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REVIEW

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Literature Review of Methods for Detecting Non-Technical Electricity Losses in Distribution Grids

Irbek D. Morgoev[1], **Roman V. Klyuev**[2,*], **and Angelika D. Morgoeva**[1]

[1] *Computer Modeling and Design Automation Department, North Caucasian Institute of Mining and Metallurgy (State Technological University), Russia*

[2] *Automation and Control Department, Moscow Polytechnic University, Russia*

Abstract: The widespread deployment of advanced metering infrastructure (AMI) and smart grid technologies has significantly expanded the availability of high-resolution electricity consumption data in distribution networks. This creates new opportunities for addressing non-technical losses (NTL). This paper presents a systematic literature review of data-driven methods for NTL detection based on an analysis of 79 relevant scientific publications from leading databases (IEEE Xplore, Springer, MDPI, and ScienceDirect) indexed in Scopus/Scimago over the period 2020–2025. The reviewed methods are categorized according to a novel triad of criteria: the analytical paradigm, the input data structure, and the required level of grid digitalization. A comparative analysis reveals distinct performance profiles: supervised classification methods, particularly hybrid and ensemble models, enable high-accuracy detection, with many studies reporting F1-scores exceeding 0.95 on benchmark datasets, yet they require extensive labeled data from AMI systems. Unsupervised clustering techniques offer a practical alternative for grids with partial or no AMI by analyzing aggregated consumption patterns. Forecasting-based (regression) methods facilitate continuous consumption monitoring and anomaly detection via deviation analysis, while scenario-modeling techniques provide strategic tools for evaluating the potential impact of NTL reduction measures. This review critically examines the causes of NTL, feature engineering strategies, software tools, and key challenges such as data imbalance, model interpretability, and real-world deployment constraints. The synthesis provides a utility-centric framework for method selection, offering practical recommendations tailored to different infrastructure profiles. The proposed systematization bridges methodological gaps and supports the development of context-aware, data-driven solutions for modern and evolving power systems.

Keywords: non-technical losses, smart grid, data analysis, electricity theft, machine learning

1. Introduction

The digital transformation of the power sector, driven by the deployment of advanced metering infrastructure (AMI) and smart grid technologies, is fundamentally changing the operational landscape for distribution network operators [1].

One of the most serious operational and economic challenges facing utilities worldwide is non-technical losses (NTL), which predominantly originate from consumers in low-voltage distribution grids. NTL is defined as the energy that is distributed but not billed, primarily due to illegal actions external to the power system and conditions that technical loss computations fail to take into consideration [2]. The phenomenon of electricity losses affects all countries. The monetary value of the world's total electricity losses in 2022 was estimated at approximately 90 billion USD, with approximately 60 billion USD attributed to emerging electricity markets [1]. To ensure a reliable power supply, NTL must be accounted for, and studies have shown that NTL constitute approximately 10%–50% of total electricity losses or supplied electricity, especially in developing countries [3, 4].

For utility companies, the transition to smart grids creates a critical opportunity to tackle NTL systematically. The vast amounts of high-resolution consumption data now available enable the shift from reactive, inspection-based detection to proactive, data-driven identification of anomalies and fraud patterns [5, 6].

NTL detection is a highly relevant topic of scientific research. Prominent modern approaches are data-driven methods. Consequently, numerous data-driven methods, particularly those based on machine learning, have been proposed. However, the rapid evolution of this field has led to a fragmented landscape of approaches. Existing literature reviews often lack a structured framework for comparing these methods based on the practical constraints faced by utilities, such as data availability, infrastructure readiness (level of digitalization), and the need for interpretable results.

In this regard, the purpose of this review is to systematize and analyze data-driven NTL detection methods, providing a utility-centric analysis that bridges the gap between methodological research and practical implementation. The objectives of the research are the following:

1) To propose a novel classification of NTL detection methods based on the input data structure, the required level of grid digitalization, and the analytical paradigm.
2) To conduct a comparative analysis of the advantages and disadvantages of the classified methodologies, with a focus on practical applicability.
3) To identify the most promising modern solutions, analyze assumptions, assess the reproducibility of the proposed approaches,

[*]**Corresponding author:** Roman V. Klyuev, Automation and Control Department, Moscow Polytechnic University, Russia. Email: mospolytech@mospolytech.ru

and provide practical recommendations for method selection tailored to different utility infrastructure profiles.

To make the proposed classification explicit and improve readability, Figure 1 presents a conceptual framework for classifying data-driven NTL detection methods. The framework links data availability and infrastructure digitalization with the corresponding analytical paradigms and typical utility-oriented application scenarios.

2. Methods and Materials

This review employs a systematic approach for analyzing data-driven methods for NTL detection, focusing on literature from 2020 to 2025. This timeframe captures the latest advancements following the widespread deployment of AMI, which has fundamentally altered the data landscape for distribution utilities. The primary objective is to move beyond a mere enumeration of techniques and provide a utility-centric framework for method selection.

The remainder of the article is organized as follows. Section 3 presents the necessary conditions for developing NTL detection models through data analysis. This section includes an analysis of the causes of NTL occurrence, software tools and programming languages, and the feature space (factors) required for data processing. The comparison of groups of NTL detection methods is described in detail in Section 4. This section contains three subsections, each of which provides a comparative analysis of the methods used and the main conclusions for each group of methods. The Conclusion section presents the main results of our review and outlines prospects for further research.

Before moving on to specific methods for detecting NTL sources, we first analyze some previous review articles on methods for reducing and detecting NTL.

Earlier review articles [7–9] provide a solid foundation for understanding the NTL problem and the evolution of detection methods. Collectively, they highlight several persistent challenges: the socio-economic complexity of NTL, the advantage of data-driven ("intelligent") methods over purely hardware-based solutions, and the need for labeled data for supervised learning. However, these reviews primarily cover literature published before 2022 and often focus on methodological typologies (e.g., classification vs. regression) without explicitly linking them to the operational context of utilities.

This review aims to bridge this gap by synthesizing recent research (2020–2025) within a novel conceptual framework. We argue that the traditional binary classification of methods as "hardware-based" or "data-driven" has become less distinct in the era of ubiquitous AMI. Modern smart meters are data-generating hardware, and the key differentiator is the level of digital infrastructure maturity and data availability. Therefore, our classification and analysis explicitly link the choice of NTL detection method (e.g., supervised vs. unsupervised learning) to practical constraints and opportunities defined by the utility's level of digitalization.

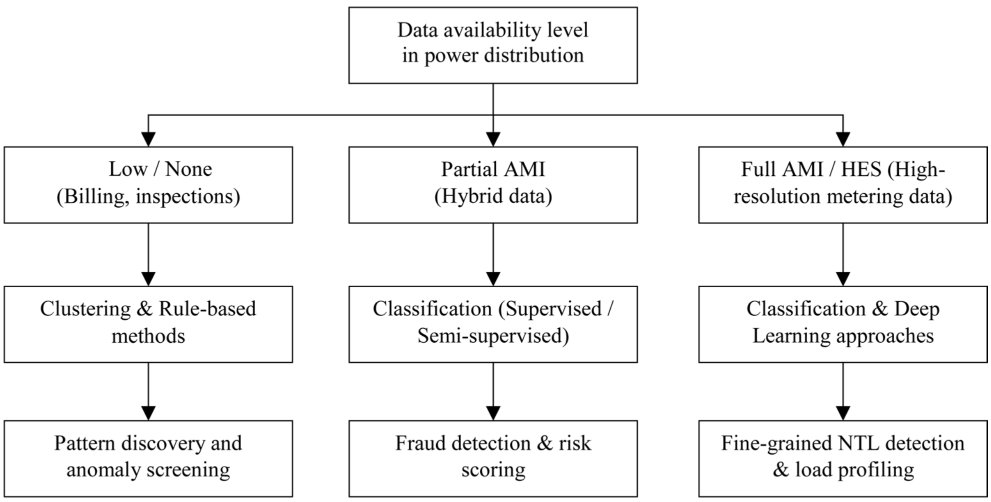
By summarizing the analysis of the review papers on the topic of NTL, the following conclusions were made:

1) The most common classification of NTL methods is into hardware and data-based (intelligent). However, it should be clarified that, at present, due to the active implementation of AMI, this classification is becoming irrelevant because modern metering devices have hardware that allows for automated transmission of readings, which are subsequently used in the analysis of electricity consumption.
2) Scientific interest in NTL methods is due to the constant improvement of electricity theft methods, the development of the instrument base, and the emergence of new artificial intelligence algorithms.
3) Most publications over the past few years focus on intelligent methods because it is possible to detect abnormal consumers with high accuracy using consumption data. The use of additional hardware beyond AMI entails high costs.

On the basis of the analysis of existing reviews, we classify methods according to their machine learning paradigm and their approaches (supervised and unsupervised) used in this study. On the basis of our experience in this area of research [7–9] and that of other scientists [10, 11], we used a classification that divides NTL intelligent search algorithms into the following types: classification, clustering, and regression. Such differentiation of methods is associated with the frequent use of various machine learning algorithms in the implementation of NTL intelligent search algorithms. The possibility of using these algorithms is due to the increasing introduction of AMI and smart grids, which allows for collecting large data samples and processing them. Therefore, such a division of methods, in our opinion, allows researchers to better navigate the subject literature, as well as identify key features of the application conditions for each type of algorithms (classification, clustering, and regression) in NTL intelligent search.

Consequently, this review proposes a classification system that moves beyond a simple listing of algorithms. We categorize methods

Figure 1
Conceptual classification framework of data-driven NTL detection methods



based on a triad of criteria: (1) the analytical paradigm (supervised, unsupervised, hybrid, and forecasting-based), (2) the structure and requirements of the input data, and (3) the level of digitalization of the distribution infrastructure for which they are most suitable. This framework allows for a coherent synthesis of diverse studies by connecting their technical contribution to a utility's practical context.

To ensure a comprehensive and unbiased selection of literature, a systematic multistage methodology was employed, comprising four key phases.

In accordance with this framework, a qualitative comparative analysis of NTL detection algorithms in the studies under consideration was performed. Each subparagraph of Section 4 compares the advantages and disadvantages of the approaches, the required data structure, and detection accuracy.

Phase 1: database search and initial identification. The primary search for literature sources was conducted in major scientific publication databases: IEEE Xplore, Springer Link, ScienceDirect (Elsevier), and the Multidisciplinary Digital Publishing Institute (MDPI). To capture the most recent advancements, the publication period was limited from January 2020 to December 2025. The search query combined key terms using Boolean operators: («non-technical loss» or «non-technical electricity loss» or «electricity theft») and («detection» or «analysis» or «machine learning» or «data-driven»).

Phase 2: screening based on titles and abstracts. The selection of literary sources for full-text review was then carried out according to the following explicit criteria:

1) The source must be a research article published between 2020 and the present, containing the keywords «non-technical losses», «non-technical electricity losses», «electricity theft».
2) The primary focus must be on presenting a novel or adapted data-driven algorithm or methodology specifically aimed at NTL detection.
3) The paper must present to the reader an algorithm or methodology aimed at finding NTL.
4) Studies focusing solely on hardware-based solutions without a core data analytics component were excluded. This screening process resulted in 156 articles selected for full-text assessment.

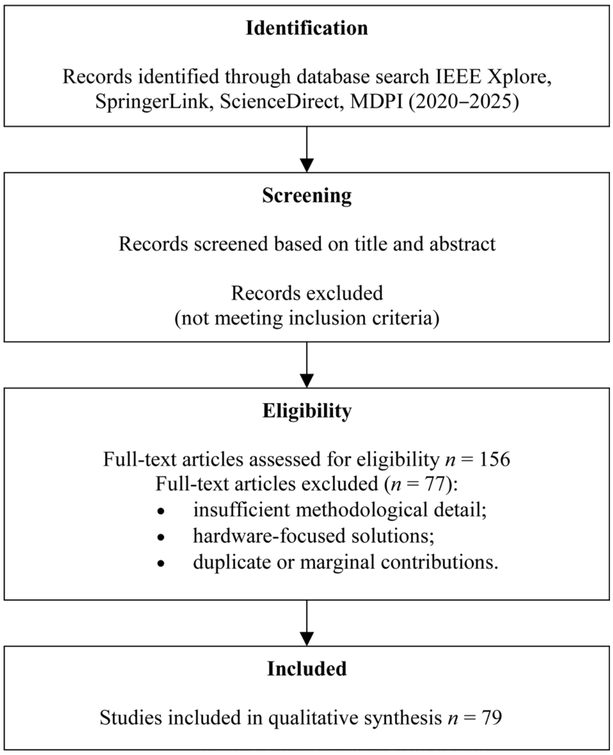
Phase 3: eligibility assessment through full-text review. The full texts of the 156 articles were examined in detail. Articles were excluded at this stage for the following reasons:

1) Insufficient methodological detail to understand or evaluate the core analytical approach.
2) Primary reliance on hardware or network-level solutions with minimal data-driven analysis.
3) The work presented a direct duplicate or a minor incremental contribution already covered by another, more comprehensive study in the corpus. This rigorous assessment resulted in the final corpus of 79 publications that form the basis of this systematic review.

Phase 4: data extraction and synthesis. From each of the 79 included studies, data were systematically extracted into a standardized template. These data included the proposed methodology, type of machine learning paradigm, input data features, software tools, performance metrics, and stated advantages and limitations. This structured extraction enabled the subsequent comparative analysis and classification presented in Sections 3 and 4.

The literature selection process is summarized in Figure 2.

Figure 2
Flow diagram of the literature selection process



The problems that the authors encountered during this review are worth noting. First, the main drawback of most empirical studies is the difficulty of reproducing their results due to differences in implementation conditions, data unavailability, insufficient detail in the solution description, and other factors that hinder objective evaluation. Therefore, the authors recommend that when choosing an existing or developing a new algorithm for detecting NTL sources, researchers pay attention not only to quantitative estimates of results but also to qualitative features: the specifics and structure of the available data.

3. Basics of NTL Detection in Data Mining

Achieving stability and reliability of power supply, increasing the capacity of electrical networks, and automating control over electricity consumption are the main goals and reasons for the gradual implementation of the smart grid concept. In solving the NTL problem, this concept allows data to be obtained and processed to detect potential consumers with NTL. To detect consumers with NTL more accurately, it is necessary to analyze the conditions and components used in the studies under review. As noted earlier, the presence of digital metering devices reduces NTL but does not guarantee their absence. Therefore, this section discusses the following aspects:

1) The reasons for the emergence of NTL in the selected literature sources.
2) The features (factors) used in the selected research articles.

In addition, the issue of choosing the programming language used by researchers to address the NTL problem is important because it can serve as a guide for new developments in the field of data mining.

3.1. Reasons for the emergence of NTL

The effective data-driven detection of NTL requires a clear understanding of the underlying causes that these methods aim to identify. NTL occurrences were classified into two main categories: intentional theft of electricity and system errors. The results of the search for NTL causes in the literature under review are presented in Table 1.

Table 1
Causes of NTL in electrical distribution networks

Type of NTL	Reason of NTL	References
Theft, fraud	Falsification, changing the accuracy of meters (hacking, flashing, using electromagnetism properties)	[5, 6, 12–35]
	Consumption of NTL energy bypassing utility meters	[6, 12, 13, 15, 17–19, 22, 24, 25, 27–30, 32, 36, 37]
	Corruption among employees of electric distribution companies	[21, 25, 35, 37, 38]
System errors	Billing violations	[4, 6, 13, 14, 16, 19, 20, 29, 36, 39, 40]
	Incorrect installation, incorrect operation, breakdown of measuring equipment	[2, 4, 8, 14, 17, 19, 20, 39–41]
	Unpaid bills	[8, 16, 19, 20, 35, 39, 41]
	Data cyberattacks	[20, 21, 22, 35, 42]

There are also other classifications of NTL. For example, in the research by Javaid et al. [13], vulnerability types were divided into three classes: physical attacks, cyberattacks, and data attacks.

In the research by Farshchian et al. [12], the normalized weight of NTL causes was analyzed and calculated. According to this article, losses are caused by the following: electricity theft (0.25), environmental conditions (0.188), incorrect reading of meters (0.168), incorrect operation of meters (0.153), lack of meters for recording the consumption of the lighting network (0.145), and incorrect calculation in billing (0.096).

The analysis reveals that NTL causes can be logically grouped into two main categories: (1) deliberate fraudulent actions (e.g., meter tampering and bypassing) and (2) technical or administrative errors (e.g., billing inaccuracies and meter faults). This distinction is critical for method selection because detecting deliberate fraud often requires identifying subtle, evolving patterns in consumption data, while flagging systematic errors may rely more on anomaly detection in metering and billing workflows. The challenge is particularly acute for partial fraud, where consumption is manipulated but not eliminated, making detection reliant on sophisticated pattern analysis of high-resolution data from AMI.

3.2. Software implementation tools for NTL detection algorithms

The choice of software tools for intelligent data processing in solving problems is one of the main components of successful research. Therefore, we considered and identified the following programming languages (PL) and software tools (ST) used in the studies: Python [14, 16, 18–59], MATLAB [53, 60], and R [61].

Thus, Python is the most popular among researchers in solving the NTL detection problem. Its dominance in NTL research is attributed to its rich ecosystem of data science libraries (e.g., Pandas, NumPy, and Scikit-learn) essential for handling time-series consumption data and frameworks for deep learning (e.g., TensorFlow and PyTorch) increasingly used for complex fraud pattern recognition. This, combined with strong community support and versatility for prototyping and deployment, makes Python the de facto standard for developing and testing data-driven NTL detection models.

3.3. Theoretical framework

To achieve the required result in modeling and detecting abnormal consumption, the main components of a successful solution are factors (features), machine learning methods selected depending on the characteristics of the original sample, and the value of the quality metrics (i.e., a quantitative assessment of the quality of the result obtained). Therefore, attention should be paid to these characteristics of the studies under consideration.

The factors used in detecting NTL in research articles were grouped and are presented in Table 2.

Table 2
Features that are used in NTL detection

No	Features	References
1	Retrospective energy consumption data	[3, 10, 11, 13, 14, 18–23, 25–33, 36, 39, 41, 42, 45–54, 57–59, 62–75]
2	Various information regarding the consumer (household) and AMI	[6, 16, 23, 34, 41, 68, 74]
3	Geographic data	[34, 67]
4	Socio-economic data	[16]
5	Infrastructure data: check, AMI verification	[6, 17, 68]
6	Meteorological data	[51]
7	Tariff rate	[16, 68, 74]
8	Payment by invoices	[16, 68]
9	NTL relapse, anomalies in accounts	[16]
10	Main equipment data	[16, 23]
11	Temporary data	[16, 34, 51, 74]

From Table 2, it can be concluded that the most frequently used factors are historical data and consumer information. Retrospective energy consumption data (Feature 1) is foundational because it enables the creation of consumer load profiles and the identification of deviations from established patterns. This directly leverages the data-generating capability of AMI.

Consumer information (Feature 2) enhances model accuracy by providing context, such as property type and contract details, which can correlate with risk profiles. Features containing consumer information are also quite frequently used because they contain some unique personal data regarding consumers or households. These characteristics allow NTL detection algorithms to significantly improve the accuracy of NTL detection. Such features are also very useful for more complex machine learning algorithms, as demonstrated in studies [6, 16, 23, 34, 41, 68, 74].

Other feature categories, although used less frequently, address specific dimensions of the problem. Features such as geographic location (3) and socio-economic data (4) can help in identifying area-based risk clusters. Infrastructure and verification data (5) are crucial for models focusing on meter integrity, while temporal features (11) are key for capturing seasonal or cyclical consumption patterns.

It should be noted that features play a crucial role in building high-quality machine learning models. For NTL detection, the most frequently used factors in various studies were the following: retrospective data and various information regarding the consumer (household) and AMI. It is also possible to use other features: geographic, socio-economic, and infrastructure data. The main criterion for using any of the factors, in addition to its proven relevance and influence on the target variable, is the availability, quality, and reliability of the data.

4. Data Mining and NTL Detection Methods

As established in the proposed classification framework, the applicability and effectiveness of data-driven methods for NTL detection are intrinsically linked to the level of distribution grid digitalization and the structure of available data. This section analyzes three principal analytical paradigms, namely, classification, clustering, and predictive/scenario modeling, in the context of practical data and infrastructure constraints faced by utilities.

Given the high practical relevance of NTL, it is essential to systematize existing approaches, identify their advantages and limitations, and highlight the most effective methodologies. Intelligent data analysis in the reviewed studies is predominantly based on three concepts:

1) Supervised classification of consumers using labeled datasets.
2) Unsupervised clustering.
3) Consumption forecasting combined with heuristic decision rules.

A key methodological challenge in this analysis is the comparability of the reported results because most studies rely on heterogeneous datasets and experimental settings. Although a fully objective comparison of NTL detection performance is therefore not feasible, the reviewed literature enables the identification of robust methodological trends and the most promising directions for further development.

4.1. Analysis of classification methods and algorithms used in detecting NTL

Supervised classification represents the most direct and accurate approach to NTL detection in fully digitalized grids with widespread AMI deployment because it requires labeled historical consumption time series for model training. In this context, NTL detection is commonly formulated as a binary classification task, where consumers are assigned to either normal or abnormal consumption classes. A wide range of machine learning algorithms has been applied to this problem, and no single universally optimal method has emerged, with performance strongly dependent on data characteristics and hyperparameter selection.

In most studies, abnormal consumption is used as a proxy for NTL, enabling an approximate comparison of classification-based solutions across the literature. A major obstacle to systematic comparison is dataset heterogeneity. However, a significant number of works rely on the publicly available dataset of the State Grid Corporation of China (SGCC). This benchmark dataset comprises smart meter time-series data for 42,372 consumers with 1,037 features and binary labels (normal/fraudulent) covering the period from January 2014 to October 2016. Its widespread adoption provides a rare opportunity for controlled comparison of algorithmic performance, motivating the separate analysis of SGCC-based studies (Table 3) and those using alternative datasets (Table 4).

The analyses shown in Tables 3 and 4 reveal several consistent patterns and challenges. First, hybrid and ensemble models dominate among top-performing approaches. Combinations of deep learning architectures (CNN, LSTM, and GRU) with ensemble techniques such as XGBoost, LightGBM, and CatBoost consistently achieve high performance, leveraging both representation learning and robust decision boundaries. At the same time, comparatively simple models, including random forest and CatBoost, demonstrate stable results, reflecting their suitability for structured, tabular AMI data.

Second, virtually all high-performing studies explicitly address two fundamental data challenges. The first is class imbalance because fraudulent consumers represent a small minority. The extensive use of resampling and imbalance-handling techniques such as SMOTE, SMOTEENN, and LoRAS indicates that classification performance is highly sensitive to imbalance mitigation strategies. The second challenge is data quality, particularly missing values in time series. Successful approaches integrate dedicated preprocessing stages, including interpolation methods (e.g., PCHIP) and autoencoder-based representations, underscoring that data preparation is as critical as model choice.

Third, reported performance metrics—often exceeding F1-scores of 0.95—must be interpreted cautiously. These results are typically obtained under controlled experimental conditions using curated benchmark datasets such as SGCC. In real-world utility environments, performance may degrade due to data drift, evolving fraud patterns, and increased noise. Moreover, the superior accuracy of deep and ensemble models often comes at the expense of interpretability, which remains a significant barrier for deployment in regulated power systems. Hyperparameter tuning further increases computational cost and implementation complexity.

An additional concern relates to ethical considerations and potential bias. The reliance on consumer data for classification raises risks of unfair targeting, particularly when socio-economic or geographic features are implicitly encoded in the data. False positives may lead to unjustified penalties and erosion of consumer trust, emphasizing the need for explainable, fair, and accountable AI solutions incorporating bias mitigation and XAI techniques.

Beyond supervised learning, reinforcement learning (RL), particularly deep reinforcement learning (DRL), has recently attracted attention in NTL detection. Unlike static classifiers trained on fixed datasets, RL agents learn optimal decision policies through sequential interaction with an environment. In the NTL context, the environment may represent streaming smart meter data, while agent actions correspond to consumer classification decisions, with rewards defined by detection outcomes.

This paradigm addresses several limitations identified in supervised classification. First, RL naturally accommodates class imbalance by assigning higher rewards to correctly detected fraud cases, enabling direct optimization of recall without synthetic resampling. Second, RL supports adaptive and cost-aware feature selection, allowing agents to focus on the most informative subsets of high-dimensional AMI data. Studies such as Sun et al. [59] and Lee et al. [75] demonstrate that DRL-based models can achieve competitive detection accuracy while improving robustness and efficiency.

However, RL introduces additional complexity, including environment and reward design, high computational demands, and limited interpretability of learned policies. Despite these challenges, reinforcement learning represents a promising alternative to passive classifiers, offering adaptive and sequential decision-making capabilities.

Finally, it should be emphasized that hyperparameter tuning is a critical component of all machine learning-based NTL detection approaches. Proper selection of network architectures, learning rates, batch sizes, and optimization strategies is essential for achieving

Table 3
Comparative analysis of classification methods used for detecting NTL for SGCC sample studies

Reference	Method	Metrics				
		F1-score	ROC–AUC	Accuracy	Precision	Recall
[35]	Principal component analysis and K-means clustering to extract patterns. Meta-OCSVM for classifier	0.886	0.885	0.885	0.908	0.911
[63]	Gated recurrent unit (GRU) + CNN, DL hybrid model (named HGC)	0.9452	0.987	0.9438	–	0.917
[46]	Hybrid ANN: time generative adversarial network (GAN) + Bi-LSTM + ResNet + AlexNet + CatBoostClassifier	–	0.968	–	0.966	0.968
[47]	LightGBM + LSTM + k-nearest neighbors	0.999	0.986	–	–	0.989
[48]	Convolution–non-convolution parallel deep network (CNCP)	0.968	0.940	0.969	0.951	0.987
[39]	Extremely randomized trees machine	0.980	0.996	0.980	0.970	–
[13]	Deconvolutional neural network + CNN	0.928	0.934	0.953	0.912	0.923
[49]	CatBoost	0.937	–	0.930	0.950	0.920
[66]	Feed forward DNN (deep neural network) + Bayesian optimizer + principal component analysis (PCA)	–	0.970	0.918	–	–
[72]	Genetic algorithms (GA) and XGBoost	–	0.960	0.978	0.920	0.890
[19]	LSTM-TCN (temporal convolutional networks) and deep convolutional neural network (DCNN)	0.948	0.986	–	0.932	0.964
[54]	Two-stage TimeGAN with an integrated two-layer stacking optimization configuration	–	0.840	–	–	–
[73]	LSTM and federated-learning-based stacking ensemble GRU algorithm (FL-SE-GRU)	0.967	–	0.950	0.966	–
[22]	CNN-AdaBoost	0.956	–	0.964	0.941	0.957
[57]	CNN	–	0.816	–	–	0.814
[52]	AE, the wide CNN (1-D CNN model), and the deep CNN (2-D CNN model)	0.970	0.956	0.974	0.970	0.970
[21]	Hybrid resampling technique notably + Bi-GRU	0.990	0.988	0.990	0.989	0.988
[26]	Borderline SMOTE and PCA + meta classifier (4 models LightGBM, quadratic discriminant analysis, XGBoost, AdaBoost)	0.940	0.920	0.940	0.950	0.940
[69]	SMOTE for monthly data of electricity consumption + XGBoost	0.940	–	0.990	0.980	0.900
[27]	Random forest and K-nearest neighbors (KNN)	0.900	0.890	0.890	0.830	0.980
[50]	Dynamic generative residual graph neural networks (DGRGNN)	0.873	–	–	–	–
[30]	Piecewise cubic Hermite interpolating polynomial (PCHIP) for filling missing values, combination of the synthetic minority over-sampling technique (SMOTE) and the edited nearest neighbors (ENN) + SMOTEENN for data resampling, omni-scale CNN, and AutoXGB for classification	0.955	0.984	0.992	0.975	0.941
[31]	Density-based spatial clustering of applications with noise (DBSCAN) + random forest	0.996	0.996	0.996	0.995	0.996
[32]	Anomaly models for balanced data + ANN with DenseNet121 architecture	0.805	0.870	0.940	0.864	0.903
[59]	Deep reinforcement learning with fuzzy C-means	–	0.879	0.882	–	–
[76]	LSTM + auto-encoder with attention	0.955	0.930	0.960	–	–
[58]	Largest triangle three bucket and supervised contrastive learning	–	0.816	–	–	0.814
[33]	Localized random affine shadow sampling (LoRAS) + LSTM	0.971	–	0.970	0.988	–

reported performance and often constitutes a substantial practical burden.

In summary, classification-based methods demonstrate high accuracy on benchmark datasets such as SGCC and remain the dominant paradigm for NTL detection in fully digitalized grids. Their principal limitation is a strong dependence on detailed AMI data, which restricts applicability in networks equipped with traditional metering infrastructure. This lack of universality motivates the consideration of clustering and regression-based approaches, which are better suited to settings with limited data resolution or digitalization.

Table 4
Comparative analysis of classification methods on different samples

Reference	Method	Metrics				
		F1-score	ROC–AUC	Accuracy	Precision	Recall
[44]	CNN	0.840	0.940	–	0.880	0.810
[36]	The Pearson's chi-square + boosted C5.0 decision tree (DT)	0.849	0.940	0.934	0.932	–
[6]	Multilayer perceptron (MLP) and GRU	0.920	0.930	0.930	–	–
[41]	ML ensemble classifier based on a majority voting mechanism	0.949	–	0.947	0.948	0.949
[14]	Random forest	–	0.900	–	–	–
[64]	Focal loss-based 1D densely connected convolutional network (FLB-DCNN)	0.982	–	–	0.985	0.981
[67]	K-means + MLP	–	0.981	–	–	–
[16]	CatBoostClassifier	0.985	–	–	0.980	0.985
[43]	Periodicity-enhanced deep one-class classification framework	0.833	0.973	–	–	0.877
[18]	Autoencoder + OC-SVM	0.964	–	0.956	0.922	0.998
[71]	Fully connected feedforward autoencoder	0.853	–	0.842	0.800	–
[77]	Chebyshev graph CNN	0.975	0.998	–	0.976	0.975
[55]	Random-over-sampler (ROS) and deep learning model	0.910	–	0.910	0.890	0.940
[56]	Multitask deep residual network (MDRN)	–	0.938	0.932	–	–
[34]	CatBoost	0.990	–	–	0.990	0.990
[25]	LSTM	0.885	–	–	0.885	0.885
[68]	CatBoost	0.894	–	0.897	–	–
[28]	Ensemble learning and prototype learning with CNN and LSTM	–	0.965	–	–	–
[29]	XGBoost	–	0.987	0.955	0.988	0.921
[45]	Inner product functional encryption (IPFE) + CONVLSTM	–	–	0.947	0.988	0.985
[51]	LSTM and full hybrid quantum variational circuit data-reuploading circuit (FH-QVC-DRC)	0.976	0.983	0.977	0.991	0.962
[74]	Support vector machine with radial basis function	0.690	–	0.700	0.700	0.690
[75]	Deep Q-learning + 1D-CNN	0.968	–	–	–	0.989
[62]	Multiclass random forest classifier	0.841	0.927	0.850	–	–
[60]	ConvLSTM	–	–	0.913	–	–
[78]	RF + ANN + scoring model	0.916	0.961	0.942	0.925	0.908
[11]	Ensemble metaclassifier	0.660	0.877	0.910	0.752	0.588
[79]	Robust regression + CNN	0.961	–	0.980	1	0.925

4.2. Analysis of clustering methods and algorithms in detecting NTL

Unsupervised clustering and anomaly detection methods offer a practical alternative for distribution grids with partial AMI coverage or limited availability of labeled data. These approaches can operate on aggregated consumption values and do not require a predefined target variable, making them applicable in grids with heterogeneous infrastructure. Clustering enables the identification of structurally similar consumer groups without prior knowledge of class labels, which distinguishes it from supervised classification.

Clustering is particularly valuable at the exploratory analysis stage, where predefined loss classes are absent or incomplete. This allows the discovery of previously unaccounted for imbalance patterns and anomalous consumer profiles, as well as the verification and refinement of existing loss categorizations by assessing their correspondence to data-driven groupings. Consequently, clustering supports both the identification of novel NTL manifestations and the objective validation of expert-defined loss classes.

This problem formulation has both strengths and limitations, which motivates a review of recent studies applying clustering-based methods to NTL detection. The comparative analysis focuses on the following:

1) The clustering methodologies employed.
2) Data characteristics, including feature sets, temporal resolution, and consumer scale.
3) Performance metrics used for NTL detection.

The generalized results are summarized in Table 5.

On the basis of the comparative analysis, several general advantages of the clustering-based approaches can be identified:

First, clustering algorithms are well suited for distribution systems with partial AMI deployment. Second, they are typically less

Table 5
Comparative analysis of clustering methods for NTL detection

Reference	Method	Advantages of the method	Disadvantages of the method
[80]	SA-GCN and TLSA-GCN	Mitigates data scarcity via transfer learning pre-training and fine-tuning. A single adaptable model reduces per-user training overhead. Self-supervision focuses feature extraction on salient data patterns.	High computational complexity. Recall metrics (0.814, 0.802, 0.807, and 0.802) are lower than typical supervised classifiers.
[81]	K-means and LSTM	Enables real-time theft detection through continuous model updating.	Effectiveness evaluation is complex. Requires installation of specific hardware on medium-voltage networks and 4G data transmission.
[37]	DWT, fuzzy C-means, & weighted multiclass logistic regression (ensemble)	Effective with limited labels and novel theft patterns. Combines multiscale feature extraction (DWT), fuzzy clustering, and ensemble learning for complex dependency capture.	Model acts as a "black box" with interpretability challenges. Reported performance (F1: 0.77, AUC: 0.86, accuracy: 0.88) is below supervised benchmarks.
[64]	Stacked sparse denoising autoencoder (SSDAE)	Outperforms benchmark methods such as SVM and PCA in anomaly detection.	Functions offline, not in real-time. Requires retraining for dataset shifts.
[82]	VAE-GAN & K-means (hybrid generative model)	The VAE-GAN extractor captures temporal data distributions effectively, achieving a precision of 0.92 when combined with K-means.	Computationally intensive and slow to train. Potential instability and risk of non-convergence during learning.
[15]	ANN and (C&R and SOM)	Two-stage pipeline (ANN filtering + rule-based inspection) improved field inspection success rate from 5% to 14.75%.	Final detection rate (14.75%) remains relatively low, indicating room for accuracy improvement.
[10]	K-means, interquartile range, consumption forecasting	Enables prompt detection of anomalies (theft or meter faults) suitable for AMI-equipped networks.	Cannot reliably identify theft sustained over long periods (>2 weeks) due to stabilized anomalous consumption patterns.
[53]	Comparative study (autoencoder, ANN, ANFIS, K-means)	Provides a detailed practical evaluation and comparison of multiple unsupervised and hybrid methodologies.	Autoencoder cannot specify anomaly type. K-means occasionally misclassifies honest consumers. No single method excels across all anomaly types.
[83]	SFS-GSKF and AIAD-AL	Reduces labeling cost by filtering the most valuable samples for annotation. The adaptive incremental algorithm is designed for evolving data.	Detection performance degrades when training samples lack representative load patterns.
[42]	Periodicity-enhanced deep one-class classification framework (PE-DOCC)	Two-stage approach (unsupervised representation learning + one-class classification) with a cross-periodic attention mechanism for high accuracy. Reported metrics: F1 = 0.833, AUC = 0.973, recall = 0.877.	Requires further validation across diverse theft scenarios and datasets to confirm robustness and generalizability.

computationally demanding than supervised classification methods, which is a relevant advantage when scaling analysis to millions of consumers. Third, clustering-based detection schemes often exhibit structurally simpler decision pipelines, reducing implementation complexity.

In addition, Meng et al. [80] emphasized that despite the relative ease of large-scale data collection, labeled datasets remain costly and difficult to obtain. From this perspective, the absence of labeling requirements constitutes a fundamental advantage of clustering over classification-based approaches.

At the same time, the analysis reveals notable shortcomings. The most significant limitation is the generally lower detection accuracy compared to supervised classification models. Moreover, although clustering does not rely on labeled targets, it remains sensitive to feature quality and representation, which directly affects the stability and interpretability of the resulting clusters.

In summary, clustering-based methods provide a universal and flexible toolset for NTL detection under constrained data and infrastructure conditions. They enable the analysis of heterogeneous datasets, reduce dependence on labeled samples, and facilitate the discovery of emerging or unconventional NTL patterns. However, these benefits are offset by lower detection accuracy and weaker interpretability relative to supervised models, alongside continued dependence on high-quality input features.

4.3. Analysis of predictive analytics methods and scenario modeling tools to reduce NTL

Predictive analytics, including forecasting and scenario modeling, provides a versatile toolkit applicable across different levels of grid digitalization. These approaches rely on similar predictive principles but address distinct operational tasks. Forecasting-based methods focus on the direct detection of anomalies by comparing predicted and actual electricity consumption, whereas scenario modeling supports strategic decision-making by assessing the potential impact of different interventions on NTL reduction. Accordingly, this section reviews data-driven approaches employing forecasting and scenario modeling for addressing NTL.

Forecasting-based NTL detection typically involves a two-stage process applied to a set of consumers. A number of papers [2, 23, 70, 84] propose analytical models (regression) that combine two main stages:

1) The construction of a reliable household-level consumption forecast (e.g., using LSTM networks [23]).
2) The identification of suspicious consumers by evaluating deviations of actual consumption from predicted thresholds, followed by deviation classification.

The main limitation of this approach is its strong dependence on low forecasting error. Consequently, forecasting-based detection is most effective for identifying recent or emerging NTL events and is particularly suitable for systems with partial AMI deployment.

Coma-Puig and Carmona [84] demonstrated that regression-based NTL detection offers advantages in terms of reliability, explainability, and cost-effectiveness. Their approach employs Shapley values for local explanations, ensuring consistency between local and global model interpretations. The use of Shapley values, including TreeSHAP for tree-based models, provides a theoretically grounded and robust explanation framework, enhancing trust in model predictions for practical deployment.

Chen et al. [70] proposed a blending ensemble learning methodology based on a base learner selection strategy. The model performs short-term forecasts of next-day electricity consumption in station areas using historical data and identifies zones where losses exceed predefined thresholds. Experimental results demonstrate high detection performance, with the blending-LightGBM configuration achieving accuracy, ROC–AUC, and F1-score values of 0.975, 0.961, and 0.986, respectively, enabling the effective identification of theft patterns and reduction of economic losses.

Several studies integrate forecasting with classification techniques. Bondok et al. [18] first trained a predictor exclusively on normal consumption data and applied clustering to group consumers with similar load profiles, allowing the use of specialized predictors per cluster. Subsequently, an autoencoder and a one-class SVM were employed for theft classification. The approach achieved low forecasting error (MAAPE of 3.17%–3.61%) and high detection performance, with accuracy, precision, recall, and F1-scores of 95.6%, 92.2%, 99.8%, and 96.4%, respectively.

In contrast to direct detection, scenario modeling provides utilities with strategic tools to assess the effectiveness of NTL reduction measures prior to implementation, supporting investment planning and policy design. Scenario modeling typically involves analytical calculations conducted by distribution companies to monitor network performance indicators [85]. Studies in this domain employ econometric and statistical techniques, including difference-in-differences fixed-effect models [4], stochastic frontier analysis, correlation analysis, Box–Jenkins (ARIMA) models [38, 43], and spatial error models [61]. These methods enable the estimation and forecasting of commercial loss levels across regions and support the evaluation of achievable NTL reduction targets under alternative scenarios [4, 61].

From a practical perspective, such modeling supports utilities in prioritizing AMI rollout in high-loss areas, evaluating the cost-effectiveness of anti-theft campaigns, and forecasting revenue impacts of regulatory or tariff changes.

Kankonde and Bokoro [86] presented a comprehensive quantitative and behavioral analysis of electricity theft in Kinshasa (DRC), highlighting both technical and socioeconomic drivers. Their methodology combines bootstrapping for model robustness with power analysis to ensure sample adequacy. A logistic regression model, refined through Lasso-based feature selection, identified electricity supply quality, financial stress, tampering awareness, and billing transparency as key predictors of theft. The results underline the necessity of combining technical upgrades with socioeconomic and regulatory measures to effectively address electricity theft.

Decision-support modeling is also applied to rank and evaluate factors contributing to electricity losses at different grid levels [61]. Naqvi et al. employed a least squares approach to forecast total losses, achieving an adjusted R^2 of 0.57. Input features included feeder losses, total consumption, customer composition, population density, and fixed effects related to power supply devices. This enables targeted inspection campaigns in zones with the highest commercial losses, improving the efficiency of mitigation efforts.

Raggi et al. [17] proposed a data mining method for detecting and localizing NTL caused by illegal connections through the analysis of “bad” data. Detection is initially based on normalized residuals of active and reactive power measurements. To address the absence of voltage information, the authors introduce an index Ψ that combines power and voltage residuals, significantly improving detection robustness and localization accuracy. Validation on real MV and LV feeders with 1682 buses demonstrated the capability to detect NTL as low as 2 kW (LV) and 23 kW (MV), highlighting the value of large-scale smart meter deployment without additional infrastructure investments.

Vlasa et al. [87] introduced the blind sparky algorithm, which applies an optimization-based approach to identify nodes with significant NTL arising from incorrect metering. The method exploits smart metering data and incorporates multicriteria considerations addressing both technical faults and intentional tampering.

The difference-in-differences fixed-effect approach applied in [4] evaluates the impact of digital meter deployment combined with prepayment schemes. Results indicate an average increase of 13.2% in effective electricity supply, evidencing substantial pre-installation NTL. Quantile regression further revealed increased consumption across most households, except for the lowest consumption quantile.

In conclusion, predictive analytics methods offer relative simplicity and low requirements for AMI penetration and data granularity. Their effectiveness, however, depends strongly on forecast accuracy because deviations between predicted and actual consumption serve as the primary anomaly indicator. While forecasting-based approaches are less effective in identifying long-term, sustained fraud and generally exhibit higher error rates than supervised classification, they remain valuable for trend analysis and scenario evaluation. Regression-based methods, in particular, play an important role in monitoring NTL dynamics and supporting strategic decision-making for distribution companies.

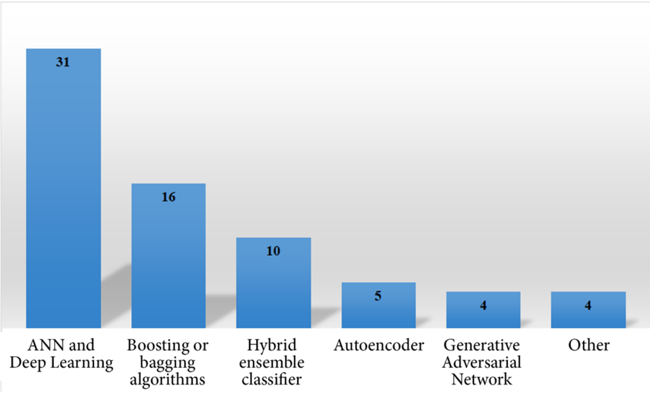
4.4. Description of research object infrastructure

The analysis of classification algorithms indicates that this group of methods constitutes a highly effective tool for data-driven NTL detection and contributes to improving the operational stability of distribution networks. In the majority of the reviewed studies, retrospective consumption data and consumer-specific features serve as the primary inputs, reflecting the ongoing modernization of power systems and the widespread deployment of AMI. This confirms supervised classification as the preferred analytical paradigm for distribution grids with a high level of digitalization.

Most datasets analyzed in the literature are characterized by hourly or daily temporal resolution and a large number of consumers. Figure 3 illustrates the distribution of the reviewed publications by machine learning classifier type, providing a quantitative overview of the most frequently applied techniques. The qualitative analysis presented in Section 4.1 supports the trends identified in this distribution.

The highest detection performance is reported for neural network architectures and ensemble-based algorithms. At the same time, several recurring challenges are identified, including target class imbalance

Figure 3
Distribution of NTL detection methods by classifier machine learning techniques



and feature selection complexity. Insufficient mitigation of these issues often leads to inflated accuracy values accompanied by substantially lower AUC scores, indicating a non-negligible risk of misclassifying NTL cases.

Despite their high reported accuracy, classification-based approaches exhibit inherent limitations. Their effectiveness depends on the availability of large, labeled training datasets and is therefore constrained to grids equipped with automated metering infrastructure. This lack of universality prevents their application in networks relying on induction (mechanical) meters and manual data collection, motivating the continued relevance of alternative paradigms.

Clustering-based methods, while generally exhibiting lower detection accuracy than supervised classification, remain attractive due to their independence from labeled data. Their key advantages include flexibility in handling heterogeneous, non–time-series data and the ability to identify anomalous consumption patterns under partial AMI deployment. These properties enable the analysis of power systems with varying degrees of digitalization and facilitate the discovery of previously unobserved NTL mechanisms. Moreover, clustering is frequently employed as a preprocessing step in classification pipelines to group consumers, reduce feature dimensionality, and improve downstream detection performance.

Regression-based approaches, focused on forecasting continuous consumption or loss-related variables, provide an effective framework for predictive analytics and scenario evaluation in distribution network management. By incorporating both exogenous and endogenous factors, regression models enable rapid construction of reliable consumption forecasts and estimation of total network losses. This functionality is particularly valuable for monitoring systems aimed at early detection of abnormal consumption and timely managerial intervention.

Importantly, regression-based solutions can be applied both in digitally advanced environments with IoT infrastructure and in systems relying on manual data collection and mechanical meters. This broad applicability significantly expands the scope of regression methods, enhancing transparency and control in distribution network operations and supporting informed decision-making at the managerial level.

4.5. Proposed classification of artificial intelligence methods used in NTL detection

On the basis of the analysis of the reviewed literature, a classification of artificial intelligence methods used for NTL detection was developed (Figure 1). The proposed classification groups methods according to the machine learning paradigm—supervised learning, unsupervised learning, and predictive analytics—and is grounded in their dependence on the level of digitalization and configuration of the power grid infrastructure. This approach enables the selection of appropriate analytical methods under specific smart grid operating conditions.

For fully digitalized distribution networks with extensive AMI deployment, supervised classification methods demonstrate the highest effectiveness due to their ability to process labeled, high-resolution consumption time series and achieve superior detection accuracy. In such environments, intelligent data analysis for NTL detection should be primarily based on classification algorithms, with the choice of specific models determined by operational constraints and validated practical experience reported in the literature [6, 11–14, 16, 18, 19, 21, 22, 25–36, 39, 41, 43–52, 54–64, 66–69, 71–79].

In grids characterized by partial digitalization, limited AMI penetration, or the absence of reliable labeled datasets, unsupervised clustering and anomaly detection methods represent a viable alternative. These approaches operate on aggregated or heterogeneous data and do not require explicit fraud labels, making them particularly relevant for developing power systems with mechanical metering devices and manual data collection. Their application, however, must consider the assumptions and limitations identified in existing studies [10, 15, 37, 42, 53, 64, 80–83].

Predictive analytics, primarily implemented through regression-based models, constitutes a universal analytical layer applicable across all types of grid infrastructure. Forecasting enables indirect NTL detection through deviation analysis in systems with predictable consumption behavior, while scenario modeling supports strategic planning and investment decision-making aimed at loss reduction. Integrating regression methods into electricity consumption monitoring systems facilitates rapid identification of abnormal consumption, quantitative assessment of losses, and timely development of corrective measures. The selection of regression models should account for data structure, temporal resolution, and the specific characteristics of energy systems [2, 4, 17, 18, 23, 38, 43, 61, 70, 84–87].

A comparative analysis of classification, clustering, and regression approaches is presented in Table 6, highlighting differences in objectives, data requirements, outputs, advantages, and limitations. These methodological approaches are not mutually exclusive and are often combined within integrated analytical frameworks. A typical architecture involves clustering for preliminary consumer segmentation and identification of risk groups, supervised classification for targeted detection of potential violators, and regression for estimating economic damage and prioritizing inspections. Such integration improves both detection accuracy and the overall efficiency of inspection planning.

Despite their advantages in terms of accuracy and operational efficiency, intelligent NTL detection methods introduce significant challenges related to privacy and cybersecurity. High-performance models require fine-grained consumption data, which may reveal sensitive information regarding consumer behavior, creating a conflict between loss minimization objectives and privacy protection. To address this issue, contemporary research increasingly focuses on privacy-enhancing technologies, including differential privacy, data aggregation, federated learning, and homomorphic encryption, which enable model training and analysis without centralizing raw personal data and facilitate compliance with regulatory frameworks such as the GDPR.

Cybersecurity is an equally critical concern because intelligent NTL detection systems form part of the smart grid's critical digital infrastructure and are potential targets for data manipulation, model poisoning, and evasion attacks. Ensuring reliability requires the development of robust and explainable models, secure data

Table 6
Comparative analysis of machine learning methods applied to identify sources of NTL

Criterion	Classification	Clustering	Regression
Main task	Assigning a consumer (or consumption profile) to a predefined class, most often "norm"/"fraud" (NTL).	Identifying hidden groups (clusters) in data without using predefined labels. Grouping similar consumption patterns.	Forecasting a continuous numerical quantity, such as the expected volume of consumption and the amount of loss.
Training type	Supervised learning (requires labeled historical data with known fraud cases).	Unsupervised learning (works with unlabeled data; group labels are not known in advance).	Supervised learning (requires data where the target continuous variable, such as actual consumption, is known).
Goal in the NTL context	Direct detection of potential intruders. Binary or multiclass anomaly identification.	Consumer segmentation and detection of anomalous patterns. Useful for identifying new, unknown types of fraud and analyzing risk groups.	Estimating the volume of losses and forecasting standard consumption. Comparing the forecast with actual readings to quantify deviations.
Key algorithms (examples)	Decision trees (random forest, XGBoost), SVM, neural networks, logistic regression.	K-means, DBSCAN, hierarchical clustering, self-organizing maps (SOM).	Linear regression, Ridge/ Lasso regression, tree-based regression (random forest, gradient boosting), neural networks.
Main benefits	1) High interpretability (especially for trees) of priority features. 2) Direct and understandable output (binary flag). 3) High accuracy with high-quality labeled data.	1) Does not require labeled data, which is critical due to the rarity and obscurity of NTL labels. 2) Ability to detect unknown anomalies and new theft patterns. 3) Allows for in-depth analysis of consumption profiles.	1) Quantitative assessment of the scale of losses in monetary or energy terms. 2) Allows for ranking suspected losses by potential damage. 3) A basis for creating benchmarks for "normal" consumption.
Typical model output	Class label: 0 (normal) or 1 (suspected NTL). Probability of class membership.	Cluster membership (group number) or outlier score (e.g., distance to centroid).	Numerical value: predicted consumption (kWh) or estimated loss level.
Main challenge	Class imbalance: legitimate consumers significantly outnumber fraudsters, which requires special techniques (undersampling, oversampling, cost-sensitive learning).	1) Interpretation of results: Experts must analyze the identified clusters to determine which ones represent fraud and which ones represent legitimate consumption patterns. 2) Selecting a metric and the number of clusters.	Forecast accuracy: consumption is affected by many external factors (weather, holidays, day type), which must be taken into account in the model.

transmission, integrity monitoring, regular vulnerability assessments, and architectures resilient to partial system compromise. Consequently, effective mitigation of commercial losses necessitates treating NTL detection systems as critical IT infrastructure with security mechanisms embedded at the design stage.

The results of this review provide a methodological foundation for the development and deployment of effective NTL detection systems, contributing to loss reduction, enhanced grid stability, and reliable power supply to end consumers.

5. Conclusion

This systematic review analyzed 79 studies published between 2020 and 2025 that address data-driven methods for NTL detection in distribution power systems. The main conclusion is that no universal NTL detection method exists; the effectiveness of a given approach is critically determined by the level of grid digitalization, AMI penetration, and data availability.

The reviewed literature confirms that data-driven NTL detection significantly contributes to reducing commercial losses and improving distribution network stability. The dominant causes of NTL are deliberate consumer actions (e.g., unauthorized consumption and meter manipulation) and metering system errors, with partial and intermittent NTL remaining particularly challenging to identify. This underscores the importance of intelligent detection algorithms capable of operating under uncertainty and incomplete information.

Most studies rely on retrospective consumption profiles, AMI data, and consumer-related attributes, often complemented by geographic, socio-economic, and infrastructure features. Data availability, quality, and reliability remain the key prerequisites for effective model deployment. Although Python-based toolchains dominate due to their flexibility and extensive libraries, computational efficiency and hardware demands remain practical constraints for large-scale implementations.

A comparative analysis of methodological approaches highlights clear application domains. Supervised classification methods, including hybrid deep learning models, achieve the highest detection accuracy in fully digitalized grids with labeled AMI data but are limited by labeling costs and reduced interpretability. Unsupervised clustering and anomaly detection methods are essential for partially digitalized or legacy grids without labeled data, enabling the discovery of previously unknown fraud patterns at the cost of lower and less stable accuracy. Forecasting and scenario-based regression models are most effective for continuous monitoring, loss quantification, and strategic planning, provided that reliable consumption patterns and exogenous data are available.

On the basis of these findings, a utility-oriented classification framework was developed (Figure 1), linking NTL detection methods to machine learning paradigms and infrastructure maturity. This framework provides a practical decision map for selecting appropriate analytical approaches and systematizes existing knowledge in the field.

Overall, this study demonstrates that the selection and development of NTL detection methods should primarily be driven by the automation level of the distribution utility and the structure of available data. Treating these factors as central design parameters enables the identification of the most suitable artificial intelligence techniques for a given grid context.

The review is subject to limitations related to dataset heterogeneity, limited reproducibility, and inconsistent evaluation protocols across studies. Moreover, many publications emphasize algorithmic performance while underreporting deployment costs, scalability, and integration challenges.

Future research should therefore focus on developing standardized benchmark datasets, improving model explainability to support operational adoption, designing robust hybrid methods adaptable to varying data quality, and conducting longitudinal real-world case studies that assess long-term effectiveness and total cost of ownership.

The results of this study may serve as a reference for researchers and practitioners involved in the development and deployment of NTL detection systems, offering a structured overview of modern methods, their capabilities, limitations, and optimal application conditions.

Recommendations

During the analysis of the review publications, it was found that NTL detection using machine learning methods is a relevant area of research in the field of loss reduction for distribution energy companies. Therefore, it is recommended to develop new NTL detection methods based on the processing of AMI energy consumption data and consumer profile information. Such tools will help employees of distribution companies minimize NTL and increase the stability of energy systems. For development, the most promising environment for modeling and training is the Python programming language.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Irbek D. Morgoev: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Roman V. Klyuev:** Conceptualization, Formal analysis, Writing – review & editing, Supervision. **Angelika D. Morgoeva:** Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Project administration.

References

[1] Ventura, L., Felix, G. E., Vargas, R., Faria, L. T., & Melo, J. D. (2023). Estimation of non-technical loss rates by regions. *Electric Power Systems Research*, *223*. https://doi.org/10.1016/j.epsr.2023.109685

[2] Rüstemli, S., Kocaman, Y., Kocaman, B., Şahin, G., & van Sark, W. (2025). The effect of using automatic meter reading system in electricity distribution systems on reducing non-technical losses: The case of Bitlis province in Turkey. *Energy Strategy Reviews*, *58*, 101674. https://doi.org/10.1016/j.esr.2025.101674

[3] Blazakis, K. V., Kapetanakis, T. N., & Stavrakakis, G. S. (2020). Effective electricity theft detection in power distribution grids using an adaptive neuro fuzzy inference system. *Energies*, *13*(12), 3110. https://doi.org/10.3390/en13123110

[4] Otchere-Appiah, G., Takahashi, S., Yeboah, M. S., & Yoshida, Y. (2021). The impact of smart prepaid metering on non-technical losses in Ghana. *Energies*, *14*(7), 1852. https://doi.org/10.3390/en14071852

[5] Koukouvinos, K. G., Koukouvinos, G. K., Chalkiadakis, P., Kaminaris, S. D., Orfanos, V. A., & Rimpas, D. (2025). Evaluating the performance of smart meters: Insights into energy management, dynamic pricing and consumer behavior. *Applied Sciences*, *15*(2), 960. https://doi.org/10.3390/app15020960

[6] Kabir, B., Qasim, U., Javaid, N., Aldegheishem, A., Alrajeh, N., & Mohammed, E. A. (2022). Detecting nontechnical losses in smart meters using a MLP-GRU deep model and augmenting data via theft attacks. *Sustainability*, *14*(22), 15001. https://doi.org/10.3390/su142215001

[7] Savian, F. de S., Siluk, J. C. M., Garlet, T. B., do Nascimento, F. M., Pinheiro, J. R., & Vale, Z. (2021). Non-technical losses: A systematic contemporary article review. *Renewable and Sustainable Energy Reviews*, *147*, 111205. https://doi.org/10.1016/j.rser.2021.111205

[8] Chuwa, M. G., & Wang, F. (2021). A review of non-technical loss attack models and detection methods in the smart grid. *Electric Power Systems Research*, *199*, 107415. https://doi.org/10.1016/j.epsr.2021.107415

[9] Saeed, M. S., Mustafa, M. W., Hamadneh, N. N., Alshammari, N. A., Sheikh, U. U., Jumani, T. A., …, & Khan, I. (2020). Detection of non-technical losses in power utilities—A comprehensive systematic review. *Energies*, *13*(18), 4727. https://doi.org/10.3390/en13184727

[10] Morgoev, I. D., Dzgoev, A. E., & Kuzina, A. V. (2024). Algorithm for operational detection of abnormally low electricity consumption in distribution. In A. A. Radionov & V. R. Gasiyarov (Eds.), *Advances in automation V* (pp. 37–49). Springer. https://doi.org/10.1007/978-3-031-51127-1_4

[11] Morgoev, I., Klyuev, R., & Morgoeva, A. (2025). Methodology for detecting non-technical energy losses using an ensemble of machine learning algorithms. *Computer Modeling in Engineering & Sciences*, *143*(2), 1381–1399. https://doi.org/10.32604/cmes.2025.064502

[12] Farshchian, G., Darestani, S. A., & Hamidi, N. (2021). Developing a decision-making dashboard for power losses attributes of Iran's electricity distribution network. *Energy*, *216*, 119248. https://doi.org/10.1016/j.energy.2020.119248

[13] Javaid, N., Jan, N., & Javed, M. U. (2021). An adaptive synthesis to handle imbalanced big data with deep Siamese network for electricity theft detection in smart grids. *Journal of Parallel and Distributed Computing*, *153*, 44–52. https://doi.org/10.1016/j.jpdc.2021.03.002

[14] Gunturi, S. K., & Sarkar, D. (2021). Ensemble machine learning models for the detection of energy theft. *Electric Power Systems Research*, *192*, 106904. https://doi.org/10.1016/j.epsr.2020.106904

[15] de Souza, M. A., Pereira, J. L. R., Alves, G. de O., de Oliveira, B. C., Melo, I. D., & Garcia, P. A. N. (2020). Detection and identification of energy theft in advanced metering infrastructures. *Electric Power Systems Research*, *182*, 106258. https://doi.org/10.1016/j.epsr.2020.106258

[16] Ghori, K. M., Abbasi, R. A., Awais, M., Imran, M., Ullah, A., & Szathmary, L. (2020). Performance analysis of different types of machine learning classifiers for non-technical loss detection. *IEEE Access*, *8*, 16033–16048. https://doi.org/10.1109/ACCESS.2019.2962510

[17] Raggi, L. M. R., Trindade, F. C. L., Cunha, V. C., & Freitas, W. (2020). Non-technical loss identification by using data analytics and customer smart meters. *IEEE Transactions on Power Delivery*, *35*(6), 2700–2710. https://doi.org/10.1109/TPWRD.2020.2974132

[18] Bondok, A., Abdelsalam, O., Badr, M., Mahmoud, M., Alsabaan, M., Alsaqhan, M., & Ibrahem, M. I. (2024). Accurate power consumption predictor and one-class electricity theft detector for smart grid "change-and-transmit" advanced metering infrastructure. *Applied Sciences*, *14*(20), 9308. https://doi.org/10.3390/app14209308

[19] Huang, Q., Tang, Z., Weng, X., He, M., Liu, F., Yang, M., & Jin, T. (2024). A novel electricity theft detection strategy based on dual-time feature fusion and deep learning methods. *Energies*, *17*(2), 275. https://doi.org/10.3390/en17020275

[20] Tsao, Y.-C., Rahmalia, D., & Lu, J.-C. (2024). Machine-learning techniques for enhancing electricity theft detection considering transformer reliability and supply interruptions. *Energy Reports*, *12*, 3048–3064. https://doi.org/10.1016/j.egyr.2024.08.068

[21] Ullah, A., Khan, I. U., Younas, M. Z., Ahmad, M., & Kryvinska, N. (2025). Robust resampling and stacked learning models for electricity theft detection in smart grid. *Energy Reports*, *13*, 770–779. https://doi.org/10.1016/j.egyr.2024.12.041

[22] Nirmal, S., Patil, P., & Kumar, J. R. R. (2025). CNN–AdaBoost based hybrid model for electricity theft detection in smart grid. *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, *7*, 100452. https://doi.org/10.1016/j.prime.2024.100452

[23] Tanwar, S., Kumari, A., Vekaria, D., Raboaca, M. S., Alqahtani, F., Tolba, A., …, & Sharma, R. (2022). GrAb: A deep learning-based data-driven analytics scheme for energy theft detection. *Sensors*, *22*(11), 4048. https://doi.org/10.3390/s22114048

[24] Ali, S., Yongzhi, M., & Ali, W. (2023). Prevention and detection of electricity theft of distribution network. *Sustainability*, *15*(6), 4868. https://doi.org/10.3390/su15064868

[25] Souza, M. A., Gouveia, H. T. V., Ferreira, A. A., de Lima Neta, R. M., Nóbrega Neto, O., da Silva Lira, M. M., …, & de Aquino, R. R. B. (2024). Detection of non-technical losses on a smart distribution grid based on artificial intelligence models. *Energies*, *17*(7), 1729. https://doi.org/10.3390/en17071729

[26] Hashim, M., Khan, L., Javaid, N., Ullah, Z., & Javed, A. (2024). Stacked machine learning models for non-technical loss detection in smart grid: A comparative analysis. *Energy Reports*, *12*, 1235–1253. https://doi.org/10.1016/j.egyr.2024.06.015

[27] Taruna, A. P., Arisona, G., Irwanto, D., Bestari, A. B., & Juniawan, W. (2025). Electricity theft detection using machine learning in traditional meter postpaid residential customers: A case study on state electricity company (PLN) Indonesia. *IEEE Access*, *13*, 7167–7191. https://doi.org/10.1109/ACCESS.2025.3526764

[28] Sun, X., Hu, J., Zhang, Z., Cao, D., Huang, Q., Chen, Z., & Hu, W. (2024). Electricity theft detection method based on ensemble learning and prototype learning. *Journal of Modern Power Systems and Clean Energy*, *12*(1), 213–224. https://doi.org/10.35833/MPCE.2022.000680

[29] Abraham, O. A., Ochiai, H., Hossain, M. D., Taenaka, Y., & Kadobayashi, Y. (2024). Electricity theft detection for smart homes: Harnessing the power of machine learning with real and synthetic attacks. *IEEE Access*, *12*, 26023–26045. https://doi.org/10.1109/ACCESS.2024.3366493

[30] Zhu, S., Xue, Z., & Li, Y. (2024). Electricity theft detection in smart grids based on omni-scale CNN and AutoXGB. *IEEE Access*, *12*, 15477–15492. https://doi.org/10.1109/ACCESS.2024.3358683

[31] Almalki, A. J. (2024). Unsupervised learning with hybrid models for detecting electricity theft in smart grids. *IEEE Access*, *12*, 187027–187040. https://doi.org/10.1109/ACCESS.2024.3498733

[32] Janthong, S., Chalermyanont, K., & Duangsoithong, R. (2023). Unbalanced data handling techniques for classifying energy theft and defective meters in the Provincial Electricity Authority of Thailand. *IEEE Access*, *11*, 46522–46540. https://doi.org/10.1109/ACCESS.2023.3274543

[33] Elshennawy, N. M., Ibrahim, D. M., & Gab Allah, A. M. (2025). An efficient electricity theft detection based on deep learning. *Scientific Reports*, *15*, 12866. https://doi.org/10.1038/s41598-025-93140-z

[34] Nwafor, O., Nwafor, C., Aboushady, A., & Solyman, A. (2024). Reducing non-technical losses in electricity distribution networks: Leveraging explainable AI and three lines of defence model to manage operational staff-related factors. *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, *9*, 100748. https://doi.org/10.1016/j.prime.2024.100748

[35] Massarani, A. H., Badr, M. M., Baza, M., Alshahrani, H., & Alshehri, A. (2025). Efficient and accurate zero-day electricity theft detection from smart meter sensor data using prototype and ensemble learning. *Sensors*, *25*(13), 4111. https://doi.org/10.3390/s25134111

[36] Saeed, M. S., Mustafa, M. W., Sheikh, U. U., Jumani, T. A., Khan, I., Atawneh, S., & Hamadneh, N. N. (2020). An efficient boosted C5.0 decision-tree-based classification approach for detecting non-technical losses in power utilities. *Energies*, *13*(12), 3242. https://doi.org/10.3390/en13123242

[37] Chen, H., Ma, R., Liu, X., & Liu, R. (2024). Detecting energy theft with partially observed anomalies. *International Journal of Electrical Power & Energy Systems*, *162*, 110323. https://doi.org/10.1016/j.ijepes.2024.110323

[38] González Rodríguez, R., Jiménez Mares, J., & Quintero M., C. G. (2020). Computational intelligent approaches for non-technical losses management of electricity. *Energies*, *13*(9), 2393. https://doi.org/10.3390/en13092393

[39] Appiah, S. Y., Akowuah, E. K., Ikpo, V. C., & Dede, A. (2023). Extremely randomised trees machine learning model for electricity theft detection. *Machine Learning with Applications*, *12*, 100458. https://doi.org/10.1016/j.mlwa.2023.100458

[40] Carr, D., & Thomson, M. (2022). Non-technical electricity losses. *Energies*, *15*(6), 2218. https://doi.org/10.3390/en15062218

[41] Mohammad, F., Saleem, K., & Al-Muhtadi, J. (2023). Ensemble-learning-based decision support system for energy-theft detection in smart-grid environment. *Energies*, *16*(4), 1907. https://doi.org/10.3390/en16041907

[42] Wu, Z., & Wang, Y. (2025). PE-DOCC: A novel periodicity-enhanced deep one-class classification framework for electricity theft detection. *Applied Sciences*, *15*(4), 2193. https://doi.org/10.3390/app15042193

[43] de Oliveira Ventura, L., Melo, J. D., Padilha-Feltrin, A., Fernández-Gutiérrez, J. P., Sánchez Zuleta, C. C., & Piedrahita Escobar, C. C. (2020). A new way for comparing solutions to non-technical electricity losses in South America. *Utilities Policy*, *67*, 101113. https://doi.org/10.1016/j.jup.2020.101113

[44] Li, J., & Wang, F. (2020). Non-technical loss detection in power grids with statistical profile images based on semi-supervised learning. *Sensors*, *20*(1), 236. https://doi.org/10.3390/s20010236

[45] Anin, J., Khan, M. J., Abdelsalam, O., Nabil, M., Hu, F., & Alsharif, A. (2024). Efficient and privacy-preserving ConvLSTM-based detection of electricity theft cyber-attacks in smart grids. *IEEE Access*, *12*, 153089–153104. https://doi.org/10.1109/ACCESS.2024.3478068

[46] Sun, Y., Sun, X., Hu, T., & Zhu, L. (2023). Smart grid theft detection based on hybrid multi-time scale neural network. *Applied Sciences*, *13*(9), 5710. https://doi.org/10.3390/app13095710

[47] Xia, R., Gao, Y., Zhu, Y., Gu, D., & Wang, J. (2022). An efficient method combined data-driven for detecting electricity theft with stacking structure based on grey relation analysis. *Energies*, *15*(19). https://doi.org/10.3390/en15197423

[48] Wang, Y., Jin, S., & Cheng, M. (2023). A convolution–non-convolution parallel deep network for electricity theft detection. *Sustainability*, *15*(13), 10127. https://doi.org/10.3390/su151310127

[49] Hussain, S., Mustafa, M. W., Jumani, T. A., Baloch, S. K., Alotaibi, H., Khan, I., & Khan, A. (2021). A novel feature engineered-CatBoost-based supervised machine learning framework for electricity theft detection. *Energy Reports*, *7*, 4425–4436. https://doi.org/10.1016/j.egyr.2021.07.008

[50] Zhuang, W., Jiang, W., Xia, M., & Liu, J. (2024). Dynamic generative residual graph convolutional neural networks for electricity theft detection. *IEEE Access*, *12*, 42737–42750. https://doi.org/10.1109/ACCESS.2024.3379201

[51] Blazakis, K., Schetakis, N., Badr, M. M., Aghamalyan, D., Stavrakakis, K., & Stavrakakis, G. (2025). Power theft detection in smart grids using quantum machine learning. *IEEE Access*, *13*, 61511–61525. https://doi.org/10.1109/ACCESS.2025.3558143

[52] Kumawat, M., Onaolapo, A., Sharma, G., Barutcu, I. C., Adefarati, T., & Bansal, R. (2024). Integrated encoder–decoder-based wide and deep convolution neural networks strategy for electricity theft arbitration. *Journal of Engineering and Applied Science*, *71*(94). https://doi.org/10.1186/s44147-024-00428-4

[53] Žarković, M., & Dobrić, G. (2024). Artificial intelligence for energy theft detection in distribution networks. *Energies*, *17*(7), 1580. https://doi.org/10.3390/en17071580

[54] Ge, L., Li, J., Du, T., & Hou, L. (2025). Double-layer stacking optimization for electricity theft detection considering data incompleteness and intra-class imbalance. *Energy Systems*, *165*, 110461. https://doi.org/10.1016/j.ijepes.2025.110461

[55] Saqib, S. M., Mazhar, T., Iqbal, M., Shahzad, T., Almogren, A., Ouahada, K., & Hamam, H. (2024). Deep learning-based electricity theft prediction in non-smart grid environments. *Heliyon*, *10*(15), 1–26. https://doi.org/10.1016/j.heliyon.2024.e35167

[56] Zheng, S., Gao, Y., Gu, D., Shi, J., Chen, K., & Li, Y. (2024). Electricity theft recognition and time period detection considering based on multi-task learning. *International Journal of Electrical Power and Energy Systems*, *155*, 109570. https://doi.org/10.1016/j.ijepes.2023.109570

[57] Nirmal, S., Patil, P., & Shinde, S. (2025). Adversarial measurements for convolutional neural network-based energy theft detection model in smart grid. *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, *11*, 100909. https://doi.org/10.1016/j.prime.2025.100909

[58] Liu, Z., Ding, W., Chen, T., Sun, M., Cai, H., & Liu, C. (2023). A electricity theft detection method through contrastive learning in smart grid. *Journal on Wireless Communications and Networking*, *2023*, 1–17. https://doi.org/10.1186/s13638-023-02258-z

[59] Sun, S., Liu, C., Zhu, Y., He, H., Xiao, S., & Wen, J. (2022). Deep reinforcement learning for the detection of abnormal data in smart meters. *Sensors*, *22*(21), 8543. https://doi.org/10.3390/s22218543

[60] Alkuwari, A. N., Al-Kuwari, S., Albaseer, A., & Qaraqe, M. (2025). Anomaly detection on smart grids with optimized convolutional long short-term memory model. *IEEE Access*, *13*, 40399–40412. https://doi.org/10.1109/ACCESS.2025.3547037

[61] Naqvi, I., Poorthuis, A., & Govind, A. (2021). Urban governance and electricity losses: An exploration of spatial unevenness in Karachi, Pakistan. *Energy Research and Social Science*, *79*, 102166. https://doi.org/10.1016/j.erss.2021.102166

[62] Zidi, S., Mihoub, A., Mian Qaisar, S., Krichen, M., & Abu Al-Haija, Q. (2023). Theft detection dataset for benchmarking and machine learning based classification in a smart grid environment. *Journal of King Saud University - Computer and Information Sciences*, *35*(1), 13–25. https://doi.org/10.1016/j.jksuci.2022.05.007

[63] Khattak, A., Bukhsh, R., Aslam, S., Yafoz, A., Alghushairy, O., & Alsini, R. (2022). A hybrid deep learning-based model for detection of electricity losses using big data in power systems. *Sustainability*, *14*(20), 13627. https://doi.org/10.3390/su142013627

[64] Huang, Y., & Xu, Q. (2021). Electricity theft detection based on stacked sparse denoising autoencoder. *International Journal of Electrical Power and Energy Systems*, *125*, 106448. https://doi.org/10.1016/j.ijepes.2020.106448

[65] Chen, J., Nanehkaran, Y. A., Chen, W., Liu, Y., & Zhang, D. (2023). Data-driven intelligent method for detection of electricity theft. *International Journal of Electrical Power and Energy Systems*, *148*, 108948. https://doi.org/10.1016/j.ijepes.2023.108948

[66] Lepolesa, L. J., Achari, S., & Cheng, L. (2022). Electricity theft detection in smart grids based on deep neural network. *IEEE Access*, *10*, 39638–39655. https://doi.org/10.1109/ACCESS.2022.3166146

[67] Emadaleslami, M., Haghifam, M. R., & Zangiabadi, M. (2023). A two stage approach to electricity theft detection in AMI using deep learning. *International Journal of Electrical Power and Energy Systems*, *150*, 109088. https://doi.org/10.1016/j.ijepes.2023.109088

[68] Arias-Marín, C., Barragán-Escandón, A., Toledo-Orozco, M., & Serrano-Guerrero, X. (2025). Methodological validation of machine learning models for non-technical loss detection in electric power systems: A case study in an Ecuadorian electricity distributor. *Applied Sciences*, *15*(7), 3912. https://doi.org/10.3390/app15073912

[69] Norouzi, A., Ahmadi, I., Nazari, M., Pourrostami, H., & Hoseini-Kordkheili, H. (2025). A novel framework to detect electricity theft in regions with traditional metering; applying a hybrid machine learning-based approach to low-sampling-rate data. *Results in Engineering 2025*, *25*, 104478. https://doi.org/10.1016/j.rineng.2025.104478

[70] Chen, D., Li, W., & Fang, J. (2025). Blending-based ensemble learning low-voltage station area theft detection. *Energies*, *18*(1), 31. https://doi.org/10.3390/en18010031

[71] Alshehri, A., Badr, M. M., Baza, M., & Alshahrani, H. (2024). Deep anomaly detection framework utilizing federated learning for electricity theft zero-day cyberattacks. *Sensors*, *24*(10), 3236. https://doi.org/10.3390/s24103236

[72] Mehdary, A., Chehri, A., Jakimi, A., & Saadane, R. (2024). Hyperparameter optimization with genetic algorithms and XGBoost: A step forward in smart grid fraud detection. *Sensors*, *24*(4), 1230. https://doi.org/10.3390/s24041230

[73] Wang, J., Si, Y., Zhu, Y., Zhang, K., Yin, S., & Liu, B. (2024). Cyberattack detection for electricity theft in smart grids via stacking ensemble GRU optimization algorithm using federated learning framework. *International Journal of Electrical Power & Energy Systems*, *157*, 109848. https://doi.org/10.1016/j.ijepes.2024.109848

[74] Arisona, G., Taruna, A. P., Irwanto, D., Bestari, A. B, & Juniawan, W. (2025). Classification based on the support vector machine for determining operational targets for controlling electricity usage with conventional meters: A case study of industrial and business tariff customers from PT PLN (Persero) Indonesia. *IEEE Access*, *13*, 12388–12398. https://doi.org/10.1109/ACCESS.2025.3529295

[75] Lee, J., Sun, Y. G., Sim, I., Kim, S. H., Kim, D. I., & Kim, J. Y. (2022). Non-technical loss detection using deep reinforcement learning for feature cost efficiency and imbalanced dataset. *IEEE Access*, *10*, 27084–27095. https://doi.org/10.1109/ACCESS.2022.3156948

[76] Takiddin, A., Ismail, M., & Serpedin, E. (2022). Robust data-driven detection of electricity theft adversarial evasion attacks in smart grids. *IEEE Transactions on Smart Grid*, *14*(1), 663–676. https://doi.org/10.1109/TSG.2022.3193989

[77] Liao, W., Yang, D., Ge, L., Jia, Y., & Yang, Z. (2025). Electricity theft detection in integrated energy systems considering multi-energy loads. *International Journal of Electrical Power & Energy Systems*, *164*, 110428. https://doi.org/10.1016/j.ijepes.2024.110428

[78] Gresoi, S., Stamatescu, G., & Făgărășan, I. (2025). Advanced methodology for fraud detection in energy using machine learning algorithms. *Applied Sciences*, *15*(6), 3361. https://doi.org/10.3390/app15063361

[79] Yi, Z., Min, C., Yang, Z., Rong, X., Chen, G., & Hua, L. (2024). Detection of medium-voltage electricity theft types based on robust regression and convolutional neural network. *International Journal of Electrical Power & Energy Systems*, *160*, 110130. https://doi.org/10.1016/j.ijepes.2024.110130

[80] Meng, S., Li, C., Tian, C., Peng, W., & Tian, C. (2023). Transfer learning based graph convolutional network with self-attention mechanism for abnormal electricity consumption detection. *Energy Reports*, *9*, 5647–5658. https://doi.org/10.1016/j.egyr.2023.05.006

[81] Shen, Y., Shao, P., Chen, G., Gu, X., Wen, T., Zang, L., & Zhu, J. (2021). An identification method of anti-electricity theft load based on long and short-term memory network. *Procedia Computer Science*, *183*, 440–447. https://doi.org/10.1016/j.procs.2021.02.082

[82] Zhang, Y., Ai, Q., Wang, H., Li, Z., & Zhou, X. (2020). Energy theft detection in an edge data center using threshold-based abnormality detector. *International Journal of Electrical Power and Energy Systems*, *121*, 106162. https://doi.org/10.1016/j.ijepes.2020.106162

[83] Cai, Q., Li, P., Zhao, Z., & Wang, R. (2024). Dynamic electricity theft behavior analysis based on active learning and incremental learning in new power systems. *International Journal of Electrical Power & Energy Systems*, *162*, 110309. https://doi.org/10.1016/j.ijepes.2024.110309

[84] Coma-Puig, B., & Carmona, J. (2022). Non-technical losses detection in energy consumption focusing on energy recovery and explainability. *Machine Learning*, *111*(2), 487–517. https://doi.org/10.1007/s10994-021-06051-1

[85] Zulu, C. L., & Dzobo, O. (2023). Real-time power theft monitoring and detection system with double connected data capture system. *Electrical Engineering*, *105*(5), 3065–3083. https://doi.org/10.1007/s00202-023-01825-3

[86] Kankonde, P., & Bokoro, P. (2025). Bridging the energy divide: An analysis of the socioeconomic and technical factors influencing electricity theft in Kinshasa, DR Congo. *Energies*, *18*(13), 3566. https://doi.org/10.3390/en18133566

[87] Vlasa, I., Gligor, A., Dumitru, C. D., & Iantovics, L. B. (2020). Smart metering systems optimization for non-technical losses reduction and consumption recording operation improvement in electricity sector. *Sensors*, *20*(10), 2947. https://doi.org/10.3390/s20102947

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