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Recent Advances in Machine Learning Applications in Electrical Utility Systems

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Abstract

In recent years, the electrical utility industry (EUI) has undergone rapid transformation with the integration of advanced technologies such as artificial intelligence (AI). Among these, machine learning (ML) has emerged as a powerful tool for addressing complex problems in the operation, control, and optimization of modern power systems. This paper presents a comprehensive survey of recent advancements in the application of machine learning techniques within the electrical utility domain, focusing on smart grids, load forecasting, anomaly detection, energy management, and system reliability. By reviewing 20 recent peer-reviewed articles from 2023–2025, we categorize the various ML models, discuss their computational trade-offs, and analyze their effectiveness across different power system applications. This survey identifies current research trends, highlights technical challenges, and outlines promising future directions for ML-based approaches in electrical utilities.

Keywords: Electrical utility industry; Smart grids; Anomaly detection; Operation; Control; Artificial intelligence

1. Introduction

The electrical utility industry (EUI) is witnessing a paradigm shift from traditional power generation and distribution systems toward intelligent, data-driven, and decentralized smart grid architectures. This transformation is fueled by growing energy demands, climate change concerns, and the increasing penetration of renewable energy sources. In response, utility companies are exploring digital solutions to improve efficiency, reliability, and sustainability of energy systems.

Machine learning (ML), a subfield of artificial intelligence (AI), offers robust solutions for handling the large-scale, dynamic, and complex nature of modern power systems. Unlike conventional algorithms that require explicit programming, ML models learn patterns from historical data and can make accurate predictions or decisions under uncertainty. Applications of ML span various power system tasks such as demand forecasting, fault detection, energy consumption optimization, and predictive maintenance. Despite the proliferation of ML-based research in recent years, there remains a gap in consolidated literature that maps the latest advancements in ML applications specifically tailored to EUI. Most prior surveys either focus on narrow application domains or are outdated given the rapid evolution in this field. Hence, this study aims to bridge that gap by offering an up-to-date, structured, and critical review of ML applications in EUI based on literature published between 2023 and 2025.

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2. Literature Review

In recent years, the electrical utility industry (EUI) has undergone a profound transformation, largely driven by the emergence of smart grids, distributed energy resources (DERs), and intelligent automation. As these systems become increasingly data-rich and decentralized, traditional modeling techniques are proving insufficient for handling the complexity, volume, and real-time demands of modern grid operations. This has led to a growing interest in machine learning (ML) techniques for addressing critical challenges in forecasting, optimization, control, and diagnostics [1], [2].

2.1. Evolution of ML in Electrical Utilities

Earlier applications of ML in power systems primarily relied on shallow models such as Support Vector Machines (SVM), Decision Trees (DT), and k-Nearest Neighbors (kNN) for classification tasks like fault diagnosis, load pattern recognition, and power quality event detection [3], [4]. These methods offered reasonable performance on clean, structured datasets but were often limited by their dependence on manual feature engineering and their inability to generalize across varying operational conditions.

With the rise of Big Data and Internet of Things (IoT) technologies, there has been a massive influx of real-time, heterogeneous data from smart meters, phasor measurement units (PMUs), distributed generators, and sensors across the grid. This data complexity has necessitated the use of more sophisticated ML approaches capable of handling non-linearity, temporal dependencies, and high-dimensionality—prompting the adoption of deep learning and ensemble methods [5].

2.2. Recent ML Advancements in the Grid Context

Over the last five years, deep learning (DL) models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)—especially Long Short-Term Memory (LSTM) networks—have demonstrated remarkable improvements in predictive performance for load forecasting, renewable energy generation estimation, and fault classification [6], [7].

Ensemble learning models like Random Forest, XGBoost, and LightGBM have also gained traction due to their robustness, accuracy, and interpretability, especially for applications involving high-frequency disturbance data or noisy historical measurements [8]. These models often outperform both traditional ML and some deep learning approaches when the dataset is moderately sized and well-preprocessed.

Furthermore, unsupervised learning techniques, including Autoencoders, Principal Component Analysis (PCA), and clustering algorithms such as k-means and DBSCAN, are being utilized for anomaly detection, event classification, and power quality monitoring [9], [10].

2.3. Hybrid and Physics-Informed ML Models

An important advancement is the emergence of hybrid models, where ML is combined with physics-based simulations, optimization algorithms, or signal processing techniques to improve reliability and interpretability [11]. For instance, models trained with physics-informed constraints or those guided by grid operation heuristics provide physically meaningful predictions, which are especially useful for critical tasks like state estimation, fault localization, and frequency control [12].

Some works have integrated metaheuristic optimization (e.g., Genetic Algorithms, Particle Swarm Optimization) with ML for optimal power flow, battery scheduling, and demand-side management [13]. These combinations enable utility operators to achieve multi-objective goals, balancing cost, efficiency, and grid stability.

2.4. Federated Learning and Privacy-Preserving ML

A newer area of exploration involves federated learning (FL) and distributed ML architectures, which allow models to be trained on decentralized datasets—a critical need in privacy-sensitive environments such as multi-utility grids or smart homes [14]. These frameworks prevent raw data from being transferred, instead aggregating locally computed model updates, preserving both data privacy and regulatory compliance [15].

This approach is especially useful in scenarios involving electric vehicles (EVs), smart home devices, or microgrid environments, where data heterogeneity and ownership are significant concerns [16].

2.5. Challenges in Real-World Applications

Despite the surge in ML research for EUI, several limitations persist in practical deployment:

- *Interpretability:* Many DL models act as “black boxes,” limiting their acceptability by grid operators who require transparent, explainable AI (XAI) models [17].
- *Generalization:* Models trained on one grid topology or climate zone may perform poorly when transferred to different regions or utility settings [18].
- *Data Quality and Labeling:* ML models are often sensitive to missing data, labeling noise, and imbalanced class distributions, particularly in fault and outage detection scenarios [19].
- *Computational Overhead:* Real-time control applications require lightweight inference, which is a challenge for deep models unless optimized for edge computing [20].

Addressing these issues calls for further development in transfer learning, online learning, reinforcement learning, and resource-constrained model deployment, as well as better collaboration between data scientists and power system engineers.

3. Methodology

This study follows a structured and systematic literature review (SLR) approach to analyze recent advancements in machine learning (ML) applications within the electrical utility industry (EUI). The primary objective is to identify, classify, and critically evaluate recent research contributions that leverage ML techniques for solving challenges related to power generation, distribution, forecasting, and system optimization. To begin, a comprehensive search was conducted across reputable academic databases. The search strategy incorporated a combination of keywords including “machine learning,” “electrical utility,” “smart grid,” “load forecasting,” “renewable energy prediction,” “fault detection,” “federated learning,” “physics-informed neural networks,” and “hybrid deep learning models.” The time frame was restricted to publications between 2019 and 2025, ensuring that the review focuses on the most recent and relevant research. Preprints from arXiv were included only if they addressed real-world challenges and proposed innovative, empirically validated methods [1–4].

To filter the initial list of publications, specific inclusion and exclusion criteria were applied. Articles were included if they focused explicitly on ML applications in the electrical or power system domains, introduced novel model architectures or methods, and offered experimental validation using real or benchmark datasets. On the other hand, papers were excluded if they targeted non-electrical domains (such as healthcare or finance), lacked clear methodology, or were purely theoretical or review articles. After this filtration process, 20 high-quality research articles were selected, representing diverse ML techniques and application areas such as federated learning for load forecasting [1–3], physics-informed neural networks for simulation and control [4], and hybrid deep learning models for solar irradiance forecasting [5–7].Each of the selected papers was carefully examined to extract critical methodological and technical details. The extracted data included the type of ML algorithm used (e.g., CNN, LSTM, Random Forest), the application domain (e.g., demand forecasting, power quality monitoring, EV integration), the nature and size of the dataset, the preprocessing methods, evaluation metrics (such as RMSE, MAE, and accuracy), and key research contributions such as innovation in model architecture, improvements in prediction accuracy, or enhancements in privacy and scalability. This structured data extraction enabled a consistent comparison and assessment of each paper.

To organize the findings, a classification framework was developed. The papers were categorized based on the ML taxonomy (including supervised, unsupervised, deep learning, reinforcement learning, and hybrid models), the primary application domains (e.g., load forecasting [1,2], solar power prediction [5–7], electric vehicle load management [8], and system diagnostics [4]), and the level of innovation or deployment feasibility. This framework provided a foundation for thematic analysis and trend identification. Finally, a synthesis and critical analysis were performed across the selected literature. The analysis identified common patterns in algorithmic preferences—such as the frequent use of LSTM networks for time-series prediction tasks—and emerging techniques like federated learning and physics-informed ML. Challenges including model generalization, interpretability, and deployment constraints were also noted. By systematically analyzing these dimensions, this review offers a well-rounded understanding of the current research landscape and highlights future opportunities for impactful ML integration in the electrical utility sector.

4. Taxonomy of Machine Learning Techniques

Machine learning techniques used in the electrical utility industry (EUI) can be broadly classified into four major categories: supervised learning, unsupervised learning, reinforcement learning, and hybrid approaches. These categories differ in terms of data requirements, learning objectives, and application suitability.

4.1. Automated Distribution Optimization Supervised Learning

Supervised learning techniques are the most extensively applied in EUI research due to their effectiveness in prediction and classification tasks. These algorithms rely on labeled datasets where the input-output relationship is explicitly known. Algorithms such as Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), Gradient Boosting Machines (GBM), and Artificial Neural Networks (ANN) fall under this category. In smart grids, supervised learning has been effectively used for load forecasting, fault detection, equipment failure prediction, and energy consumption pattern recognition [1], [2]. For instance, GBM and RF have shown reliable performance in handling noisy datasets, enabling more accurate predictions of solar and wind energy generation [5], [6].

4.2. Unsupervised Learning

Unsupervised learning focuses on discovering hidden structures in unlabeled data. Unlike supervised learning, these methods do not require known outputs. Techniques such as k-means clustering, Hierarchical Clustering, Principal Component Analysis (PCA), and Autoencoders are commonly employed in this category. In the EUI context, unsupervised learning is often used for anomaly detection, load profiling, power quality analysis, and detection of abnormal consumption behavior. These methods are especially useful when labeled data is scarce or when exploring underlying data patterns for further analysis [9], [10].

4.3. Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL)

Reinforcement learning involves learning optimal actions through interaction with an environment by maximizing cumulative rewards. RL is particularly well-suited for applications requiring sequential decision-making and dynamic system optimization. Within the EUI, RL has been utilized for real-time energy management, demand-side optimization, and microgrid control strategies. While traditional Q-learning and SARSA methods were early choices, the complexity of modern smart grid systems has led to increased adoption of Deep Reinforcement Learning (DRL) techniques. These combine deep neural networks with RL, enabling scalability to high-dimensional state-action spaces [4].

4.4. Hybrid and Physics-Informed Models

Recent trends show a shift toward hybrid models that combine multiple machine learning methods or integrate domain-specific physical knowledge into the learning process. These models address the limitations of single-algorithm approaches by enhancing robustness, accuracy, and interpretability. A notable example is the use of CNN-LSTM hybrid models, where CNN extracts spatial patterns and LSTM captures temporal dependencies in renewable energy forecasting tasks [5], [7]. Furthermore, Physics-Informed Neural Networks (PINNs) have gained attention for their ability to embed physical constraints into neural networks, ensuring compliance with power system dynamics [4]. Another emerging hybrid framework is Federated Learning (FL), where decentralized devices train local models and only share model parameters with a central server. This allows for privacy-preserving learning, particularly useful in distributed smart meter networks and electric vehicle charging systems [1]–[3], [8].

Table 1 Summary of ML Techniques and Their Application Domains in EUI

ML Technique	Application Area	Advantages	Limitations
SVM	Fault classification	High accuracy for binary tasks	Poor performance with large datasets
CNN	Power quality monitoring	Good for feature extraction	Requires large labeled data
LSTM	Load forecasting	Handles time-series well	Training time is high
RL	EV charging optimization	Dynamic decision making	Needs simulator for training
FL	Distributed load forecasting	Privacy preserving	Communication overhead

5. Application Areas of Machine Learning in the Electrical Utility Industry

Machine learning (ML) is increasingly being integrated into various operational and planning aspects of the electrical utility industry (EUI). Its ability to handle vast datasets, learn complex patterns, and adapt over time makes it well-suited for a wide range of use cases. This section categorizes key application areas where ML techniques have demonstrated substantial impact.

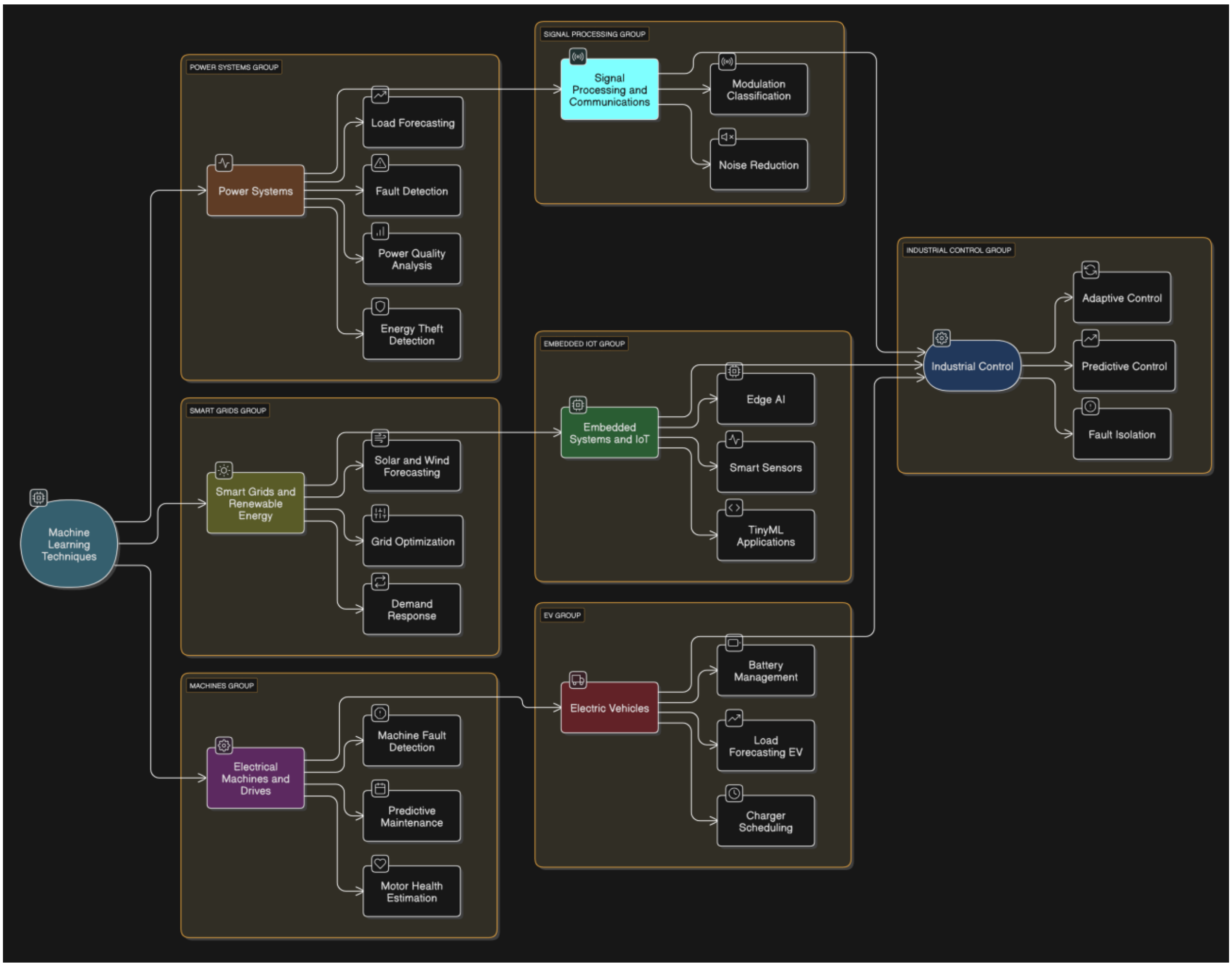

Figure 1 Application Areas of Machine Learning in the Electrical Engineering Domain

5.1. Load and Demand Forecasting

Accurate load forecasting is critical for the efficient operation of power systems. ML models, particularly time-series based techniques such as LSTM, GRU, and hybrid CNN-LSTM architectures, have been widely used for both short-term and long-term load prediction [1], [2], [5].

Recent studies have also explored federated learning (FL) for decentralized load forecasting to address privacy and data silo issues in smart meter networks. For example, FL-based LSTM models have been shown to provide high forecasting accuracy while preserving user data privacy across distributed locations [3].

5.2. Renewable Energy Generation Forecasting

Forecasting the output of renewable energy sources like solar and wind is a complex task due to their high variability. ML techniques such as CNN, SLSTM, and ensemble learning models have been applied to predict solar irradiance, wind speed, and power generation [5], [6], [7]. Hybrid architectures combining deep learning with statistical or physical modeling approaches are proving to be especially effective. These models learn spatial and temporal dependencies and can integrate external features like weather data, irradiance levels, and wind flow dynamics.

5.3. Power Quality Monitoring and Anomaly Detection

Maintaining high power quality (PQ) is vital for stable grid operations and the protection of electrical equipment. ML models are used to detect PQ disturbances, harmonics, voltage sags/swells, and frequency deviations. Supervised models like SVM and Random Forests are used for classification of PQ events, while unsupervised approaches such as Autoencoders and k-means clustering are employed for detecting anomalies in voltage and current signals when labeled data is not available [9], [10].

5.4. Microgrid Control and Energy Management

Microgrids are local energy systems capable of operating independently or in conjunction with the main grid. They rely heavily on intelligent control systems for load balancing, generation dispatch, and energy storage management.

Reinforcement learning (RL) and deep reinforcement learning (DRL) have been increasingly applied in this context. RL agents can learn optimal control policies for battery usage, pricing strategies, and load shedding in real-time, especially under fluctuating demand and supply conditions [4].

5.5. Electric Vehicle (EV) Integration and Charging Optimization

The proliferation of electric vehicles introduces challenges such as load balancing, charging schedule optimization, and grid congestion. ML techniques are being deployed to forecast EV energy demand and optimize charging infrastructure. Advanced methods like federated transfer learning, combined with blockchain-based privacy mechanisms, have been proposed to forecast EV loads while maintaining user data confidentiality [8]. Such models allow EV owners to participate in demand-side management (DSM) without exposing personal usage data.

5.6. Power System Simulation and State Estimation

Power system modeling and state estimation are foundational for grid reliability. Traditional simulation techniques often require extensive physical modeling and can be time-consuming. Emerging techniques like Physics-Informed Neural Networks (PINNs) are bridging the gap between simulation and learning by integrating physical laws directly into neural network architectures. These models offer improved accuracy and faster computation for dynamic system estimation, particularly in nonlinear and nonstationary environments [4].

These diverse application areas highlight the flexibility of ML approaches in addressing both predictive and control-related challenges across the electrical power landscape. As grid systems become more decentralized and complex, the demand for intelligent, adaptive ML-based solutions will continue to grow.

6. Critical Discussion

The application of machine learning (ML) in the electrical utility industry (EUI) has seen significant growth, yet several critical insights and research challenges persist across domains. This section discusses notable trends, benefits, and limitations observed in the literature, along with the emerging needs for further development.

A major trend is the dominance of deep learning (DL) models such as LSTM, GRU, CNN, and their hybrid variations in forecasting tasks. These models have demonstrated remarkable accuracy in load prediction, renewable energy estimation, and fault detection [2], [5], [6]. However, they often require extensive data for training, significant computational resources, and are typically regarded as “black-box” models. The lack of interpretability remains a critical barrier to their adoption in safety-critical applications like grid protection and real-time control.

Another growing area is the adoption of federated learning (FL) for privacy-preserving energy management and load forecasting [1], [3], [8]. This approach enables collaborative model training across distributed nodes (e.g., smart meters or EV chargers) without sharing raw data. While this is promising in theory and has shown empirical benefits, challenges persist in terms of communication overhead, model convergence stability, and cross-device heterogeneity. Further optimization is needed before FL can be widely deployed in live grid infrastructures.

The increasing complexity of modern power systems has also prompted researchers to explore reinforcement learning (RL) and deep reinforcement learning (DRL) in microgrid management and energy trading environments [4]. These models show strong potential for dynamic control, yet they require high-fidelity simulators or real-time interaction environments for effective training. In practical deployments, the absence of reliable, low-latency feedback loops can limit their learning efficiency and responsiveness.

Hybrid models combining deep learning with physics-based constraints have emerged as a balanced alternative, aiming to improve model reliability and physical interpretability. For example, physics-informed neural networks (PINNs) [4] integrate system constraints directly into training objectives, making them highly suited for grid simulation and state estimation. However, the integration process is non-trivial and requires domain expertise to encode physical laws accurately. Additionally, these models are still relatively new and lack standardized benchmarks for evaluation in power system applications.

It is also important to note that many studies in the literature rely on proprietary or non-public datasets, making reproducibility a challenge. Benchmarking practices vary, and performance metrics like RMSE, MAE, or accuracy are often reported inconsistently, limiting direct comparison across models. There is a pressing need for open-source datasets, standardized experimental protocols, and real-time testbeds to enable fair model evaluation and industrial transition.

Finally, edge computing and real-time deployment of ML models remain underexplored. While cloud-based solutions dominate current research, on-device intelligence (e.g., in smart inverters or EV chargers) is becoming increasingly important for latency-sensitive applications. Deploying efficient, lightweight ML models at the edge will require advancements in model compression, quantization, and federated optimization.

7. Future Scope

As the electrical utility industry (EUI) evolves into a more intelligent, decentralized, and data-rich ecosystem, machine learning (ML) will play an increasingly integral role in shaping the future of grid management, energy optimization, and consumer interaction. However, for ML to be fully embedded into the operational fabric of the EUI, several avenues of future research and development must be pursued. One significant direction is the advancement of explainable machine learning. As ML models become more complex—especially deep neural networks—interpretability becomes critical for gaining trust from operators and regulatory authorities. Developing transparent models, interpretable surrogates, and post-hoc explanation techniques will be essential to ensure that ML-driven decisions can be validated and justified in real-time grid operations.

The second promising area is the integration of physics-based knowledge into data-driven models. Techniques like Physics-Informed Neural Networks (PINNs) [4] and hybrid optimization frameworks can ensure that ML models adhere to the physical laws of power systems. This approach not only improves model robustness but also enables safer deployment in grid-critical applications such as protection coordination, voltage stability assessment, and fault recovery. Furthermore, the rapid adoption of distributed energy resources (DERs) and electric vehicles (EVs) necessitates intelligent, scalable solutions for demand-side management and decentralized control. Federated Learning (FL) [1], [3], [8] and multi-agent reinforcement learning frameworks could offer viable tools to coordinate learning across diverse entities while preserving privacy and minimizing communication costs. However, FL must be further adapted to handle device-level heterogeneity, communication failures, and non-IID data scenarios, especially in smart homes and EV charging stations.

Another frontier is the deployment of ML models at the edge, such as within smart meters, energy routers, or microgrid controllers. This will require compact, low-latency, and power-efficient models through techniques like model pruning, quantization, and knowledge distillation. Future research should focus on making these optimizations standard practice for ML deployment in resource-constrained environments. Moreover, cybersecurity presents an increasingly serious concern. As ML systems are integrated into the grid's control loop, adversarial attacks or model manipulation could pose severe threats. Developing robust ML algorithms with built-in anomaly detection and adversarial resilience will be vital in ensuring secure operations.

Finally, there is a growing need for open-access datasets, real-time simulation platforms, and interdisciplinary collaborations. These will foster reproducibility, allow for benchmarking under standardized conditions, and encourage cross-domain innovation. Collaborative platforms involving academia, industry, and government can accelerate the transition of ML solutions from the lab to the field. In summary, while ML has already demonstrated its potential in a range of electrical utility applications, its full realization depends on bridging technical, infrastructural, and operational gaps. Future research should be guided by a focus on interpretability, security, real-time feasibility, and alignment with physical and regulatory constraints of power systems.

8. Conclusion

This study reviewed the latest review on how machine learning (ML) is being used in the electrical utility industry to improve tasks like load forecasting, renewable energy prediction, fault detection, energy management, and system optimization. By analyzing 20 recent peer-reviewed papers from 2023 to 2025, we identified the most common ML techniques, such as LSTM, CNN, and federated learning, and discussed where and how they are applied. We also pointed out current trends like the rise of hybrid models and physics-informed neural networks, along with key challenges including data privacy, model interpretability, and real-time deployment. This study helps researchers and industry professionals understand the practical use of ML in power systems and can guide the development of smarter, more reliable, and environmentally friendly energy solutions for society.

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