Applications of Supervised and Unsupervised Machine Learning Models in Energy Systems

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Modern energy systems are facing growing complexities, including the integration of renewable resources, the expansion of decentralized networks, and dynamic changes in consumption patterns. While traditional physics-based models may perform well under steady conditions, they exhibit clear limitations when confronted with uncertainties and real-time variations. In this context, data-driven and machine learning approaches have emerged as innovative tools that, by leveraging historical and real-time data, enable the analysis of nonlinear relationships and the identification of hidden patterns. The purpose of this study is to examine and compare two categories of artificial intelligence models in energy systems: supervised learning and unsupervised learning. The findings indicate that each category has its own strengths and limitations: supervised learning models are effective in load forecasting and energy generation prediction, whereas unsupervised learning models are valuable for pattern discovery and anomaly detection. The novelty of this paper lies in presenting an integrated analytical framework for comparing the applications of these models in energy systems, addressing both practical applications and theoretical challenges. Despite significant progress, a key research gap remains: the need for scalable and transparent models that can ensure both predictive accuracy and interpretability. The results show that while each approach individually addresses part of the requirements of energy systems, combining them in semi-supervised methods or hybrid frameworks can be an effective step toward improving efficiency, resilience, and sustainability. This advancement not only contributes scientifically but also leads, in practice, to optimized resource management, cost reduction, and enhanced grid security.

Keywords: *Energy system models, Artificial intelligence, Supervised Learning, Unsupervised Learning, Load forecasting*

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1. Introduction

Modern energy systems are increasingly confronted with greater complexity due to the integration of renewable energy sources, the development of decentralized networks, and dynamic patterns on the demand side [1], [2], [3]. Traditional physics-based models, such as differential analyses for power flow or thermodynamic models in power plants, while effective under steady and controlled conditions, demonstrate serious limitations when exposed to real-world uncertainties. These limitations include heavy computational requirements, reliance on precise physical parameters, and the inability to adapt to real-time data [4], [5]. For instance, solar irradiance forecasts based solely on atmospheric physical models often fail to account for sudden changes in cloud cover, which can lead to grid instability [6].

In response to these challenges, data-driven and machine learning models have emerged as innovative approaches. By leveraging historical and real-time data, these models can uncover hidden patterns, capture nonlinear relationships, and optimize system operations. They not only enhance predictive accuracy but also enable more intelligent and flexible decision-making in the operation of energy systems [7], [8], [9].

Recent advances in data acquisition technologies, including smart meters, IoT devices, and satellite-based monitoring, have significantly expanded the amount and diversity of data available for modeling. This growing data ecosystem has enabled the development of more adaptive, data-driven frameworks that complement traditional physics-based approaches and improve forecasting, optimization, and fault detection accuracy [10], [11].

From a conceptual perspective, modern approaches to energy system modeling can be divided into three main categories [12], [13], [14]:

- Data-driven models that rely on historical datasets and statistical methods to uncover patterns and correlations, without necessarily depending on explicit physical laws. A common example includes regression analysis for load forecasting and clustering algorithms for segmenting energy consumers.

- Machine learning models, which are in fact a subset of data-driven approaches, employ algorithms such as neural networks, decision trees, deep learning, and reinforcement learning. These models learn directly from data and progressively enhance prediction accuracy and decision-making quality.
- Hybrid physics–machine learning models which seek to combine the strengths of both approaches. In such models, physical equations are integrated with data-driven algorithms to preserve domain knowledge while also benefiting from the adaptability of machine learning.

The application of machine learning in energy systems is expanding rapidly, covering a wide range of tasks from load and generation forecasting to fault detection and operational optimization [4], [7]. Within this context, four key categories of machine learning models have gained prominence in the energy domain:

1. Supervised learning models
2. Unsupervised learning models
3. Deep learning models
4. Physics-informed hybrid models

The objective of this paper is to examine and compare two categories of data-driven and machine learning models in energy systems, namely supervised and unsupervised learning models. Within this framework, the paper aims to provide a comprehensive picture of the strengths and limitations of each category, and to demonstrate how they can be applied to enhance the optimization and stability of energy systems.

To achieve this, the study introduces a conceptual comparison framework that systematically maps machine learning applications in energy systems across three dimensions: task type, data regime, and model interpretability. The framework distinguishes forecasting, anomaly detection, and segmentation tasks under different data conditions (labeled, unlabeled, or hybrid) and evaluates each category in terms of interpretability and scalability. This structure enables a unified comparison of supervised and unsupervised approaches and clarifications where each performs most effectively.

Furthermore, the framework reveals three priority research gaps that should guide future investigations:

I. the need for interpretable models that remain robust under concept drift;

II. scalable semi-supervised frameworks for limited labeled data; and

III. integration of physics-informed components to enhance transparency and reliability in real-time operation.

The structure of the paper is as follows: Section 2 reviews the literature and previous studies; Section 3 introduces the key definitions and presents supervised and unsupervised learning models; Section 4 presents comparative results in the form of a table along with detailed analysis; and finally, Section 5 concludes with a summary of the findings and future directions.

2. Literature Review

The evolution of energy systems in recent decades has been strongly influenced by the development of data-driven and machine learning models. These approaches have addressed many of the limitations inherent in traditional physics-based models, which were grounded in principles of thermodynamics, fluid dynamics, and electrical circuit theory [15], [16], [17]. For instance, the Newton–Raphson method, widely used in power flow analysis, provided the foundation for numerous calculations in power networks; however, it lacked the flexibility to cope with the variability of renewable resources and the stochastic behavior of consumers [5], [18]. With the expansion of data collection infrastructures such as SCADA in the 1990s, the first steps toward data-driven approaches were taken. During this period, statistical methods like ARIMA were extensively applied for short-term load forecasting, while artificial neural networks were tested for demand prediction [19], [20]. Nevertheless, the limited computational capacity and lack of large-scale datasets hindered their widespread adoption. A major turning point occurred in the 2010s with the emergence of large-scale datasets collected from smart meters, IoT sensors, and satellite observations, which enabled the application of more sophisticated models and spurred a rapid growth in the use of machine learning for energy systems [7]. Numerous studies have demonstrated the effectiveness of these approaches across different domains of energy systems. Hochreiter and Schmidhuber [21], through the introduction of long short-term memory (LSTM) networks, paved the way for more accurate forecasting of solar and wind energy generation using meteorological data. Antonanzas et al. [6] showed that combining statistical models with neural networks can reduce the forecasting error of solar radiation by up to 30 percent. Similarly, Wang et al. [11] trained machine learning algorithms on multi-decade wind farm datasets, achieving higher accuracy compared to purely physics-based simulations.

From an operational perspective, Mocanu et al. [22] proposed the application of reinforcement learning to optimize the scheduling of energy storage, a strategy that helps mitigate fluctuations arising from renewable generation. In the context of network security, Li et al. [23] and Chen et al. [24] highlighted the use of autoencoders for detecting anomalies associated with electricity theft and cyberattacks. Big data and IoT technologies have thus provided the foundation for this transformation, enabling continuous monitoring through smart meters, real-time equipment diagnostics from sensor data, and improved forecasting accuracy from satellite imagery [6], [12], [23].

From an application perspective, machine learning has transformed nearly every segment of the energy value chain. In the domain of generation, the use of models such as long short-term memory (LSTM) networks and hybrid approaches has significantly improved the accuracy of renewable energy forecasts, particularly for wind and solar, where variability is inherently high [6], [11]. In transmission and distribution, the deployment of graph neural networks and autoencoders has enabled rapid and accurate detection of faults and even cyberattacks, thereby enhancing network reliability [4], [24]. In the consumption sector, time series models and deep learning algorithms have markedly reduced load forecasting errors and improved the efficiency of demand response programs [7], [20]. Within the field of energy storage, especially in battery management, Gaussian process regression and Q-learning algorithms have proven effective in predicting battery lifetime and optimizing their utilization [14], [25]. Moreover, real-world implementations such as Google DeepMind have demonstrated that reinforcement learning can reduce operational costs in data centers by approximately 40 percent, underscoring the remarkable potential of machine learning to enhance the efficiency of energy systems at scale [26].

Overall, a review of the literature indicates that data-driven and machine learning models have fundamentally reshaped the energy chain, successfully overcoming the constraints of traditional physics-based models. Nonetheless, challenges remain, including dependence on data quality, limited transparency and interpretability of algorithmic decisions, and high computational costs. Consequently, future research directions are expected to move toward the development of physics-informed hybrid models, the integration of edge AI for faster and more cost-efficient processing, and the design of scalable and trustworthy frameworks aimed at narrowing the gap between theoretical potential and practical deployment of these methods.

3. Methodology

This study employs a structured literature review approach to analyze and compare the applications of supervised and unsupervised learning models in energy systems. A total of 55 peer-reviewed scientific articles were examined to identify how these machine learning paradigms are utilized across various energy-related tasks such as demand forecasting, renewable energy prediction, anomaly detection, smart grid optimization, and energy diagnostics.

The literature was identified through a structured search across major academic databases, including Scopus, ScienceDirect, and IEEE Xplore. A combination of keywords such as “machine learning,” “supervised learning,” “unsupervised learning,” “energy systems,” and “optimization” was used. The search primarily covered the period from 2012 to 2025, focusing on peer-reviewed journal and conference papers written in English. Studies included if they applied supervised or unsupervised algorithms to energy-related problems, reported methodological frameworks or performance metrics, and demonstrated relevance to system-level or operational optimization. Publications that lacked methodological details, were purely hardware-oriented, or duplicated similar content were excluded. This process ensured both the transparency and reproducibility of the literature selection.

To ensure the relevance and quality of the review, the selected papers met three main inclusion criteria: they were published between 2012 and 2025, they focused specifically on machine learning applications in energy systems, and they explicitly applied either supervised or unsupervised learning models. This inclusion ensured coverage of both traditional and recent state-of-the-art approaches.

The reviewed articles were classified into two major categories: supervised and unsupervised learning models. Supervised models included regression, decision trees, SVM, and neural networks, typically used when labeled data is available. Unsupervised models encompassed clustering (e.g., k-means, DBSCAN), dimensionality reduction (e.g., PCA, t-SNE), anomaly detection (e.g., Isolation Forest, GMM), and generative models like GANs and VAEs, suitable for exploratory tasks without labeled data.

For each study, we extracted key elements such as data sources (e.g., smart meters, SCADA, satellite imagery), main applications (e.g., forecasting, segmentation, anomaly detection), evaluation metrics (e.g., RMSE, accuracy), and reported challenges. This allowed for a comparative synthesis of model performance and deployment contexts. The analysis also highlighted trends in algorithm selection, the critical role of data preprocessing, and trade-offs between prediction accuracy and interpretability—laying the foundation for the discussion and conclusion.

4. Theoretical Framework

Data-driven and machine learning models in energy systems are designed to address specific challenges in the areas of generation, transmission, and consumption. By using historical data and advanced algorithms, these models enable more accurate forecasting, faster decision-making, and more efficient resource management [27], [28]. In the following, the main categories of these models, their applications, and relevant references are presented.

4.1. Supervised Learning Models

Supervised learning models are among the most important branches of machine learning, in which the model is trained using labeled data to predict unknown outputs or classify samples into different categories [29]. In the context of energy systems, this approach plays a key role in tasks such as load forecasting, fault detection, and the estimation of renewable energy production, tasks that all rely on historical data with known outputs. These models learn the relationships between input-output pairs and optimize their parameters to minimize prediction errors and enhance the reliability of results [30], [31], [32].

Supervised methods are generally divided into two main categories: regression models and classification models. In regression models, the goal is to predict continuous variables. For example, linear and multivariate regression have been successfully used to forecast household and commercial electricity consumption, achieving mean absolute percentage errors of less than five to eight percent [33]. Moreover, more advanced approaches such as decision trees, random forests, and gradient boosting machines have been employed to model complex nonlinear relationships and improve prediction accuracy in applications such as wind turbine fault detection, defective solar panel identification, and solar radiation estimation [6], [20], [34].

In classification models, algorithms such as Support Vector Machines (SVM), neural networks, and k-nearest neighbors (k-NN) have found the most widespread applications. SVM, by defining optimal hyperplanes, has been able to detect transient instabilities in power systems with 94% accuracy and has also proven effective in identifying faulty components of the grid and even detecting electricity theft using smart meter data [35], [36]. Deep neural networks, due to their capacity to model nonlinear relationships, have been employed for processing satellite images and forecasting the output of solar power plants [37]. In addition, the k-NN algorithm has been applied to classify household electricity consumption patterns, enabling distribution companies to design demand response programs with greater precision [38].

The practical applications of supervised learning models in energy systems are extensive, ranging from load forecasting with long short-term memory networks (LSTM), reporting root mean square errors between 0.03 and 0.05 kWh, to fault detection in wind turbines with accuracy exceeding 90%, and renewable energy prediction achieving up to 20% error reduction compared to traditional physics-based models [20], [34]. Despite these successes, two major challenges remain: data quality and overfitting. Labeled datasets are often affected by noise, missing values, and class imbalance, which necessitate robust preprocessing and data augmentation techniques [39]. Moreover, complex models such as deep neural networks are prone to overfitting; to address this issue, methods like Dropout and L2 regularization are commonly applied [29]. Ultimately, supervised learning forms the foundation of data-driven analysis in energy systems, and its success depends on the quality of training data and the careful design of models grounded in domain-specific expertise.

4.2. Unsupervised Learning Models

Unsupervised learning models aim to uncover patterns, structures, and hidden relationships within unlabeled data, and they become particularly important when labeled datasets are scarce or costly to obtain [40]. In energy systems, these models have been widely applied for exploratory analysis, load profiling, dimensionality reduction, anomaly detection, and feature extraction, proving to be powerful tools for gaining deeper insight into the behavior of networks and energy equipment. One of the most prominent areas in this context is data clustering, which organizes information based on feature similarity. The k-means algorithm has been extensively used to segment energy consumers according to their consumption patterns, successfully identifying high-demand households for demand response programs [38], [41], [42]. More advanced approaches such as density-based clustering (DBSCAN) have been applied to wind turbine data analysis and to define spatial clusters for solar panel installations [43], [44]. In addition, hierarchical clustering has enabled regional demand analysis and the discovery of correlations among industrial consumption patterns.

Table 1. Comparison of supervised and unsupervised learning in energy systems [9], [54], [55], [56].

Criterion	Supervised Learning	Unsupervised Learning
Input Data Type	Labeled data (defined input–output pairs)	Unlabeled data
Example Application	Day-ahead load forecasting with regression or LSTM	Clustering consumers using smart meter data
Primary Objective	Prediction and estimation of future values	Pattern discovery, grouping, and anomaly detection
Advantages	High prediction accuracy; quantitative error evaluation	No need for labeled data; ability to reveal hidden structures
Challenges	Requires high-quality labeled data; sensitive to missing or noisy data	Difficult result interpretation; dependent on similarity metrics
Energy System Implementation	Demand forecasting, renewable generation prediction	Consumer segmentation, electricity theft detection, or cybersecurity intrusion detection

In addition to clustering, dimensionality reduction plays a fundamental role in handling large-scale datasets. Principal Component Analysis (PCA) has been widely applied to isolate critical features in wind turbine data, achieving a 70% reduction in dimensionality while still retaining 95% of the original variance [45]. Autoencoder neural networks have also been employed to create compact representations of energy data, proving effective for anomaly detection in power lines and for reconstructing corrupted signals [46], [47]. Moreover, techniques such as t-distributed Stochastic Neighbor Embedding (t-SNE) enable the visualization of high-dimensional data in two- or three-dimensional spaces, providing valuable insights into correlations between climatic variables and solar power generation [6].

Anomaly detection is another core application of unsupervised learning, with direct implications for grid security and equipment health monitoring. The Isolation Forest algorithm has shown strong performance in flagging abnormal energy flows and detecting cyberattacks with high accuracy [48]. Gaussian Mixture Models (GMMs) have also demonstrated notable success in identifying unusual voltage fluctuations, achieving up to 89% accuracy in fault detection [49]. Furthermore, Self-Organizing Maps (SOMs) have been used to project high-dimensional sensor data into two-dimensional maps, thereby revealing regions of the grid susceptible to blackouts. Similarly, One-Class Support Vector Machines (OC-SVMs) have been employed to detect suspicious or fraudulent consumption patterns in smart meter data [50].

Another category of these models is generative models, which produce synthetic data resembling the real distribution, thereby addressing the limitations of actual datasets. Generative Adversarial Networks (GANs) have been successfully used to generate training data for rare scenarios such as grid faults [51]. Similarly, Variational Autoencoders (VAEs) have been applied to simulate renewable energy generation under uncertain climatic conditions [11], [47].

Despite these applications, unsupervised learning still faces persistent challenges, such as the limited interpretability of clusters or extracted features, insufficient scalability when dealing with big data, and concept drift in dynamic environments that require adaptive models. Nevertheless, these approaches have proven valuable in tasks ranging from consumer segmentation and predictive maintenance to network performance optimization and facilitating renewable energy integration. Ultimately, close collaboration with domain experts is indispensable for validating results and aligning models with practical operational constraints [38], [52], [53].

5. Results and Discussion

Supervised and unsupervised learning models, despite their shared foundation in utilizing energy data, exhibit significant differences in terms of application, accuracy, and interpretability. A review of reported performance metrics across the literature also indicates consistent quantitative trends. For instance, supervised models such as regression and LSTM generally achieve lower forecasting errors (commonly reported MAPE below 10% in load prediction), while classification tasks using SVM or Random Forest often exceed 90% accuracy. In contrast, unsupervised algorithms, particularly clustering and anomaly detection, tend to provide strong pattern recognition capabilities rather than direct numerical precision. Supervised learning is primarily employed when labeled datasets are available and clear quantitative relationships between inputs and outputs can be defined. For instance, linear and polynomial regression algorithms are widely applied for forecasting energy demand and load consumption. In contrast, unsupervised learning is suitable when data is unlabeled, and the goal is to uncover hidden structures or patterns. The k-means clustering algorithm is one of the most common tools used for segmenting consumers based on energy usage profiles [20], [38]. Table 1 presents a key comparison between these two categories of models.

Based on Table 1, it can be observed that supervised learning in energy systems is generally employed for tasks that require forecasting and estimating future values. This approach, when labeled data such as load demand or renewable energy generation are available, offers high accuracy and allows for quantitative error assessment. Especially in areas such as short-term load forecasting and power plant performance optimization, these methods play a key role in improving efficiency and reducing costs. In contrast, unsupervised learning becomes important when labeled data are not available and the goal is to uncover hidden patterns and structures in the data. Applications such as clustering energy consumers or detecting anomalies in smart grids are prominent examples of this approach. The main advantage of these methods lies in their independence from costly data labeling; however, interpreting their results and assigning meaning to clusters or anomalies can be challenging.

The choice between these two approaches depends on three main factors:

- Data quality: When data is incomplete or noisy, unsupervised models (such as robust clustering) can perform better, whereas supervised models require clean and labeled datasets to achieve high accuracy.
- Computational cost: Classical supervised methods such as regression or Random Forest are usually lighter and less expensive, while unsupervised algorithms demand iterative computations to determine clusters or hidden dimensions, resulting in higher costs.
- Dynamic environments: In energy networks characterized by rapid load changes and fluctuations of renewable resources, both approaches are valuable: supervised models for quantitative forecasting, and unsupervised models for detecting emerging patterns or anomalies.

Both approaches depend heavily on high-quality data and careful preprocessing. In supervised learning, labeled data such as historical load values or market prices play a vital role, while in unsupervised learning, data from SCADA sensors and smart meters form the foundation of the analyses. To enhance the performance of these models, preprocessing steps are crucial: missing values can be addressed through methods such as interpolation or ARIMA, noise reduction and outlier detection can be achieved with techniques like Isolation Forest, and multisource data fusion can be carried out using tools such as Kalman filters or deep learning architectures. Moreover, feature engineering and normalization of input values are essential to improve the accuracy and stability of the models.

Overall, supervised learning, due to its ability to provide quantitative forecasts and transparent error evaluation, is better suited for applications such as load forecasting and renewable generation prediction. In contrast, unsupervised learning, with its capacity to discover hidden patterns and anomalies, is more valuable for consumer data analysis and real-time grid monitoring. Combining these two approaches in the form of semi-supervised models or hybrid frameworks offers a promising pathway to improve accuracy, resilience, and efficiency in energy systems.

Finally, it can be said that in the world of energy systems engineering and energy conversion, various artificial intelligence and machine learning models are used for optimization or prediction; whether at the model and theoretical level or more operationally, such as gas turbines [57]. The application of these advanced models in energy systems, along with paying attention to environmental issues at the micro and even urban levels, can lead to sustainable development and optimal conditions, which is interesting, and future research can also focus on this area [58].

6. Conclusion

This study conducted a structured literature review to examine and compare supervised and unsupervised machine learning models applied in modern energy systems. The analysis demonstrated that, despite their common reliance on data-driven principles, these two categories differ substantially in terms of data requirements, interpretability, and application domains. Supervised models, which depend on labeled datasets, consistently deliver higher predictive accuracy, as reflected in reported MAPE values below 10 percent for load forecasting and classification accuracy above 90 percent in fault detection. In contrast, unsupervised models excel in pattern discovery, clustering, and anomaly detection, providing essential insights in contexts where labeled data are unavailable.

Through a conceptual comparison framework introduced in this study, the capabilities and limitations of both approaches were systematically analyzed across three dimensions: task type, data regime, and interpretability. The framework revealed where each method performs most effectively and identified three research priorities for the future: (i) developing interpretable models that remain robust under concept drift, (ii) designing scalable semi-supervised frameworks for limited labeled data, and (iii) integrating physics-informed components to enhance transparency and reliability in real-time operation. Quantitative evidence synthesized from the reviewed literature further reinforces the comparative findings. Across multiple studies, supervised methods such as LSTM, regression, and SVM exhibit strong forecasting and classification performance, while unsupervised algorithms like k-means, PCA, and Isolation Forest show high effectiveness in unsupervised clustering and anomaly detection. These complementary strengths indicate that hybrid and semi-supervised architectures hold the greatest promise for future energy analytics.

Finally, the paper contributes methodologically by providing a transparent account of its literature selection process, ensuring reproducibility and representativeness. Together, the conceptual framework, comparative synthesis, and methodological clarity offer new insight into how data-driven intelligence can enhance optimization, reliability, and sustainability in next-generation energy systems.

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