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Overview Of Artificial Intelligence Applications In Smart Grids

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Abstract:
Smart Grids represent a significant evolution in electric power systems, driven by the pursuit of greater efficiency, sustainability, and resilience, which increasingly rely on advanced communication technologies and artificial intelligence techniques. This article provides a comprehensive review addressing fundamental concepts, artificial intelligence models, practical applications, cybersecurity concerns, and the strategic role of AI in the development of smart grids. It also discusses the main challenges and the current scenario of implementation, with particular attention to regulatory aspects. By consolidating these perspectives, this study aims to provide an overview of the application of models in smart grids for future research and offer guidance and support to researchers to advance the integration of artificial intelligence into smart grids.

Keyword*: Smart Grid; Energy Transition; Artificial Intelligence; Machine Learning; Predictive Maintenance; Cybersecurity.*

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I. Introduction

The transformation of the energy market is at a critical stage in the effort to develop environmentally sustainable systems and meet increasing energy demand [1]. The power sector is notoriously capital-intensive, with substantial costs and lengthy timelines for the fabrication and installation of key assets, such as generators, transformers, transmission lines, and distribution networks, which are expected to operate continuously for decades. This highlights the need for new maintenance and management techniques that proactively identify failures [2].

More sophisticated processes are now being implemented in energy systems, including new digitalization models, particularly driven by Artificial Intelligence (AI) technology [1]. The synergy between AI and the energy transition has experienced remarkable growth in research, particularly over the last four to five years, as illustrated in Figure 1. The AI, along with modern technologies such as Machine Learning (ML), Deep Learning (DL), and advanced neural networks, will make an important contribution to achieving better operational results in the future. These technological frameworks enable the better exploitation of renewable energy potential.

The digitalization of the electric power distribution systems has grown significantly over the last decade, giving rise to new data-driven applications focused on fault monitoring, quality, and predictive maintenance [3], [4]. The increasing number of measurement units and sensors in the power grid (power quality analyzers, PMUs, smart meters, etc.) provides large volumes of data that, combined with new ML methodologies, open up new possibilities for fault identification and mitigation [5]. Proactive maintenance, which uses sensors or measurements to monitor system health and performance, is a key area driven by data and digitalization [3].

The integration of distributed energy resources (DERs) and energy storage systems (ESSs) into smart grids, along with demand management, is another area where AI plays an important role [6], [7]. This requires new grid management methods due to the bidirectional supply of electrical energy. Applications such as grid reconfiguration and scheduling of DERs aim to improve the resilience of the distribution system [8]. Additionally, AI will help predict power outages, like curtailment and constrained-off, in the future. Furthermore, emerging communication technologies, such as 6G networks, AI-enabled Software-Defined Networks (SDN), and smart grids, are being investigated for their role in the energy infrastructure of smart cities, supporting grid resilience and efficient energy management in conjunction with AI techniques [9], [10].

In summary, AI techniques collectively promote making smart grids more flexible, predictable, and secure, thereby supporting the integration of renewable energy sources, optimizing resource distribution, and ensuring efficient energy delivery to consumers [11]. Therefore, this paper aims to provide an overview of the use of AI in smart grids, providing an overview of the subject for researchers dedicated to this area and encouraging the development of new applications that can contribute to the modernization, sustainability, and resilience of future electrical systems.

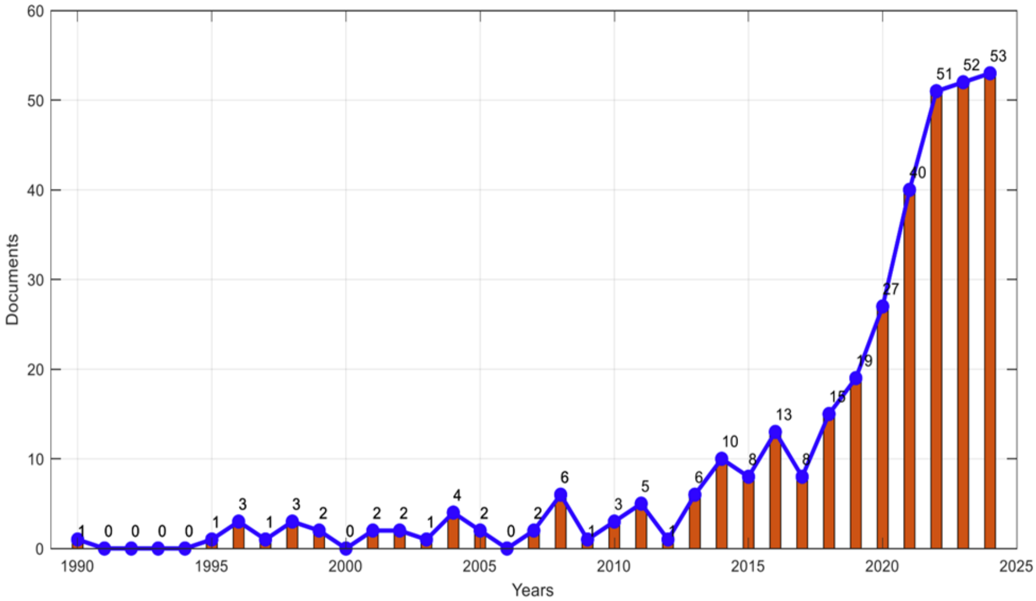

Figure 1. Publication of articles related to smart grids, energy transition and IA [1]

II. Artificial Intelligence Techniques

The AI is a key tool used in smart grid processes. It interconnects with smart grids through the application of ML techniques and metaheuristics [12]. AI has been utilized in various applications within the electricity sector, including short-term load forecasting, predicting the efficiency of electricity generation using photovoltaic panels, and quantifying short-term voltage fluctuations [13]. Therefore, some of the main AI models applied in smart grids will be discussed, which can be categorized into supervised and unsupervised learning.

Supervised Learning

Supervised learning consists of an approach in which models are trained using labeled datasets, in which each input is associated with a previously known output. The central objective is for the model to establish a mapping function between inputs and outputs, accurately reproducing the patterns observed during training and simultaneously generalizing this knowledge to predict new, previously unknown data. In view of this, Figure 2, previously introduced in [11], illustrates a series of supervised learning models.

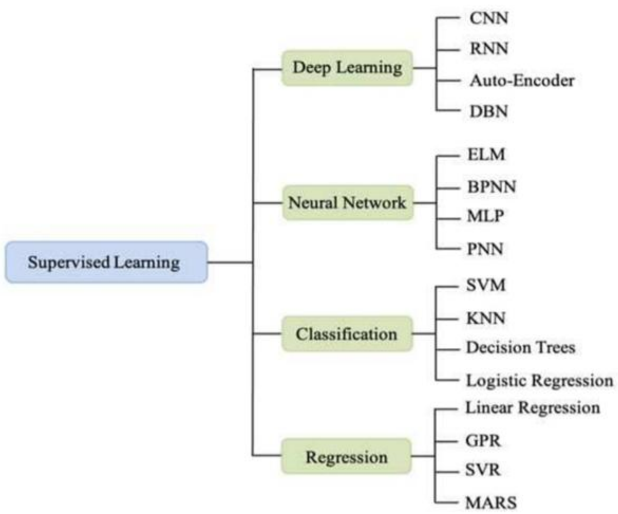

Figure 2. Supervised learning techniques in smart grids [11]

Deep Learning

Deep Learning (DL) is a subfield of ML on multi-layer artificial neural network architectures. These hierarchical structures allow the extraction and representation of complex features from data, enabling the identification of high-dimensional patterns. This approach is particularly effective in scenarios involving large volumes of data and is widely applied to tasks such as time series, image recognition, natural language processing, and speech recognition.

- **CNN (Convolutional Neural Network)**: A neural network specialized in processing grid-structured data, such as images. It uses convolutional layers to automatically extract spatial features, serving as a benchmark in computer vision and visual pattern recognition. It also features pooling layers to reduce dimensionality and highlight the most relevant information [14], [15].
- **RNN (Recurrent Neural Network)**: Neural network focused on sequential data (time series, text, audio). It has recurrent connections that allow "memory" of previous states, making it ideal for modeling sequences and temporal dependencies [13], [16].
- **Auto-Encoder**: Neural network used to learn compact representations of data (dimensionality reduction). It consists of two parts: an encoder (for compression) and a decoder (for reconstruction). It is widely used in preprocessing, compression, and noise removal [14].
- **DBN (Deep Belief Network)**: A set of stacked neural networks, where each layer learns to represent the data probabilistically. Widely used for unsupervised pre-training, before supervised fine-tuning [15].

Neural Network

Neural networks or Artificial Neural Networks (ANNs) are computational models inspired by the functioning of the human brain, composed of layers of interconnected processing units called artificial "neurons." These architectures can range from single-layer structures to more complex, multi-layer configurations capable of representing highly complex, nonlinear relationships between input and output variables.

- **ELM (Extreme Learning Machine)**: Consists of a single-layer neural network architecture characterized by a highly efficient training process. In this model, the hidden layer weights are randomly assigned and remain fixed, while only the output layer parameters are adjusted. This strategy significantly reduces training computational time while maintaining competitive performance in several classification and regression tasks [5].
- **BPNN (Back-Propagation Neural Network)**: ANN architecture trained using the backpropagation algorithm, in which the connection weights are iteratively adjusted based on the error between the predicted output and the desired output. This method forms the basis for training multilayer networks, enabling the modeling of complex nonlinear relationships and being widely used in classification, regression, and forecasting tasks in the electricity sector [15], [17].
- **MLP (Multilayer Perceptron):** Neural Nework composed of multiple fully connected layers, including input, hidden, and output layers. Its training is performed using the backpropagation algorithm, which enables the learning of complex and nonlinear functions. Due to its flexibility and generalizability, the MLP has been widely applied to classification and regression tasks in various domains, including applications in the electricity sector [13], such as energy forecasting [18], [19], non-technical losses [20].
- **PNN (Probabilistic Neural Network)**: Neural network architecture based on statistical principles, whose approach is based on the estimation of probability density functions to perform classification tasks. Its main features include fast training, simple implementation, and robustness to the presence of noise in the data, making it an efficient alternative in uncertain scenarios [5].

Classification

Classification is a supervised learning approach in which models are trained to distinguish and assign data to previously defined categories or classes. The central objective is to identify, based on input features, the class to which a new sample belongs, ensuring correct generalization of the knowledge acquired during training.

- **SVM (Support Vector Machine):** Supervised learning algorithm used in classification and regression tasks, whose formulation is based on determining the optimal hyperplane that separates data classes with the largest possible margin. To deal with nonlinear problems, SVM employs kernel functions, which allow data to be projected into higher-dimensional spaces, expanding its discrimination and generalization capabilities [5].
- **KNN (K-Nearest Neighbors):** Model based in instance, in which the classification of a new sample is performed considering the k closest observations in the training set. The class assigned to the latest point generally corresponds to the most frequent among its neighbors, which gives the method simplicity of implementation and good adaptability to different data distributions [11], [21].
- **Decision Tree:** Supervised learning technique that organizes decisions into a hierarchical tree structure. Each node represents a condition based on data characteristics, branches indicate possible outcomes, and leaves

correspond to classes or final decisions. The model generates classification or regression rules that are easy to interpret and visualize [21], [22].

- **Logistic Regression:** A statistical model widely used in binary classification tasks. It is based on the logistic (sigmoid) function to map the relationship between input variables and the probability of a sample belonging to a given class, with output values ranging from 0 to 1. It is a benchmark technique for its simplicity, interpretability, and efficiency in linear problems [13], [23].

Regression

Consists of a supervised learning approach focused on predicting continuous values, that is, estimating a numerical output from input variables. These models enable the identification of relationships between data and are widely used in forecasting and quantitative analysis tasks.

- **Linear Regression:** Statistical model that seeks to represent the linear relationship between input variables and the output variable. It is widely used for predicting numerical values and analyzing trends, standing out for its simplicity, interpretability, and efficiency in linear problems [3], [15].
- **GPR (Gaussian Process Regression)**: Nonparametric regression method that uses Gaussian processes to model uncertainty and predict continuous values. In addition to providing point estimates, it presents confidence intervals associated with the predictions, making it particularly useful in scenarios that require uncertainty quantification and greater statistical robustness [3], [22].
- **SVR (Support Vector Regression)**: Corresponds to the extension of the SVM algorithm for regression problems. Its objective is to find a function that presents minimal deviations from the real values, within a predefined tolerance margin, while preserving the simplicity and generalizability of the model [3], [13], [24].
- **MARS (Multivariate Adaptive Regression Splines)**: Regression technique that models nonlinear relationships by adaptively dividing data into segments, to which linear functions are fitted. This approach enables the representation of complex interactions between variables and adapts to the data structure, offering greater flexibility compared to traditional linear regression models [2], [3].

Unsupervised Learning

Unsupervised learning is an approach in which the model seeks to identify hidden patterns and structures in unlabeled data sets, that is, without the need for previously known outputs. In this paradigm, the algorithm autonomously organizes and explores the data, extracting relationships, groupings, and representations that aid in understanding complex phenomena and reducing dimensionality. This strategy is particularly relevant in scenarios where data labeling is costly or impractical, enabling the discovery of latent behaviors and the generation of exploratory knowledge. Additionally, Figure 3 presents the main branches of unsupervised learning, previously presented in [11].

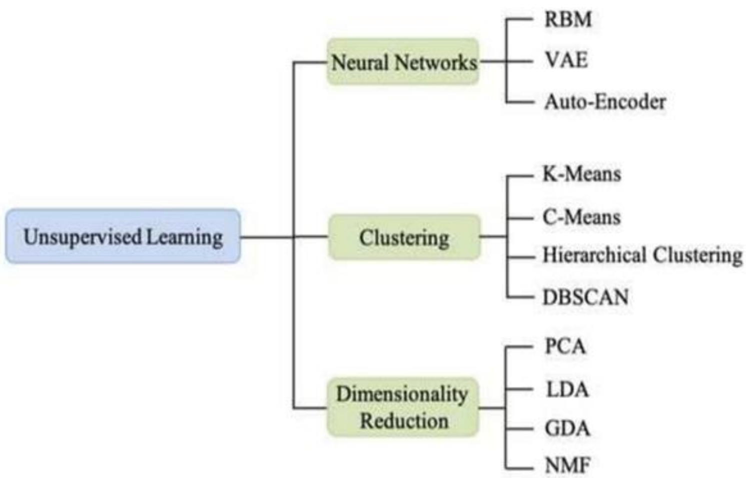

Figure 3. Unsupervised learning techniques in smart grids [11]

Neural Networks

ANNs can also be applied in unsupervised contexts, where output labels are not available. In these cases, the architecture is used to identify hidden patterns, extract relevant representations, and autonomously organize data.

- **Restricted Boltzmann Machine (RBM):** This is a stochastic neural network applied to unsupervised learning, whose structure is composed of an interconnected visible layer and a hidden layer. Its objective is to learn the probability distributions underlying the input data, allowing the extraction of latent features and the modeling of complex dependencies [5], [13].

- **Variational Autoencoder (VAE):** Corresponds to a type of probabilistic autoencoder used in unsupervised learning, whose formulation allows not only dimensionality reduction and the extraction of latent features, but also the generation of new data samples similar to those in the training set [12], [15].
- **Autoencoder:** Used to reduce data dimensionality and extract representative features. Its structure is composed of two main parts: the encoder, responsible for mapping the input data to a lower-dimensional latent space, and the decoder, which reconstructs the data from this compressed representation [22].

Clustering

Clustering is an unsupervised learning technique that aims to group data samples into subsets, or clusters, based on their similarity or proximity in terms of characteristics [25]. Unlike supervised classification, clustering does not rely on predefined labels, allowing the model to discover latent structures and patterns in the data autonomously. This approach is widely used to identify behavioral profiles, segment heterogeneous databases, and detect anomalies, and is particularly useful in contexts with large volumes and high-dimensionality of information.

- **K-Means:** A widely used clustering algorithm whose objective is to partition data into k predefined groups. Groups are formed based on the proximity of samples to the centroid of each cluster, which is updated iteratively until convergence. It is a simple, efficient, and scalable method for large volumes of data [14].
- **C-Means:** Variant of K-Means algorithm, it allows each sample to belong simultaneously to multiple clusters, with different degrees of association represented by probability values. This approach provides greater flexibility in data representation, especially in scenarios where the boundaries between groups are not clearly defined [14].
- **Hierarchical Clustering:** A clustering method that organizes data into a hierarchical structure of clusters, represented by a dendrogram. This process can be conducted agglomeratively (bottom-up), starting with each sample in an individual cluster and progressively merging them, or divisively (top-down), beginning with a single cluster and subdividing it into smaller groups [14].
- **DBSCAN (Density-Based Spatial Clustering of Applications with Noise):** Density-based clustering algorithm capable of identifying clusters of arbitrary shape by grouping points that present high local density. One of its main advantages is the ability to detect noise points or outliers, which do not belong to any cluster [12].

Dimensionality Reduction

Dimensionality reduction is an unsupervised learning technique that aims to transform high-dimensional datasets into more compact representations, preserving as much relevant information as possible. This process is especially useful in scenarios where an excess of variables complicates analysis, increases computational cost, and can introduce redundancies or noise. By projecting data into lower-dimensional spaces, these methods facilitate visualization, the interpretation of latent structures, and the training of more efficient machine learning models. Key applications include data compression, the removal of spurious correlations, pattern detection, and the preparation of baselines for predictive algorithms.

- **PCA (Principal Component Analysis):** A statistical dimensionality reduction technique that projects data into a new coordinate system defined by the principal components. These components are linear combinations of the original variables that explain most of the variance in the data. Thus, PCA simplifies the representation of high-dimensional sets, reducing redundancies and facilitating visualization and processing, while preserving the most relevant information [14].
- **LDA (Linear Discriminant Analysis):** A statistical technique that seeks to identify linear combinations of variables capable of maximizing separability between two or more classes. Unlike PCA, which aims solely at dimensionality reduction based on data variance, LDA incorporates class information, optimizing discrimination between groups [14].
- **GDA (Generalized Discriminant Analysis):** Corresponds to a non-linear extension of LDA, developed to deal with data sets that are not linearly separable. This technique uses kernel functions to project the data into higher-dimensional spaces, where class separation can be performed more effectively. GDA extends the discriminative capabilities of traditional LDA, making it particularly useful in scenarios of greater structural complexity [14].
- **NMF (Non-Negative Matrix Factorization):** a matrix factorization technique used to decompose a data set into non-negative components, so that both the obtained factors and their transfers are interpretable in additive terms. This feature becomes especially useful in applications that turn off partial or constructive representations, such as image processing, text analysis, and feature extraction in high-dimensional data [14].

Therefore, ML can be broadly divided into supervised and unsupervised categories that have distinct and complementary purposes. In supervised learning, models are trained using labeled data, enabling the establishment of relationships between input variables and known outputs, making them suitable for tasks such as load forecasting, estimating renewable energy generation, and fault classification in smart grids. Conversely, in unsupervised learning, algorithms operate on unlabeled data, seeking to identify hidden patterns, latent structures, or compact representations. These algorithms are useful in applications such as clustering consumption profiles, detecting anomalies in measurements, and reducing dimensionality in large databases from smart meters.

While various models have been discussed, the field is vast and constantly evolving, encompassing a broader set of techniques capable of handling different levels of complexity and uncertainty. Choosing the most appropriate approach depends directly on the application's purpose, the characteristics of the available data, and the operational or strategic demands of smart grids. In this sense, the judicious use of ML techniques has the potential to strengthen the resilience, efficiency, and sustainability of smart grids.

III. Applications Of Artificial Intelligence Models In The Context Of Smart Grids

The applications of AI in the energy transition and power systems are vast, encompassing different stages of the energy value chain. One of the central aspects is load forecasting, essential for the efficiency, reliability, and adaptability of smart grids [11]. Given the growth in global energy demand and the increasing integration of renewable sources, maintaining grid stability and reliability is becoming a growing challenge, for which traditional methodologies prove insufficient. In this context, AI has established itself as a strategic tool, enabling forecasts across multiple time horizons, from the short-term (minutes) to the long-term (years). Several approaches are being used for load forecasting, including Long Short-term memory (LSTM) [2], [26], Gated Recurrent Unit (GRU) [26], Convolutional Neural Network (CNN), RNNs [26], hybrid applications with CNN-LSTM [27], [28] and CNN-GRU [29], and Random Forest [2], [21], [23].

In the grid optimization process, AI enables the analysis of large volumes of data in real time, identifying patterns, predicting scenarios, and supporting rapid decisions about the direction of electricity flow. This automation capability enables a dynamic balance between supply and demand, even in contexts of high variability in renewable generation. This enables the grid to operate close to its maximum potential, minimizing waste, deferring expansion investments, and ensuring continuous control over parameters such as voltage and frequency. Thus, AI transforms the electricity grid into a dynamic, adaptable, and cost-effective system, capable of integrating multiple agents and supporting the energy transition [5], [8], [12], [15], [24], [30].

Another strategic area is fault detection, prediction, and management. AI significantly expands smart grids' ability to continuously monitor the system, identify anomalies, and anticipate potential failures. Techniques such as Isolation Forests, SVMs, ANNs, CNNs, RNNs, Fuzzy, and Probabilistic Boolean Networks (PBNs) have been applied in this domain, offering greater robustness even in noisy environments [17]. In addition to improving diagnostics, AI enables networks to self-heal, ensuring rapid isolation and restoration of power. Typical failures include short circuits, transformer and insulator defects, as well as occurrences resulting from overloads, severe weather, and cyberattacks [1], [11], [12], [13], [17].

In this scenario, predictive maintenance emerges as a fundamental approach to ensuring supply continuity. Unlike reactive maintenance, which takes action after a failure, and preventive maintenance, which follows fixed schedules, predictive maintenance utilizes sensor data, historical records, and AI models to anticipate failures in critical components, thereby reducing costs, minimizing downtime, and extending the useful life of equipment [4], [24]. The digitalization of the electricity sector has boosted the adoption of this strategy, which is essential for the operation of smart grids [2], [3], [12], [13], [15], [24].

The integration of renewable energy sources is another area where AI plays a decisive role. The variability and intermittency of solar and wind energy generation hinder the development of robust forecasting and control methods. AI assists in estimating renewable production and efficiently managing these resources, promoting the stability, reliability, and resilience of smart grids [11], [12], [22], [31].

Additionally, cybersecurity is also gaining prominence in the context of the digitalization of the electricity sector. Smart Grids become potential targets of attacks, such as false data injection (FDI), replay attacks, and denial-of-service (DoS) attacks, which can result in blackouts, infrastructure damage, and consumer safety risks. AI helps mitigate these threats by analyzing large volumes of real-time data from sensors, smart meters, and Internet of Things (IoT) devices, identifying anomalies and intrusion patterns. Models based on neural networks, reinforcement learning, SVMs, decision trees, and random forests have been applied to detect and classify cyberattacks. Furthermore, strengthening security in software-defined networking (SDN) architectures, combined with robust encryption, authentication, and continuous monitoring protocols, provides an additional layer of protection [5], [12], [21], [30], [31].

In this sense, AI should be understood not only as a support tool, but also as a strategic pillar in the digital and sustainable transformation of the electricity sector [1], [11]. With the continuous advancement of research and technological development, AI-based methodologies are consolidating themselves as scalable and innovative solutions, fundamental to the global energy transition. In this context, smart grids become capable of more efficiently addressing the challenges of growing demand, integrating DERs, and building more resilient, sustainable, and adaptable systems to meet future requirements [5], [30].

IV. Challenges Of Integrating AI Into Smart Grids

Data complexity and quality represent one of the main challenges for applying AI to Smart Grids. These systems generate massive volumes of heterogeneous information from sensors, smart meters, and DERs, which need to be processed and analyzed in real time. However, this task is hampered by the presence of noisy, incomplete, or inconsistent data, which compromises the reliability of the analyses [15]. In this context, efficient management, combined with data quality and accessibility assurance, becomes essential for AI algorithms to achieve accurate predictions and provide effective decision-making support [15]. Furthermore, data quality is directly linked to information security, as corrupted or manipulated data can compromise both prediction models and grid stability.

Cybersecurity concerns are also gaining prominence as the digitalization of power grids, driven by AI, expands the attack surface and exposes the system to potential cyber threats. Decentralized smart grids are among the most vulnerable due to their distributed architecture and extensive connections with IoT devices, which can serve as entry points for attackers [11], [12]. Furthermore, AI systems themselves can become targets of specific attacks, such as data poisoning, compromising the integrity of prediction and decision models [11], [12]. In this context, information security is considered a key concern in the implementation of smart grids, requiring increasingly sophisticated preventive and reactive measures [11], [12]. Protection against these threats requires a multilayered approach that encompasses robust cybersecurity protocols, advanced intrusion detection systems, and incident response plans, ensuring the resilience and reliability of the electricity sector in digital environments. These cybersecurity aspects also directly connect to interoperability issues, as the lack of standard protocols expands the surface area of exploitable vulnerabilities.

Interoperability and standardization issues pose another significant challenge for integrating AI into existing electrical infrastructures. Smart grids are composed of heterogeneous systems that use different communication protocols and have varying levels of technological advancement. This lack of homogeneity hinders cross-platform compatibility, introduces security vulnerabilities, and limits operational efficiency. Incorporating AI solutions into already installed, often aging, equipment requires careful planning and strong coordination among industry players. In this context, the development and adoption of open standards become essential to ensure interoperability, increase grid robustness, and reduce dependence on specific suppliers, fostering the construction of more flexible and resilient ecosystems. The lack of these standards impacts not only technological integration but also the ability to reduce implementation costs and ensure security.

Furthermore, interoperability is a fundamental requirement for the full functioning of Smart Grids. To achieve this, it is necessary to define and adopt communication standards and protocols that ensure compatibility between smart meters, energy management systems, control devices, and other elements of the grid infrastructure. In this sense, the report prepared by the National Institute of Standards and Technology (NIST) highlights the importance of standardization as a central element in enabling interoperability in smart grids, reinforcing its importance for the reliability, security, and scalability of these systems [11]. Thus, interoperability and cybersecurity must be viewed in an integrated manner, as standardization contributes to both operational efficiency and protection against attacks.

The adoption of AI technologies in smart grids involves high implementation costs, representing one of the main obstacles to their widespread dissemination. The initial investment required can be substantial, ranging from upgrading existing infrastructure to deploying sensors, advanced communication systems, and data processing platforms. Furthermore, the costs associated with developing AI algorithms and training specialized personnel, who are crucial for the efficient operation of these solutions, must also be taken into account. Added to this are long-term capital expenditures, which include maintenance, ongoing system updates, and cybersecurity measures, aspects that require careful planning to ensure the economic viability and sustainability of smart grids. These costs are intensified in the absence of clear regulatory standards, which hinders strategic planning and the attraction of investment.

Finally, the regulatory and policy challenges represent a critical aspect for the adoption of AI in smart grids. The rapid pace of digital advancements and AI applications has outpaced the speed of adaptation of regulatory frameworks, resulting in a regulatory environment that is often fragmented and outdated. This lag limits the ability to respond to the new demands imposed by the digitalization of the electricity sector. In this scenario, public policymakers must develop clear and consistent regulations that address issues such as data privacy and cybersecurity. Only with an updated and coherent regulatory framework will it be possible to ensure the reliability, transparency, and security necessary for the consolidation of smart grids. Furthermore, a stable regulatory environment can reduce implementation costs, encourage technological standardization, and strengthen trust in cybersecurity and data management.

V. Conclusion

Smart grids represent a fundamental transformation in electric power systems, offering significant benefits in terms of efficiency, sustainability, and resilience. The integration of advanced communication technologies, combined with the application of AI techniques, plays a crucial role in the optimization, automation, and dynamic control of these networks. The vast amount of data generated by the different components of the grid paves the way for AI to be applied to a wide range of functions, from load forecasting to predictive maintenance and cybersecurity.

Despite its potential, the literature indicates that the large-scale implementation of AI in smart grids faces significant challenges. These include data complexity and quality, cybersecurity-related vulnerabilities, interoperability issues, a lack of protocol standardization, and high implementation and maintenance costs. These factors require not only robust technological solutions but also regulatory advances, coordination among industry agents, and continued investment in research and development.

In this sense, AI applications in smart grids have the potential to promote substantial improvements, such as increased grid stability, reduced operational costs, optimized resource use, minimized failures and interruptions, and more efficient integration of renewable energy sources. In conclusion, this paper aims to support researchers and professionals in the field by providing a solid foundation on the state of the art and the main challenges, thus guiding future studies and contributing to the consolidation of innovative solutions in the context of the energy transition, AI, and smart grids.

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