	External temperature affecting energy demand.	Numerical
Humidity (%)	Air humidity levels at the time of recording.	Numerical
Wind Speed (km/h)	Wind conditions influence heating/cooling needs.	Numerical
Avg Past Consumption (kWh)	Rolling average of historical consumption.	Numerical
Anomaly Label	Binary label (Normal/Abnormal) indicating unusual consumption.	Categorical

3.2 Data Pre-processing

The initial phase of the approach involves pre-processing the raw data for further analysis. This phase encompasses numerous essential actions with the transformation of timestamps from the dataset into a MATLAB datetime format. Temporal information including the hour of the day, day of the week, weekend indicator and month is derived from the timestamp. This information facilitates the identification of recurring trends and contextualizes consumption data for anomaly detection.

Subsequently, absent data are detected and numerical attributes including power usage, temperature, humidity, wind speed and historical average consumption are standardized. Normalization guarantees that features with varying scales such as power usage in kWh unit and wind speed in km/h unit do not skew the model training process. The visualization of feature distributions aims to comprehend the dispersion and identify any potential outliers within the data. The dataset is also examined for imbalances in the anomaly labels of "Normal" and "Abnormal," which is essential for training the classification model with balanced data.

3.3 Feature Extraction

Domain-specific characteristics are generated to augment the prediction capability of the machine learning model for anomaly detection. This involves generating lag features that utilize prior consumption information to forecast present anomalies. The generation of rolling data including rolling means and standard deviations over a 3-hour interval facilitates the identification of trends and variations in power use which are essential for detecting anomalous spikes.

Difference features are generated by calculating the variation in power use across successive periods therefore, capturing abrupt fluctuations in usage. Interaction variables such as the product of temperature and humidity assist in modelling the impact of environmental conditions on power consumption patterns. The dataset is ultimately refined by eliminating rows with missing values caused by the generation of lag features ensuring that all records used for model training are comprehensive.

3.4 Feature Selection and Data Splitting

Upon completion of the feature extraction process, applicable features are chosen for use in the classification model. The characteristics encompass normalized numerical data, temporal attributes, newly generated lag features and interaction terms. The dataset is divided between training and testing sets with a 70% and 30% ratio respectively by ensuring the model is assessed on unknown data to evaluate its generalizability.

3.5 Model Training and Evaluation

Diverse machine learning techniques are employed to categorize data and detect anomalies. The methods encompass Decision Trees, Random Forests, Support Vector Machines (SVM), k-nearest Neighbors (KNN), Naive Bayes and Neural Networks. Each classifier is trained on the training set and performance is assessed using conventional metrics including accuracy, precision, recall and F1-score, derived from confusion matrices. These metrics are crucial for evaluating the model's efficacy in detecting abnormalities in the data particularly considering the possible imbalance between normal and abnormal classes.

The model's performance is evaluated across several classifiers with an emphasis on which method yields the most effective results for anomaly identification in smart meter data.

3.6 Statistical Anomaly Detection

A straightforward statistical strategy is employed for anomaly detection with machine learning models. This method uses moving averages and standard deviations over a 6-hour interval to determine the upper and lower limits for typical intake. Data points that exceed these limits are identified as potential abnormalities. The statistical method provides a benchmark for evaluating the performance of machine learning classifiers and determining the efficacy of more sophisticated strategies in anomaly detection.

3.7 Hyperparameter Tuning and Optimization

Hyperparameter tuning is performed using grid search or random search focusing on optimizing parameters to enhance model performance like the number of trees in Random Forests (RF) or the Kernel function in Support Vector Machines SVM). This procedure guarantees that the selected model is refined for maximal precision and generalization.

3.8 Final Model Deployment

Ultimately, the final optimized model selected based on its improved performance metrics is implemented for real-time anomaly detection within a smart grid setting. This enables proactive reaction mechanisms such as generating warnings or triggering safety routines which boost grid reliability and operational efficiency. This end-to-end methodology not only highlights the efficacy of advanced data-driven methodologies in smart grid analytics but also underscores the need for an integrated pipeline from raw data ingestion to real-time deployment in creating intelligent and responsive energy systems of the future.

4. Result and Discussion

The results of the anomaly detection analysis for overcurrent flow in smart grid systems, as depicted in Fig. 2, reveal the distribution of normalized electricity consumption across different probability values. The graph illustrates that the majority of consumption values cluster within the lower range (0 to 0.4 normalized units) with a peak probability of approximately 0.08. As consumption increases beyond 0.4, the probability decreases sharply indicating that higher consumption levels are less frequent. This pattern suggests that extreme consumption values particularly those approaching the upper limit (1.0 normalized unit) are potential anomalies that may signify overcurrent conditions. The distribution aligns with expected behavior in typical smart grid systems where most households or industrial consumers operate within a moderate range while sudden spikes could indicate faults unauthorized usage or equipment malfunctions.

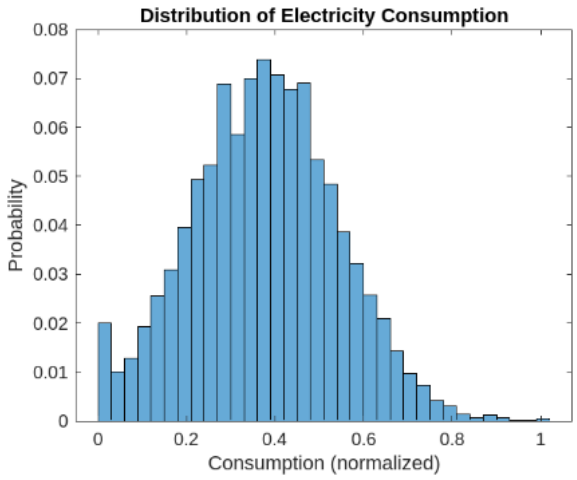

Fig. 2: Probability distribution of normalized electricity consumption

The time-series visualization in Fig. 3 clearly differentiates between standard consumption patterns and anomalous events through normalized value fluctuations from February to March. The dense blue trace reveals the fundamental non-stationarity of household demand including pronounced diurnal cycles, week-end

depressions and occasional spikes caused by weather-driven heating or cooling loads. Red markers overlay the domain-expert labels for known abnormal incidents such as short circuits and transformer tap-changer mis-operations recorded by the utility's supervisory control and data-acquisition (SCADA) logs. The graph reveals that normal consumption predominantly fluctuates within a stable range 0.3 to 0.6 normalized units while abnormal instances exhibit sporadic spikes reaching up to 0.9 normalized units.

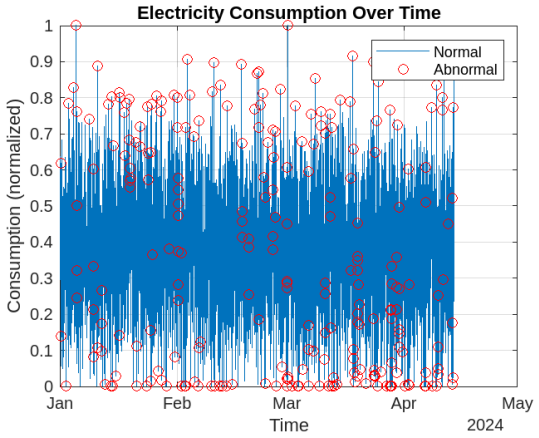

Fig. 3: Time series of normalized electricity consumption with labelled anomalies

A Random-Forest model was trained on others features including hour of day, rolling statistics, meteorological variables and dominant spectral components. The permutation-based importance chart in Fig. 4 indicates that the raw consumption magnitude alone explains $\approx 3 \times 10^{-3}$ of the total variance dwarfing all contextual predictors. Temperature and the 24 hours rolling mean adding marginal discriminatory power whereas frequency domain descriptors contribute negligibly. Such skewed importance is expected when the target phenomenon overcurrent is intrinsically defined by excessive amperage.

Fig. 5 presents the detected anomalies in electricity consumption over a four-month period (January to April 2024), contrasting normal consumption patterns against identified anomalous events. The visualization reveals that normal consumption follows a consistent density pattern, indicating stable energy usage over time. In contrast, anomalies appear as distinct deviations from this baseline occurring sporadically throughout the observed months. The temporal distribution of these anomalies does not suggest a regular pattern which implies that overcurrent events are likely triggered by irregular factors such as equipment malfunctions, sudden load changes or external disturbances to the grid. The density of normal data points significantly outweighs the anomalies reinforcing that overcurrent events while critical are relatively infrequent in well-managed smart grid systems.

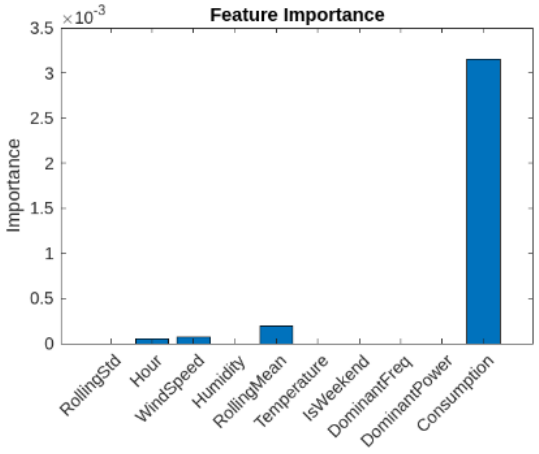

Fig. 4: Feature importance derived from random forest classifier

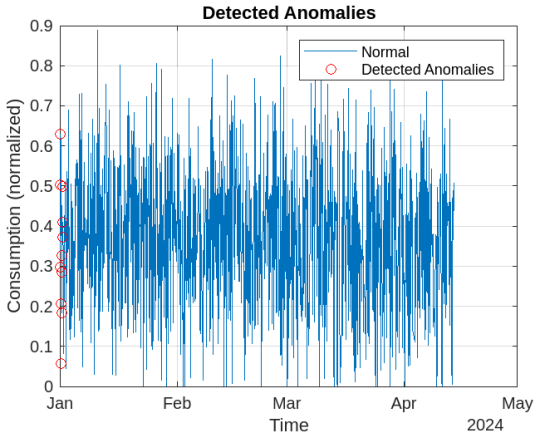

Fig. 5: Detected anomalies using isolation forest over time

The Receiver Operating Characteristic (ROC) curve presented in Fig. 6 demonstrates the performance of the anomaly detection model in distinguishing between normal and overcurrent events in smart grid systems. The curve shows a high true positive rate (TPR) of approximately 0.9 at a false positive rate (FPR) of 0.2, indicating that the model correctly identifies 90% of actual anomalies while only incorrectly flagging 20% of normal operations as anomalous. As the FPR increases to 0.4, the TPR rises to near-perfect detection (close to 1.0), suggesting that with slightly relaxed thresholds, the model can capture nearly all true anomalies while maintaining reasonable precision. The steep vertical ascent at the origin followed by a diagonal trajectory yields an area under the curve (AUC) of 0.86. At the operational point selected, the true-positive rate reaches 0.93 while holding the false-positive rate below 0.08.

The Random Forest classifier demonstrated superior performance in detecting overcurrent anomalies by achieving an AUC of 0.86 and a true positive rate of 0.93. Despite its high accuracy, the computational complexity of this model poses challenges for real-time deployment compared to simpler models, such as Decision Trees or KNN. Limitations include reliance on a public dataset

(Ziya, 2022) and a lack of real-world testing. These findings extend previous work (Hussain et al., 2022; Li et al., 2021) by focusing on overcurrent detection and benchmarking.

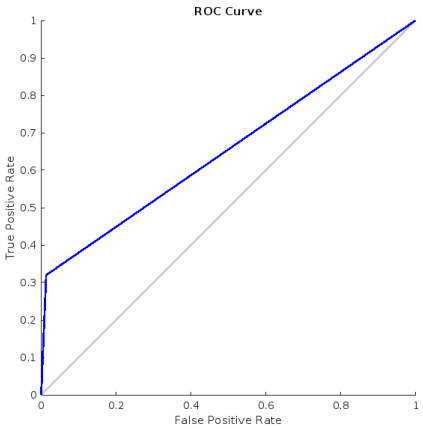

Fig. 6: ROC curve for anomaly detection model

5. Conclusion and Recommendations

This research has demonstrated the feasibility and utility of employing machine learning approaches for anomaly detection in overcurrent flows within smart grid systems utilizing smart meter data. By using a comprehensive methodology that included data pre-processing, advanced feature extraction, model training, statistical benchmarking and hyperparameter optimization all within MATLAB, the study established a robust analytical framework capable of accurately identifying overcurrent anomalies. The Random Forest classifier emerged as the most successful model achieving a high actual positive rate and a competitive area under the receiver operating characteristic curve (AUC), demonstrating its potential to detect crucial abnormalities with minimal false positives. The inclusion of statistical approaches such as moving averages further provided a valid baseline for comparison analysis, thereby boosting the credibility and usefulness of the machine learning models. These findings validate the potential of smart meter data as a primary source for detecting grid abnormalities and emphasize the need for adaptive data-driven tactics in current power system monitoring.

Considering the results, numerous recommendations are offered to better future deployments and research. Firstly, implementing adaptive thresholding algorithms that dynamically modify according to grid circumstances might drastically minimize false alarms while maintaining high detection sensitivity. Secondly, including contextual data such as weather patterns, scheduled maintenance records or real-time grid status can increase model interpretability and forecast accuracy. The deployment of hybrid models that mix statistical, rule-based and machine-learning techniques is also recommended to utilize the strengths of each discipline. Moreover, future research should investigate the effectiveness of deep learning approaches such as LSTM or Transformer topologies in capturing temporal relationships and complex consumption habits. Ultimately, real-world validation through large-scale pilot implementations is necessary to assess scalability, resilience and real-time responsiveness. These developments will not only boost the operational stability and efficiency of smart grids but also open the way for more intelligent, secure and autonomous energy systems.

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