

# ARTIFICIAL INTELLIGENCE IN ELECTRICAL SYSTEMS: A STRUCTURED NARRATIVE REVIEW OF FOUNDATIONS, APPLICATIONS, DIGITAL ARCHITECTURES AND CHALLENGES IN GRID MODERNIZATION

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**ABSTRACT:** The incorporation of Artificial Intelligence (AI) into electrical systems has become one of the central drivers of energy-sector digitalization. The growing operational complexity of power networks, the integration of intermittent renewable sources, the expansion of distributed energy resources, and the need for increasingly faster decisions have strengthened the relevance of machine learning, deep learning, expert systems, and reinforcement learning methods. This article presents a structured narrative review of the foundations, applications, and limitations of AI in electrical systems, with emphasis on load and renewable generation forecasting, predictive maintenance, fault diagnosis, operational optimization, and emerging digital architectures. Rather than providing a merely descriptive overview, the study organizes the literature into analytical axes, compares methodological families in terms of objectives, data requirements, strengths, and constraints, and discusses contemporary concepts such as cyber-physical energy systems, digital twins, distributed energy resource management, and edge intelligence. The results indicate that AI expands grid observability, automation capability, and anticipation of critical events, but large-scale deployment still depends on trustworthy data, interoperability, explainability, cybersecurity, and regulatory compliance. It is concluded that AI should not be understood only as an incremental automation tool, but as a structural component of the modernization of intelligent, resilient, and decentralized power grids.

**Keywords:** Artificial Intelligence. Electrical systems. Smart grids. Energy digitalization. Operational optimization.

## 1 INTRODUCTION

The modernization of electrical systems is no longer a process limited to the physical expansion of infrastructure; it increasingly involves digital capabilities for monitoring, forecasting, control, and coordination. The diffusion of smart meters,

distributed sensors, automation systems, and Internet of Things (IoT) platforms has altered the informational regime of power networks, shifting operations away from exclusively deterministic models and toward greater dependence on real-time analysis (IEA, 2017; NIST, 2014). In this context, Artificial Intelligence (AI) emerges as a technology capable of transforming large volumes of heterogeneous data into operational support, diagnostics, and decision-making.

The relevance of this transition has been further amplified by the growing penetration of intermittent renewable sources, electric vehicles, distributed energy resources, and arrangements such as microgrids and prosumers. The variability of solar and wind generation, combined with the decentralization of loads and the heightened sensitivity of the system to local disturbances, poses challenges that traditional models do not always address adequately. Fang et al. (2012) already noted that smart grids would require simultaneous integration of electrical infrastructure, communication, and management intelligence; more recently, international reports and specialized reviews reinforce that AI-driven digitalization has become a key component of grid security, efficiency, and flexibility (Chen et al., 2024; IEA, 2025; Alam et al., 2025).

In applied settings, AI has been employed in tasks such as load forecasting, renewable generation forecasting, fault diagnosis and classification, predictive maintenance, dispatch optimization, demand response, anomaly detection, and microgrid operation support. The advancement of supervised, unsupervised, and reinforcement learning methods, as well as the use of deep neural networks, has broadened the capacity to model nonlinear relationships and complex temporal dependencies (Russell; Norvig, 2020; Goodfellow; Bengio; Courville, 2016; Sutton; Barto, 2018).

However, the literature on AI in the electric power sector is extensive and heterogeneous. A significant portion of studies focuses on specific applications, while other reviews tend to present listings of techniques without sufficiently exploring the actual conditions of deployment, data requirements, institutional limitations, and the relationship between algorithms and new digital architectures. As a result, there remains a need for syntheses that articulate technical performance, application context, and adoption barriers in a more integrated manner.

Against this backdrop, the present article aims to critically analyze the foundations, applications, and challenges of AI in electrical systems, organizing the discussion around thematic and comparative axes. The study argues that AI does not constitute merely an incremental automation tool, but a structural element in the modernization of power grids — provided its adoption is accompanied by requirements for data governance, explainability, interoperability, and cybersecurity.

## **2 THEORETICAL FRAMEWORK**

AI can be understood, in broad terms, as the field dedicated to the development of systems capable of perceiving, learning, inferring, and acting in dynamic environments (Russell; Norvig, 2020). In electrical systems, this definition takes on an operational character: learning demand patterns, inferring equipment states from measurements, classifying anomalies, selecting control actions, and supporting decisions under uncertainty. Goodfellow, Bengio, and Courville (2016) show that deep learning methods are particularly relevant when a problem involves strong nonlinearity and high dimensionality — two attributes frequently encountered in networks with large volumes of metered data and diverse operational events.

In the domain of smart grids, AI integrates into a larger infrastructure of communication, automation, and analytics. Fang et al. (2012) describes the intelligent grid as the convergence of electrical infrastructure, management systems, and protection systems, while NIST (2014) emphasizes that interoperability is an indispensable condition for the coordinated functioning of this ecosystem. This interpretation broadens the discussion: beyond selecting algorithms, it becomes necessary to understand the institutional and technological architecture within which these algorithms operate.

This conceptual expansion leads to contemporary notions such as cyber-physical energy systems, distributed energy resource management, digital twins, and distributed edge intelligence. Rather than viewing the network merely as an electrical system monitored by centralized software, recent literature describes it as infrastructure in which sensors, communication, analytical models, and decision mechanisms interact in near-real time. Recent reviews on distributed energy resource

management systems and digital twins show that AI is being incorporated not only for forecasting or classification, but also for hierarchical coordination, operational simulation, maintenance, and decision support under uncertainty (Pourghasem Gavvani *et al.*, 2024; Mchirgui *et al.*, 2024).

In the field of forecasting, Hong and Fan (2016) highlight that probabilistic, data-driven techniques enhance the capacity to represent uncertainties and outcome distributions, while Kong *et al.* (2019) demonstrate the suitability of LSTM architectures for residential short-term time series. For renewable generation, Voyant *et al.* (2017) show that machine learning methods and hybrid approaches play a relevant role in irradiance forecasting and, by extension, in the integration of intermittent sources into operations.

In maintenance and fault diagnosis, the potential gain from AI lies in transforming operational data into condition and risk indicators. Chen *et al.* (2024) note that AI/ML applications in the electric power sector already span asset inspection, monitoring, forecasting, planning, and operations. In parallel, recent literature on explainable AI indicates that adoption in critical environments depends not only on accuracy, but also on the ability to justify decisions, identify influential variables, and build regulatory and operational trust (Ribeiro; Singh; Guestrin, 2016; Shadi; Mirshekali; Shaker, 2025).

### **3 METHODOLOGY**

The present study is characterized as a structured narrative review, with an explicit protocol for literature search, selection, and thematic synthesis. This design was chosen because the field of AI applied to electrical systems encompasses review articles, methodological studies, sectoral applications, technical reports, and empirical investigations with different scales, objectives, and indicators — rendering uniform quantitative aggregation unfeasible and making an analytical-interpretive synthesis more appropriate.

The bibliographic search was conducted in the Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar databases, using descriptors in Portuguese and English related to Artificial Intelligence in power systems, load

forecasting, renewable generation forecasting, predictive maintenance, smart grids, cybersecurity in smart grids, digital twins, and distributed energy resource management systems. The temporal scope prioritized publications between 2012 and 2025, without excluding foundational works essential to an understanding of the subject.

Inclusion criteria were: peer-reviewed studies with direct relevance to the operation, planning, monitoring, or digitalization of electrical systems; review articles and methodological papers on AI techniques relevant to the sector; and institutional technical reports of recognized relevance to the energy domain. Excluded were opinion pieces without an analytical basis, documents without direct relevance to the object of study, and publications redundant with more comprehensive works on the same topic.

The synthesis was conducted through thematic categorization and qualitative comparison. Selected studies were examined with respect to application domain, method families, type of data required, operational objective, strengths, limitations, and deployment challenges. The discussion was organized around five analytical axes: forecasting and observability; maintenance and diagnostics; optimization and control; emerging digital architectures; and technical, economic, regulatory, and governance limitations. Accordingly, the article does not claim the statistical exhaustiveness typical of systematic reviews following PRISMA protocols, but seeks sufficient methodological transparency to sustain a critical analysis that is reproducible in its general criteria.

## **4 RESULTS AND DISCUSSION**

The literature examined indicates that AI performs distinct yet complementary functions in the modernization of electrical systems. In general terms, these functions can be grouped into three layers: observability and forecasting; diagnostics and maintenance; and operational decision-making. The first enhances the capacity to anticipate future system states; the second reduces uncertainties about asset condition; and the third supports the selection of actions in environments with multiple constraints and high variability.

In the forecasting and observability axis, supervised methods and recurrent neural architectures remain among the most frequently used approaches. Hong and

Fan (2016) show that probabilistic forecasting is especially relevant in high-variability systems, as it allows for the representation of uncertainties rather than merely point values. Kong et al. (2019) demonstrate the suitability of LSTM for short-term residential time series, while Voyant et al. (2017) highlights the utility of machine learning models for irradiance forecasting. In analytical terms, the primary difference among method families lies less in any universal superiority and more in the fit between the algorithm's structure, temporal granularity, data availability, and operational objective.

#### 4.1 COMPARATIVE SYNTHESIS OF AI APPLICATIONS IN ELECTRICAL SYSTEMS

**Table 1 — Comparative synthesis of AI applications in electrical systems**

Application domain	Main objective	Recurring method families	Data typically required	Analytical strengths	Recurring limitations
Load forecasting	Anticipate demand and support operation/planning	ANN, LSTM, SVR, hybrid models, ensembles	Load history, climate, calendar, consumption profile	Captures non-linearities and seasonalities	Sensitivity to data quality and regime change
Renewable generation forecasting	Reduce operational uncertainty of intermittent sources	Supervised ML, DL, hybrid physical models	Irradiance, wind, meteorology, generation history	Improves scheduling and renewable integration	Dependence on consistent meteorological data
Predictive maintenance and diagnostics	Anticipate failures and estimate asset condition	Classification, anomaly detection, DL, XAI	Operational signals, events, inspections, sensors	Supports reliability and reduces unavailability	Low transferability across assets; interpretability required
Optimization and control	Support dispatch, demand response, and adaptive operation	RL, DRL, ML-assisted optimization	System states, costs, constraints, operational history	Well-suited to sequential decisions under uncertainty	Intensive training, operational safety, difficult validation
Digital grid architectures	Coordinate DERs, assets, and digital representation of the system	DERMS, digital twins, edge AI, analytics	Real-time data, topology, measurements, models	Integrates analysis, monitoring, and decision-making	Interoperability, governance, and deployment cost

Artificial neural networks and deep models tend to capture nonlinear relationships and complex temporal dependencies, but they require larger data volumes and more careful training processes. Simpler or hybrid methods may present

competitive performance when data are limited, when interpretability is a priority, or when operational updating needs to be less costly. Accordingly, the more robust discussion is not between a 'better algorithm' and a 'worse algorithm', but rather about methodological fit to specific forecasting, planning, and dispatch contexts.

In the maintenance and diagnostics axis, the use of AI shifts the logic from corrective to prognostic. From electrical, thermal, vibrational, or historical measurements, classification and anomaly detection models can identify degradation patterns before severe failures occur. Chen *et al.* (2024) highlights that this shift has direct implications for reliability, asset availability, and operational efficiency. Nevertheless, transferring models trained on controlled datasets to real-world environments remains a relevant challenge, especially when the system undergoes changes in topology, load regime, or measurement quality.

Another critical point in this layer is interpretability. In industrial and critical infrastructure applications, it is not sufficient for a model to present good predictive performance; it is also necessary that engineers, operators, and regulators understand, at least in part, why a given alert or recommendation was issued. In this respect, the literature on explainable AI indicates that techniques such as LIME, SHAP, and feature importance analysis can increase trust and facilitate auditing, although gaps remain regarding the standardization of explainability and its native integration into energy maintenance systems (Ribeiro; Singh; Guestrin, 2016; Shadi; Mirshekali; Shaker, 2025).

In the optimization and control axis, AI has progressed from forecasting toward decision support and, in some cases, toward autonomous control. Reinforcement learning is particularly promising in sequential problems, in which present decisions affect future system states — such as microgrid dispatch, storage control, and demand response. Sutton and Barto (2018) provide the conceptual basis for this framing, while applied reviews indicate the expanding use of RL in optimization and operation problems in the electric power sector (Sun et al., 2020). However, in critical systems, reinforcement learning algorithms face additional constraints: operational safety, the need for intensive training, sensitivity to reward function design, and difficulty in validating performance outside simulation environments.

Recent modernization also requires that the analysis of AI be articulated with emerging digital architectures. The concept of DERMS, for example, expresses the need for hierarchical coordination of distributed energy resources, aggregators, and grid operators in environments with high DER penetration. Pourghasem Gavvani *et al.* (2024) show that this field still presents relevant gaps regarding coordination between transmission and distribution and regarding the integration between management functionalities and analytical models. Likewise, digital twins broaden the discussion by enabling dynamic digital representation of grid assets and processes, supporting monitoring, simulation, and maintenance in near-real time (Mchirgui *et al.*, 2024).

## 4.2 EMERGING DIGITAL ARCHITECTURES AND CONCEPTUAL ALIGNMENT

**Table 2 — Core concepts of contemporary grid digitalization**

Concept	Role in the electrical system	AI contribution	Core challenge
Cyber-physical energy systems	Integrate physical assets, communication, and digital decision-making	Data analysis, event detection, and automation support	Ensuring security, synchronization, and resilience
DERMS	Coordinates distributed energy resources at multiple levels	Forecasting, resource prioritization, and coordination support	Interaction between transmission, distribution, and aggregators
Digital twins	Digitally represent grid assets and processes	Monitoring, prognosis, simulation, and maintenance	Continuous updating and model fidelity
Edge intelligence	Processes data near assets and reduces latency	Distributed inference and fast local responses	Limited computing capacity and security
XAI	Increases transparency of models	Explains alerts, diagnostics, and recommendations	Standardization and operational utility of explanations

In this context, AI ceases to function merely as a point-specific forecasting mechanism and begins to integrate more complex digital ecosystems, with distributed sensors, analytical models, multi-layer communication, and assisted or automated decision-making. Alam *et al.* (2025) and IEA (2025) reinforce that this movement is associated with potential gains in flexibility and efficiency, but also with new risks related to computational consumption, reliability of data flows, and system governance.

The limitations and boundary conditions of AI adoption in electrical systems are therefore central to any serious assessment of the subject. The first concerns data quality and availability. Incomplete, poorly standardized, noisy, or biased datasets compromise the training, generalization, and robustness of models. The second pertains to interoperability: advanced algorithms have reduced utility when they cannot operate consistently with legacy systems, heterogeneous protocols, and different levels of grid automation. The NIST interoperability framework (2014) remains relevant precisely because it makes explicit that energy digitalization depends on technical and institutional compatibility, not merely on algorithmic capability.

The third limitation is associated with cybersecurity. The greater the interconnectivity among sensors, assets, enterprise systems, and analytical platforms, the larger the system's attack surface. Yan et al. (2012) already treated smart grid communications as a critical security dimension; more recently, technical reports and reviews of AI/ML in power systems insist that operational reliability requires simultaneous attention to algorithmic robustness, data protection, authentication, traceability, and resilience against malicious manipulation (Chen et al., 2024).

The fourth limitation concerns deployment costs and governance. AI adoption requires investment in data infrastructure, sensing, platform integration, technical qualification, and model maintenance. Furthermore, decisions of greater autonomy raise questions about accountability, auditability, and regulatory compliance. For this reason, the maturity of AI in the electric power sector should not be measured solely by the sophistication of algorithms, but by the capacity to integrate them with safety, transparency, and operational feasibility.

Considering these elements, the analytical contribution of recent literature can be synthesized in two movements. The first is the expansion of AI's role: from a forecasting tool to a transversal component of observability, diagnostics, optimization, and digital coordination. The second is a shift in evaluative focus: from isolated accuracy comparisons to more comprehensive assessments that consider interpretability, architectural integration, robustness, and deployment readiness. It is in this transition that the discussion of AI in electrical systems gains scientific depth and practical relevance.

## 5 CONCLUDING REMARKS

The analysis conducted has demonstrated that Artificial Intelligence occupies a strategic position in the modernization of electrical systems, particularly in contexts marked by decentralization, operational variability, and the intensification of data flows. Its value is not limited to accuracy gains in specific tasks, but extends to enhancing grid observability, supporting predictive maintenance, optimizing operational decisions, and integrating with new digital architectures.

The reinterpretation of the subject through a structured narrative review made it possible to organize the field into comparative axes and to make explicit that the choice of methods depends on the problem addressed, the type of data available, the temporal horizon of interest, and the deployment conditions. In other words, there is no universal superiority among ANNs, LSTMs, hybrid models, expert systems, or reinforcement learning; rather, there are different levels of fit between technique, context, and operational objective.

It was also found that the contemporary agenda of the sector can no longer be discussed merely in terms of smart grids in a generic sense. Concepts such as DERMS, digital twins, explainability, and distributed intelligence show that AI tends to be incorporated as a constitutive layer of digitalized electrical ecosystems — not merely as an auxiliary analysis resource. This shift expands the technology's potential, but also makes its limitations more visible.

Among these limitations, the following stand out: dependence on quality data, interoperability with legacy infrastructures, cybervulnerability, modernization costs, and requirements for transparency and governance. Therefore, the advancement of AI in electrical systems depends on a multidimensional approach that articulates engineering, data science, security, regulation, and management.

As future research directions, the following are highlighted: development of more explainable and auditable models; integration between AI and digital twins in real operational environments; algorithm validation on multi-site and multi-utility datasets; incorporation of security and reliability criteria in reinforcement learning models; and deepening the coordination among distributed energy resources, storage, electric mobility, and grid operation. In these areas, the most relevant scientific contribution will

come not only from more complex algorithms, but from technically robust, interoperable, and institutionally viable solutions.

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