Current and Future Applications of Artificial Intelligence in Power Systems: A Critical Appraisal

Ricardo J. Bessa, *Fellow*, *IEEE*, Spyros Chatzivasileiadis, *Senior Member*, *IEEE*, Ning Zhang, *Senior Member*, *IEEE*, Chongqing Kang, *Fellow*, *IEEE*, and Nikos Hatziargyriou, *Life Fellow*, *IEEE*

Abstract—**This paper provides an overview of the application potential of artificial intelligence (AI) in power systems and points towards prospective developments in the fields of AI that are promised to play a transformative role in the evolution of power systems. Among the basic requirements, also imposed by regulation in some places, are trustworthiness and interpretability. Large language models, foundation models, as well as neuro-symbolic and compound AI models, appear to be the most promising emerging AI paradigms. Finally, the trajectories along which the future of AI in power systems might evolve are discussed, and conclusions are drawn.**

Index Terms—**Artificial intelligence (AI), power system, generative AI, interpretability, large language model, neuro-symbolic AI, trustworthiness.**

I. Introduction

THERE are numerous definitions of artificial intelligence (AI) in the literature. One influential proposal comes from François Chollet, who defines intelligence as "the skill-acquisition efficiency of a system over a scope of tasks, with respect to priors, experience, and generalization difficulty" [1]. In simpler terms, intelligence refers to the ability of a system to efficiently learn new tasks and improve its skills, while leveraging prior knowledge, inductive biases, and structural assumptions.

In power systems, this translates into systems that can continuously learn from data and enhance their performance, while incorporating prior knowledge about physical components. Such systems should be capable of moving toward higher generality, adapting and evolving to perform new and diverse tasks. This trajectory extends beyond traditional machine learning (ML) and advances into AI and generative AI, ultimately pointing toward the long-term goal of artificial general intelligence.

AI implementations have already been deployed in practical power systems and embedded into energy stakeholders' daily operations (e.g., see [2] for a recent compilation of real-world applications reported by system operators). As discussed in the companion paper [3], practical applications of AI algorithms primarily include the use of various types of now considered classical models (e.g., linear regression, tree-based models, and neural networks (NNs)) for the estimation and forecast (short-term, long-term) of a variety of variables and parameters, including electricity market prices and/or bidding strategies, electrical energy production (including renewables), power demand, and loading of lines. From the network operation perspective, estimation of the expected solar generation and electric vehicle charging demand has been used to a certain extent to define the required volume of energy flexibility that will need to be acquired (e.g., via balancing and flexibility markets or direct contracts) to avoid grid congestion events and to facilitate the deployment of demand response programs and the increase of integration of renewable energy sources (RESs). Advancements in AI are also triggering a paradigm shift in power system protection, while predictive maintenance, fault detection and location, assets, and outage management are other areas with already somewhat mature AI applications. It is clear, however, that advancing toward a new generation of AI models with higher accuracy and reduced computational requirements is essential to exploit the growing volume and heterogeneity of available data and to provide more effective decision-support tools. Moreover, new requirements for trustworthiness and interpretability are imposed by practical needs and legislation like the European Union AI Act.

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R. J. Bessa is with INESC TEC, 4200-465 Porto, Portugal (e-mail: ricardo.j.bessa@inesctec.pt).

S. Chatzivasileiadis is with Technical University of Denmark, 2800 Kgs. Lyngby, Denmark (e-mail: spchatz@dtu.dk).

N. Zhang and C. Kang are with Tsinghua University, Beijing, China (e-mail: ningzhang@tsinghua.edu.cn; cqkang@tsinghua.edu.cn).

N. Hatziargyriou (corresponding author) is with National Technical University of Athens, Athens, Greece, and he is also with the School of Technology and Innovations, University of Vaasa, Vaasa 65200, Finland (e-mail: nh@power.ece.ntua.gr).

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What makes the transition to the new generation of AI applications possible for power systems is the availability of reliable, high-quality data. Smart grids, enabled by technologies like smart meters, Internet of Things (IoT) devices, remote sensing (e.g., satellite images), and advanced sensors, greatly increase data availability and enable more sophisticated management and optimization of energy systems. Smart meters now provide granular, real-time consumption data, supporting both grid operators and consumers in managing demand and efficiency, although some regions face regulatory constraints such as general data protection regulation (GDPR) in Europe. IoT sensors and phasor measurement units (PMUs) further enhance monitoring by collecting diverse, high-frequency data for diagnostics and stability assessment, while wide area monitoring systems (WAMSs) use these inputs to analyze grid behavior across large areas. Integrating these with robust cybersecurity and data management is essential due to the scale and sensitivity of this information. Advanced communication protocols, 5G communication technology, and edge computing ensure secure, efficient data transmission and processing. Together, these advancements—from high-fidelity sensing and secure data infrastructures to the exponential growth in computational power and specialized AI software frameworks, as discussed in the companion paper [4] —have significantly enhanced the feasibility of training and deploying large-scale data-driven models for power system applications.

In this paper, the application potential of AI in several areas of power systems is first overviewed. This includes real-time decision-making, forecasting, operational and long-term planning, security and stability, as well as power system control and simulation. Then, the critical requirements of interpretability and trustworthiness are explained. The capability of AI to interpret model-driven approaches and the provision of explainable and trustworthy AI tools (safe-by-design, NN verification, worst-case guarantees) are discussed. Finally, the application of emerging AI methods, i.e., large language models (LLMs), foundation models (FMs), neuro-symbolic AI, compound AI, and human−AI co-working is briefly presented.

II. Application Potential of AI in Power Systems

A. Real-time Decision-making

The increasing integration of RESs and the rising occurrence of both natural and human-made perturbations introduce significant operational challenges for power systems. These include increased uncertainty, reduced system inertia, and the need for faster and more informed decisions. To ensure secure and reliable system operation under these conditions, advancements in real-time monitoring and decision-support software are essential, particularly in enabling the timely identification and application of remedial and preventive control actions.

Traditional optimization-based tools such as power flow, state estimation, and optimal power flow (OPF) continue to play a critical role in supporting human operators. However, AI methods can complement these tools by, for instance, generating real-time action recommendations for contingency scenarios by leveraging their ability for fast inference. Moreover, AI methods are particularly well-suited to operate under conditions of partial observability and uncertainty, where conventional optimization may struggle or require excessive computational resources.

Among AI methods, reinforcement learning (RL) is gaining interest for deriving remedial actions for congestion management under $N-1$ conditions. Its ability to learn policies that map system states to control actions enables fast adaptation to system state changes, offering, for instance, a potential tool for real-time topological changes, redispatch, and demand-side flexibility activation [5]. In parallel, supervised learning approaches have been employed to construct surrogate models (or proxies) such as power flow computation and dynamic security assessment. These models enable rapid contingency analysis and severity classification by approximating the outputs of more computationally intensive simulations [6].

Network topology information plays an essential role in applications such as voltage control and congestion management. As a result, graph neural networks (GNNs) have emerged as powerful architectures capable of capturing the spatial dependencies and structural characteristics of power grids. GNNs have been employed in both supervised and RL settings. However, challenges remain in representing the cascading propagation of events, where a disconnection in one region can affect distant areas of the grid. Recent efforts have focused on integrating domain-specific physical knowledge such as physics-informed GNNs [7] or influence graphs into GNN architectures [8].

Furthermore, the integration of AI with constrained mathematical optimization problems opens promising avenues for scaling decision-making to large-scale systems. One example is the use of a self-supervised primal-dual learning framework to approximate the optimal solutions for large-scale security-constrained OPF, thus reducing the computational burden while preserving security constraints [9].

Another emerging application is the intelligent processing of alarm data. With the growing complexity of modern power systems, alarm flooding has become a critical issue, often overwhelming operators and weakening their ability to identify and respond to the most consequential events [10]. To address this, classical ML techniques (clustering, text mining, among others) are being combined with natural language processing techniques and LLMs to process, classify, and prioritize alarms in real-time. These AI-based systems can also support ex-post analysis of alarm sequences, providing valuable insights into root causes and system dynamics during disturbances.

B. Forecasting in Power Systems

Forecasting forms the backbone of operational and long-term planning of modern power systems. As the system becomes increasingly complex with the integration of RESs, the proliferation of smart meters, and the liberalization of electricity markets, the demand for high-resolution (both spatial and temporal), adaptive, and robust (e. g., to missing or erroneous data) forecasting tools is greater than ever. AI-based forecasting methods have emerged as powerful alternatives to traditional statistical techniques, offering, in several cases, enhanced accuracy and flexibility across multiple forecasting tasks. In power systems, forecasting can be broadly categorized into three key applications: load forecasting, RES generation forecasting, and electricity price forecasting. These forecasts and their associated uncertainties also serve as critical inputs for several operational planning tasks such as dynamic reserve allocation and market result validation.

Load forecasting is essential for balancing supply and demand on multiple time scales. It primarily encompasses several scenarios, including system-level forecasting, regional-level forecasting, bus-level forecasting, user group-level forecasting, and individual user-level forecasting. As electricity consumption patterns become increasingly complex and diverse, for example, due to the growth of behind-the-meter distributed energy resources such as rooftop photovoltaic (PV) systems, new challenges arise in accurately forecasting load demand. To enhance forecasting accuracy under such conditions, AI-based cloud detection models and forecasting methods increasingly leverage recurrent architectures and attention mechanisms to capture complex spatiotemporal dependencies [11]. With the widespread deployment of smart meters, personalized load forecasting has also become increasingly relevant. Recent studies propose adaptive personalization strategies that fine-tune global models using user-specific data only when beneficial, thereby balancing generalization and specificity [12]. Privacy and computational constraints are addressed by federated learning frameworks [12], which allow collaborative model training among cloud, edge servers, and edge devices while minimizing communication and memory overhead.

RES generation forecasting, especially for wind and PV power, introduces additional challenges due to the high variability and spatiotemporal correlation. AI models are particularly effective at learning complex, nonlinear relationships between historical generation and meteorological features. Hybrid methods that combine physical knowledge (e. g., numerical weather prediction) with ML have been shown to outperform purely data-driven or physics-based methods, while sky cameras and satellite images processed by vision transformer-based models enhance the performance in shorter-term periods [13]. Probabilistic forecasting has become a research focus, aiming to capture forecast uncertainty via ensemble learning, quantile regression, or diffusion-based generative methods. These methods are crucial for integrating RESs into system operation and providing reserve margins consistent with forecast confidence levels [14]. In operational planning, the effective integration of such uncertainty information into decision-making remains a pressing challenge. This includes not only improving the visualization and communication of uncertainty to human operators but also designing decision-support algorithms that strike a balance between computational tractability and model interpretability.

Electricity price forecasting is another critical task for market operators, retailers, and participants. A variety of interrelated factors, including demand, supply, market rules, renewable energy penetration, and cross-border exchanges, influence price dynamics. AI methods such as gradient boosting, long short-term memory networks, and transformers have been employed to capture nonlinear dependencies and regime changes in price series. Compared to traditional time-series-based methods, AI methods better handle non-stationarity and uncertainty by incorporating a wide range of exogenous variables. These methods, however, still face challenges related to data quality, interpretability, and robustness against sudden market shocks or policy changes.

Taken together, AI methods have significantly advanced state-of-the-art power system forecasting. They offer improved predictive accuracy, scalability to high-dimensional inputs, and the ability to incorporate heterogeneous data sources. However, several challenges remain: the risk of overfitting in personalized models, the difficulty of deploying large models in edge environments, and the interpretability of "black-box" architectures in safety-critical applications. Addressing these challenges is crucial for the reliable and transparent deployment of AI in power system forecasting and remains an active area of research. A promising direction is decision-focused learning, which integrates ML with constrained optimization and trains models to directly improve downstream decision quality rather than forecasting accuracy. Such methods have been explored for operational resilience, including proactive scheduling and early intervention strategies [15].

C. *Operational and Long-term Planning*

AI methods are increasingly reshaping the computational landscape of power system operation, offering new pathways to handle the complexity, scale, and uncertainty of real-time decision-making tasks. Core optimization problems such as power flow, economic dispatch (ED), and unit commitment (UC) often require solving large-scale, nonlinear, and mixed-integer formulations under stringent time constraints. Traditional mathematical solvers can become computational bottlenecks in such settings, particularly with high-resolution spatiotemporal data and frequent changes in load and RES output. Two principal lines of AI-enhanced methodologies have emerged to address this: ① end-to-end prediction-based approximations; and ② hybrid model-accelerated solvers.

End-to-end prediction-based approximations directly approximate optimal solutions, aiming to replace traditional optimization pipelines with data-driven models [16]. However, their application remains constrained by their limited generalizability to unseen conditions, lack of guarantees on constraint satisfaction, and dependence on extensive offline training. To solve these problems, transfer learning and GNN methods that account for topological variations have been increasingly applied [17]. Alternatively, hybrid model-accelerated solvers embed AI modules into classical optimization frameworks to accelerate tasks such as constraint screening, warm-starting, or surrogate modeling, while retaining established structures.

One representative application is in data-driven power flow modeling. Rather than solving nonlinear algebraic equations in every iteration of an optimization, ML models such as partial least squares [18] or lifting-dimension regressions [19] can approximate the mappings between nodal injections and voltage or angle variables with high fidelity. These surrogates significantly reduce computation time in iterative solvers, particularly in distribution grids where topology or parameter uncertainty undermines model-based methods [20].

In large-scale UC with grid constraints, the combination of model-driven formulation and data-driven variable/constraint reduction has proven especially powerful. Recent methods leverage offline solution databases and clustering of nodal net load profiles to identify redundant or inactive constraints and binary variables, thus reducing the problem size before online optimization. These reductions enhance computational tractability while preserving solution quality and feasibility. Moreover, such methods have been adapted to stochastic and robust UC formulations, including those with scenario-based uncertainty representations and reserve co-optimization [21].

Beyond acceleration, AI methods are also being used to improve robustness and adaptability in dispatch and scheduling. For instance, AI classifiers or learning-based constraint approximators can be embedded into rolling optimization frameworks to eliminate infeasible regions or suggest high-quality initializations rapidly. Reference [22] uses ML to learn active constraints and accelerate optimization, while [23] uses decision trees to learn the active sets and solve large mixed-integer linear programs successfully, which are intractable to solve with conventional commercial solvers.

In contrast to the real-time demands of operation, long-term planning tasks such as RES siting, power grid expansion, or security of electricity supply assessment typically involve long-term horizons and more profound uncertainty. AI can effectively construct uncertainty sets and generate scenarios. Probabilistic modeling tools such as copula-based sampling or flexible Bayesian models enable planners to accurately represent correlated and non-Gaussian uncertainties.

Dimensionality reduction techniques further help to retain the tractability of the resulting long-term planning models [24]. Recent work explores how data-driven models can enhance operational planning by balancing economic cost and risk, and improve long-term transmission expansion through scenario generation under high integration of RESs [25], [26]. These contributions align with hybrid and uncertainty-aware AI strategies in power system decision-making.

Although the integration of AI into long-term planning is still in its early stages compared to its more established role in operational optimization, several advances developed for operational time horizons can already be leveraged to accelerate simulation and scenario analysis in planning tasks. Nonetheless, long-term planning introduces additional challenges (e.g., modeling weather scenarios under climate change or forecasting demand driven by emerging loads like electric vehicles and data centers) that require new AI developments. In this context, generative AI holds significant potential, particularly for producing realistic and diverse scenarios that better capture future uncertainties.

In summary, AI has demonstrated substantial value in accelerating and enhancing operational decision-making in power systems, particularly through hybrid formulations that retain domain structure while exploiting learned approximations. Emerging techniques such as decision-focused learning [15] and differentiable optimization layers [27] allow models to directly optimize decision quality and integrate seamlessly with classical solvers. Future research should focus on enhancing the scalability and accuracy of end-to-end models across diverse network topologies, improving the interpretability and reliability of AI models, and developing efficient simulation FMs tailored for long-term planning of power systems.

D. Security and Stability

The increasing penetration of RESs has raised critical concerns over the security and stability of power systems. Traditional model-based stability assessment and control methods are often too computationally intensive or structurally rigid to accommodate the diversity and uncertainty inherent in the operation of power systems under high integration of RESs. Against this drawback, AI methods have emerged as promising tools to enhance both power system security and stability assessment, by learning embeddable security and stability constraints for power system optimization, particularly in power systems dominated by inverter-based resources.

AI has been widely adopted for stability assessment and prediction across various stability dimensions, including voltage, frequency, and rotor angle stability. These assessment tasks are often framed as classification or regression problems, utilizing supervised learning on simulated or measured data. For example, real-time transient stability assessment models based on decision trees, NNs, and ensemble methods have been extensively studied and are now considered for practical deployment due to their speed and accuracy [28], [29]. Transfer learning techniques further enable these models to generalize across unseen faults or operation conditions with limited retraining [30]. Physics-informed neural networks (PINNs) have also been explored to embed differential-algebraic equations into stability assessment models, enhancing physical consistency and data efficiency in scenarios like transient stability assessment of microgrid [31]. Meanwhile, integrating data-driven and physics-based models for frequency stability, such as combining system frequency response models with ML estimators, offers a hybrid approach that maintains interpretability while improving robustness [32]. Recent studies also highlight the cyber-vulnerability of data-driven stability assessment models, especially under adversarial attacks that manipulate input measurements without violating physical limits, revealing the need for resilient and secure design of AI models [33].

Recent advances have pushed AI beyond stability assessment toward embedding learned security and stability rules directly into optimization models. These efforts aim to bridge the gap between high-fidelity assessments and real-time operational optimization such as UC and ED. One representative paradigm is the extraction of stability constraints from data using ML models that approximate the feasible region boundary. For example, optimal decision trees [34] and sparse oblique decision trees [35] have been proposed to derive interpretable and linearly embeddable security rules, which can be included in optimization models using big-M formulations [36], [37]. Various methods have been developed in the voltage stability domain to learn rules from simulation data, such as regression trees, support vector machines, or convex polyhedrons, and embed them into ED or UC problems as stability constraints. When properly regularized and localized, these learned constraints have demonstrated the ability to significantly improve stability margins without sacrificing computational efficiency [38].

A significant challenge in this line of work is transforming non-convex, nonlinear stability boundaries into tractable, embeddable forms. Several studies have introduced convex approximations using multiple polyhedrons or semidefinite relaxations to address this, enabling efficient integration into mixed-integer or conic programming models. Furthermore, constraint learning frameworks have been proposed to iteratively refine the constraint set based on geometric alignment and local data consistency, thereby ensuring both reliability and tightness of the embedded constraints [39]. These techniques offer a pathway to encode previously intractable physical constraints into scalable optimization solvers, potentially transforming the way we co-optimize security and economics in future power systems.

In summary, data-driven approaches to stability assessment and rule embedding represent a significant step toward achieving secure, efficient, and intelligent operation in power systems with high penetration of RESs. While stability assessment tasks benefit from advances in general-purpose AI models, embedding security and stability constraints into optimization workflows requires customized architectures that honor domain knowledge and operational tractability. Ongoing research continues to explore new forms of hybridization between physics-based and data-driven techniques, with a particular focus on convexity, scalability, and robustness.

E. Power System Control and Simulation

As modern power systems become increasingly complex and converter-dominated, traditional model-based methods to simulation and control often face limitations in terms of flexibility and computational cost. Data-driven methods have emerged as practical tools to support faster simulation and more adaptive control.

AI models often replace specific physical modules or serve as full-system surrogates in simulation tasks. For example, power electronic converters with proprietary internal logic can be modeled using "black-box" or "grey-box" AI-based models that track their dynamic behavior under various conditions. However, accurately modeling inverter dynamics for electro-magnetic transient (EMT) simulations remains highly challenging in practice due to their intricate nonlinear control loops and high-dimensional internal states (e.g., up to 17 states), making surrogate construction a non-trivial research problem [40]. These surrogates reduce the computational burden of EMT simulations and facilitate hardware-in-the-loop applications [41]. Hybrid frameworks combining physics-based and data-driven components have also been developed, enabling more accurate outage estimation and counterfactual resilience assessment [42]. More recently, a new approach, involving a PINN-based simulator called PINNSim [43], has emerged. It utilizes PINNs to capture the dynamics of individual components (lines, generators, loads) and replaces the conventional numerical integration method with a solver tailored for NNs, potentially achieving solution speeds that are orders of magnitude higher. At the moment, it has been shown that PINNs can capture the dynamics of whole power systems 20-1000 times faster than conventional Runge-Kutta solvers for root mean square (RMS)-based dynamic simulations [44], and PINNs can capture the equivalent model of a wind farm 25-100 times faster than PSCAD for EMT simulations [45]. Integrating just a single PINN in an EMT simulation, to replace only the phase-locked-loop (PLL) controller of a single generator in a 9-bus system, has been shown to achieve 4-5 times acceleration compared to the PSCAD implementation [46]. Therefore, we expect that PINNSim has the potential to be approximately 10-100 times faster than conventional solvers, especially for EMT simulations.

In control, RL has gained traction for tasks like voltage regulation, where deep RL agents can autonomously learn control strategies through simulation. Multi-agent architectures such as those using the multi-agent deep deterministic policy gradient algorithm allow decentralized agents to coordinate voltage control with limited communication and local measurements, showing strong performance across varying loads and topologies [47]. As discussed in Section II-A, recent efforts have also demonstrated the promise of deep RL and hybrid methods for more common control tasks such as network topology optimization and generation redispatch, further expanding the role of AI in real-time grid operation.

Recent advances have also explored projection-based architectures to improve safety guarantees. For example, feasibility restoration networks such as FRMNet [48] and constraint-satisfying neural layers such as GLinSAT [49] incorporate projection mechanisms or differentiable optimization modules, thereby ensuring that the learned control actions inherently comply with power system constraints. These methods offer a promising direction for embedding constraint satisfaction directly into AI-based decision-making and control processes. In fact, safe RL is rapidly emerging as an enabler of autonomous decision-making in future power systems. By moving beyond ad hoc reward penalization toward principled constraint-aware learning, emerging techniques, including projection and trust-region methods, Lyapunov-based stability guarantees, shielding and safety layers for action correction, barrier and primal-dual formulations, and uncertainty-aware Gaussian-process and robust learning approaches

[50], provide complementary mechanisms to directly encode physics, operational limits, and risk into learning agents.

In summary, AI-driven simulation and control methods are proving increasingly valuable for enhancing responsiveness, efficiency, and insight in modern power systems. While deep learning and RL offer new possibilities for approximating complex dynamics and learning control strategies, their real-world application remains challenging. In particular, ensuring scalability across large state-action spaces, guaranteeing constraint satisfaction in safety-critical operations, and maintaining accuracy and efficiency under limited training data are all active research problems. These challenges are especially pronounced in continuous or hybrid control tasks such as voltage regulation, where traditional optimization methods often remain competitive.

III. Interpretability Augmentation of Model-driven Approaches Using AI

A. Improve Interpretability of Model-driven Approaches

In the AI literature, interpretability and explainability are typically discussed in the context of understanding the outputs of ML models, as discussed in Section IV. However, in a distinct and complementary setting, AI can also be used to improve the interpretability of traditional model-driven or mathematical approaches, which have long been foundational in power systems and are widely trusted by human operators and decision-makers. One key contribution lies in improving the interpretability of outputs from complex mathematical models, particularly in the presence of uncertainty, a challenge that often impedes effective decision-making. For instance, optimization results under stochastic conditions can be challenging to interpret without additional tools or techniques [51].

To address this, statistical and ML methods originally developed for improving the explainability of AI systems are being adapted to interpret optimization outcomes. These methods help deconstruct and explain different components of mathematical models. For instance, [52] proposes a method for generating coherent local explanations across multiple components of an optimization problem. This method draws inspiration from local interpretable model-agnostic explanations, which is a widely used technique in explainable AI.

A practical application of this hybrid method can be found in dynamic electricity pricing for electric vehicle charging. In such settings, a surrogate AI model can approximate the behavior of a complex stochastic optimization algorithm. Explainability techniques, particularly those based on Shapley values, can then be applied to explain how different input features such as forecasted demand or carbon intensity influence pricing decisions. This improves both the transparency and communicability of results to decision-makers operating under uncertainty [53].

This shows a promising direction where AI is not only integrated with operation research for improved performance (as discussed in Section II) but also leveraged to extract interpretable insights that support trust, understanding, and informed action. Other potential applications are the OPF under uncertainty or RES market trading.

B. Explain Large-scale Energy Systems

The growing interconnection of cross-country power systems and the integration of electricity markets have significantly increased the complexity and volume of data to be analyzed, which often encompasses spatiotemporal dimensions. This requires advanced analytical techniques to handle large-scale datasets and generate interpretable and actionable insights for long-term planning and operational decision-making of power systems in increasingly complex and RES-integrated power systems.

Traditional correlation-based methods frequently fall short in this setting, as they may detect coincidental or spurious relationships that do not reflect underlying system dynamics. In contrast, causal inference techniques present a more robust framework by identifying cause-and-effect relationships among variables. This highlights the increasing relevance of causal AI in large-scale power system analytics by uncovering true causal mechanisms [54]. This trend opens the door to the application, in energy systems, of the causal forecasting concept [55], where predictive models are informed by causal structures, leading to more resilient and explainable predictive analysis.

Established rule-based methods are helpful to explain power system events, for instance, to identify key drivers (e.g., excess demand, limited generation capacity, and interconnection congestion) of scarcity events from data simulated by the ENTSO-E's Pan-European electricity market model [56]. Nonetheless, modern AI explainability techniques based on Shapley values [57] are increasingly employed to interpret complex behaviors in power systems, including the identification and analysis of critical events like transient stability violations, and uncover the influence of various power system variables on stability margins [58]. The neuro-symbolic AI models discussed in Section V-B can also be used to generate explanations in the shape of mathematical equations.

In that respect, multimodal LLMs are emerging as a promising tool to process data types (e.g., time series, textual, and visual) and can be used to explain events such as fault diagnosis in wind turbines [59]. However, additional research is needed to address limitations in LLMs, particularly their challenges in efficiently handling large-scale datasets and extracting causal relationships without domain-specific knowledge. While knowledge graphs are not AI models themselves, they play a crucial supporting role in AI systems by offering structured, semantically rich representations that can be combined with LLMs to improve reasoning and factual consistency [59]. Nevertheless, their interpretability remains challenging for end-users unless complemented by effective visualization or summarization tools.

IV. Trustworthy and Interpretable AI

As presented in Section II, there is a wide range of applications where AI can benefit power system operations. However, none of these AI tools will gain widespread practical application if they cannot be trusted. First, the intended users, who are usually the electricity utilities, will avoid adopting any tool they cannot understand and trust. Second, regulations to enforce the trustworthiness of these tools are gradually being established. The European Union AI Act [60], which is the first attempt in the world to enforce rules for AI, designates the supply of electricity as critical infrastructure and considers the AI tools deployed in the power system as high-risk AI systems. For those, additional requirements are applied. For example, high-risk AI providers must design their AI tools to "achieve appropriate levels of accuracy, robustness, and cybersecurity", and "establish a quality management system to ensure compliance". High-risk AI tools must also "allow human oversight". But can the high-risk AI providers "explain" their AI tools and offer guarantees about their accuracy and robustness? This is where the methods for trustworthy and interpretable AI become essential.

The most popular tool to interpret AI models is the SHAP toolbox, a Python toolbox based on SHapley Additive exPlanations [57]. Essentially, the SHAP toolbox uses input-output sensitivities to determine how the inputs change when applying marginal changes to the output. Through this, the user gains valuable insights into feature importance, i. e., which inputs a specific output mostly depends on, and how changes to these inputs affect the output. SHAP toolbox can be applied to any AI model, including regression models with exogenous variables such as autoregressive integrated moving average with exogenous inputs (ARIMAX), decision trees, NNs, and transformer models, as it focuses on the interaction between inputs and outputs. Figure 1 shows an output example of SHAP toolbox for an NN performing solar PV forecasting [61], where the x-axis represents the NN output (solar PV forecast for the next 1 hour, in kWh), and the y-axis lists the five most important features for this model, along with the impact of high or low values for each feature. The SHAP toolbox has already been used in a number of power system applications, e.g., [58], [61], and a useful overview of the explainable AI tools for power systems is provided in [62].

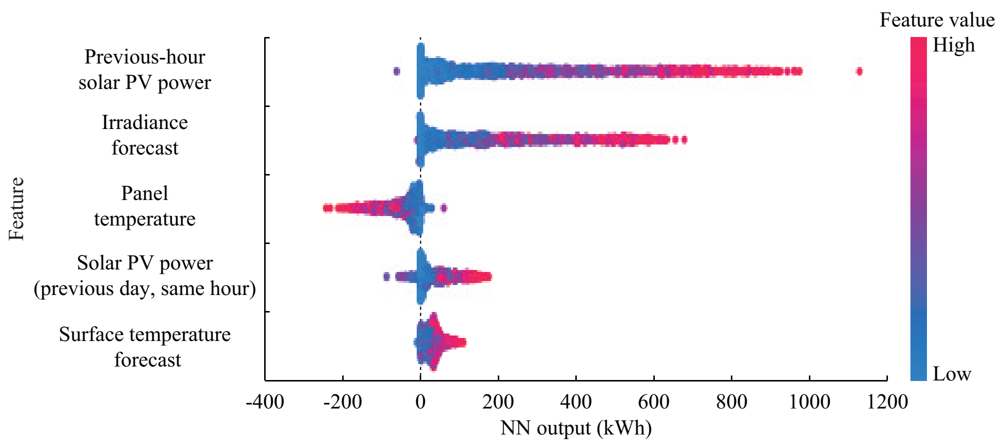

Fig. 1. Output example of SHAP toolbox for an NN performing solar PV forecasting.

Although interpretability can help a lot in understanding and better use of AI tools that are often considered a "black box", it cannot provide guarantees about the performance of an AI tool; for instance, "Will my AI tool always perform the appropriate remedial action to avoid the blackout?" or "Will it always determine an optimal set-point without violating any of the constraints?". These are questions that extend beyond interpretability and require approaches that can provide guarantees.

Based on the existing literature for power systems, we can currently distinguish among three families of methods: ① AI tools that are designed to be safe; ② verification methods for AI tools performing classification tasks, e.g., determining if an operating point is stable or unstable; and ③ methods that extract guarantees about the worst-case performance of an AI tool.

In the existing literature on trustworthy AI tools for power systems, the majority of research focuses on the first family of methods: AI tools that are safe by design. This family includes three main approaches.

First, to "clamp" the AI output. Considering that most constraints are upper and lower bounded, such as by voltage limits, generator limits, and controller limits, a reliable option is to constrain the AI output so that it does not violate these bounds. For example, if an AI tool aims to determine the power set-point of a generator, it is easy to "adjust" any output that violates its bounds by "clamping" it to the closest permissible value before sending it as a control action to the generator [63]. Obviously, implementing the clamped control actions is sub-optimal compared to the performance the AI tool was trained to achieve. Considering the large, nonlinear nature of power system applications, even small perturbations of the AI output could potentially lead to a significant deterioration in performance. This is something that must be assessed through extensive simulations and case studies, and if clamping results in unacceptably poor performance, then the AI developers should adjust the training of their tool. Second, to develop so-called dependable AI tools, where the NN structure for AI-based controllers is designed to prevent vanishing gradients or with built-in closed loop stability guarantees [64]. A third main approach in this family includes AI tools that function as the first stage of a two-stage framework, and are followed by a conventional algorithm trusted by utilities (and human experts) to verify and ensure compliance with safety-critical constraints. Successful examples have been shown to use RL to pick the five best candidates for line switching, which are then passed to a conventional optimization tool to determine if re-dispatching is necessary to maintain the system safe under each of the five new topologies. Then, the tool picks the action with the lowest re-dispatching [65]. Such an approach has won the competition organized by the French Transmission System Operator, RTE, on "learning to run a power network". Similarly, AI tools can also be used to predict an optimal setpoint, which is then passed to a power flow or OPF to determine the closest feasible operating point. Similar to the "clamping" approach, these approaches "distort" the AI output to enforce safety constraints, which can impact the overall performance of the tool.

In order to maintain the performance of AI tools while satisfying critical constraints, which is the main challenge in this first family of methods, approaches such as the so-called "differentiable layers" have been proposed. The idea here is that we encode power flow constraints or an optimization problem (e. g., minimizing re-dispatching subject to constraints) in differentiable layers through which we can backpropagate during NN training. In those cases, the NN can learn to deliver outputs that offer optimal re-dispatching or satisfy the power flow constraints. Differentiable layers cannot guarantee NN performance, but they can drive NN training to learn outputs that require minimal adjustments when passed through conventional second-stage algorithms, resulting in improved performance [66].

The second family of methods revolves around verification. These are rigorous methods that offer formal guarantees about the performance of an AI tool, and they are primarily developed for NNs. The AI community is using them for the purpose of verifying the performance of NNs in self-driving cars or in image classification in the healthcare sector, e.g., when using AI tools to read magnetic resonance imaging images and determine if a patient has cancer. Assuming that the NN uses ReLU activation functions, there is an exact transformation that embeds the whole NN in a mixed-integer linear optimization problem [67]. Through this optimization, we can determine input regions for which the NN maintains the same classification. This can help us map the complete output domain of the NN in a rigorous manner and anticipate its performance. Let us emphasize that NN verification does not require sampling and does not verify just for discrete points; instead, it delivers guarantees about the classification for continuous input regions. Figure 2 shows an actual result from a power system security assessment problem, which used a NN to classify safe from unsafe points [68]. P_{G2} and P_{G3} are the normalized active power outputs for generators G2 and G3, respectively, in this test power system. The figure presents the computed regions around four verification samples in which classification is guaranteed not to change. The illustrated green, blue, and red points in the figure are not necessary for the verification; we have only generated them to demonstrate that NN verification can indeed accurately determine continuous regions where the classification does not change.

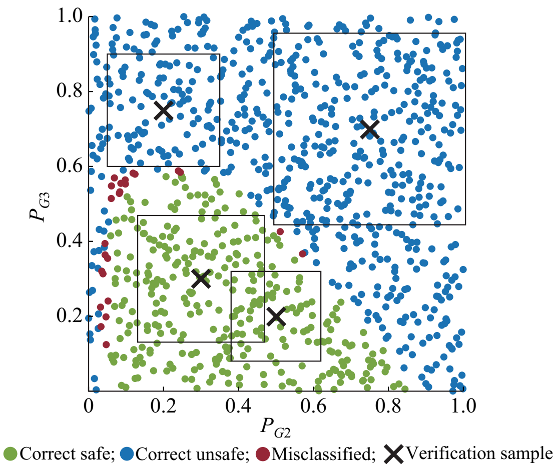

Fig. 2. Regions around four verification samples in which classification is guaranteed not to change.

Similarly, NN verification can be used to systematically identify adversarial points in an NN classification. Significant progress has been made over the past five years, and several NN verification algorithms are now available. For instance, $\alpha\beta$-crown is the algorithm that has won the NN verification competition for the past years. It is open-source and available also for power system researchers to use and tailor to their problems [69]. Although it started with the verification of NNs containing ReLU activation functions, it has recently been extended to consider any activation function [70].

The third family of methods focuses on extracting worst-case guarantees about the performance of an AI tool. Such methods can apply well to NNs performing regression or control tasks. To the best of our knowledge, such methods were first proposed for the field of power systems [71], and later, similar methods were proposed in the automatic control community [72]. The main reason that such methods seemed to have appeared first in power systems is that in contrast with the usual application domains of the AI community (computer vision, natural language processing, forecasting, etc.), where there is no efficient way to model images, text, or price interdependencies from first principles, power systems are physics-based systems with well-established and trusted numerical models. As a result, we can combine the NN verification algorithms discussed in the previous paragraph with the equations that model the power flows in a single optimization problem. This allows us to determine, for example, for which NN input we have the largest violation of the line flow limit across the whole continuous input domain of the NNs. Similarly, one can check for any other critical constraint. Reference [71] found that the worst-case violations can be 3-7 times greater than those identified by discrete sampling of the input domain (i.e., by assessing all the points used for training and testing the NN).

The challenge with this family of methods is its scalability. Working towards directions to boost scalability, [73] used graphics processing units (GPUs) and introduced a transformation to the $\alpha\beta$-crown, enabling efficient assessment of line flow violations. This method achieved a speedup of over 100 times compared to the dominant commercial solvers. However, there are still challenges to be addressed when we consider nonlinear constraints or differential equations that are necessary to verify, e. g., if an NN is an accurate representation of an inverter dynamic model. Assessing violations of nonlinear constraints transforms the optimization problem from a mixed-integer linear program to a mixed-integer nonlinear program, which is usually much harder to solve. The task becomes even more difficult if we need to consider state-space models with differential equations for verification, where discretization is probably the only viable path forward [74]. Similarly, the task to extract worst-case guarantees for NNs that, instead of the ReLU, employ tanh or other non-piecewise linear activation functions becomes more difficult. In that case, worst-case guarantees might not be tight or exact. However, as we mentioned earlier, $\alpha\beta$-crown has already incorporated such activation functions for the verification of NNs that perform classification tasks. We expect that the algorithms developed for tools like $\alpha\beta$-crown can form the basis for extracting worst-case guarantees in NNs performing regression tasks as well.

In summary, trustworthy and interpretable AI for power systems is a growing field that is expected to gain significant importance, as AI tools will likely not be deployed in safety-critical power system operation if they are not trustworthy. In Europe, there are efforts to develop testing and experimentation facilities (TEFs) for AI in the energy sector [75], [76], where AI vendors can submit their AI tools, and independent entities can test, verify, and certify that these tools comply with all safety constraints of the intended users, e.g., utilities. This appears to be the first step toward establishing standards and certification for AI tools in the energy sector.

V. Emerging AI Methods and Paradigms

A. LLMs and Foundation Models

While still in the early (but fast) deployment stage, LLMs are promising in supporting unstructured information processing and interactive decision-making workflows across long-term planning, operation, and control domains.

One of the most immediate applications lies in document understanding and knowledge retrieval. Power system operators often rely on lengthy technical reports, operating manuals, or regulatory documents to guide decisions. LLMs can process such unstructured textual data and support summarization, question answering, and compliance-related checks. When combined with retrieval-augmented generation (RAG), these capabilities gain improved factual grounding and traceability. This approach has been demonstrated in tasks such as parsing grid codes and regulatory orders to answer specific technical questions with more reliable, context-aware outputs [77]. For instance, by employing multi-agent frameworks with error-feedback loops, hallucination-induced execution errors can be reduced significantly, achieving simulation success rates of over 96% while ensuring high retrieval precision for complex grid codes [78].

Beyond document understanding, LLMs are also being explored as interactive agents that facilitate optimization or control workflows in power systems. By translating user instructions or preferences into structured queries or decision objectives, these models can help bridge the gap between human–system interactions. While still in a prototypical stage, some applications of LLMs in scenarios such as explaining electric vehicle charging tariffs to end-users [79] or performing real-time OPF with linguistic stipulations from grid codes or operational handbooks [80] underline their ability to interpret unstructured language, translate it into formalized constraints, and generate context-aware guidance. These examples demonstrate how LLMs can overcome limitations of traditional rule-based or manually configured systems, particularly their inability to process free-form text or adapt to heterogeneous documentation formats, and suggest the potential of LLMs to support decision-making by providing interpretable, text-grounded recommendations (e. g., translating linguistic rules into optimization-ready inputs, as discussed in Section III-A) and automating parts of the configuration process.

While current applications of LLMs remain largely in the proof-of-concept stage, their long-term potential in power systems is significant. An urgent need is to construct a comprehensive and multimodal knowledge database for power systems and develop deep reasoning LLMs for power system operation analysis, leveraging techniques like RAG and Chain-of-Thought.

In parallel, advances in transformer-based architectures, particularly in the context of LLMs, have motivated the development of FMs aimed at general-purpose AI tasks [81]. An FM can be defined as a pre-trained model trained in a self-supervised manner on large and diverse datasets spanning multiple distributions, with the capacity to generalize effectively to previously unseen datasets.

In the energy sector, particularly for power grids, the application of FMs is still in its early stages of development. One notable initiative is the open-source project GridFM, which aims to develop scalable FMs for steady-state power system analysis, including AC power flow, state estimation, contingency analysis, and OPF [82]. GridFM leverages transformer-based encoder-decoder architectures pre-trained on synthetic grid datasets, which is a strategy adopted to address the significant barriers associated with sharing real-world grid data. These pre-trained models can subsequently be fine-tuned using internal (confidential) datasets specific to grid operators.

FMs exhibit excellent next token prediction skills, making them well-suited for various energy system applications such as time series data imputation, anomaly detection, and forecasting. Furthermore, they show potential to emulate physics-based simulations with high accuracy and computational efficiency [83], without relying on strict a priori assumptions. This capability could significantly accelerate power system simulations compared to traditional numerical methods, which iteratively solve partial differential equations, thereby opening avenues for transient stability analysis and real-time operation support.

In contrast to conventional AI methods, which are typically trained for narrow, task-specific goals, FMs offer broader and more scalable value for power systems by enabling cross-domain generalization, unifying diverse data modalities, and achieving fast inference across multiple applications without requiring retraining. Moreover, model sharing between utilities, complemented by internal fine-tuning, can facilitate collaboration while preserving data confidentiality. For instance, in load forecasting, FMs enable a single model to forecast across multiple substations, including those with limited historical data, thereby reducing the operation and maintenance burden of maintaining a separate model for each power grid node.

However, several key challenges must be addressed. Access to realistic, large-scale, and representative grid data (e.g., topology, load, and generation measurements) remains a significant obstacle, delayed by confidentiality concerns and insufficient incentives for data sharing. Overcoming this barrier will likely require advances in synthetic data generation, federated learning, and development of data spaces and data marketplaces that incentivize secure and responsible data exchange [84].

Finally, it is essential to recognize that FMs inherit the risks associated with AI technologies, such as vulnerability to adversarial attacks, sensitivity to out-of-distribution data, and challenges regarding model interpretability. Addressing these risks is fundamental to ensuring the safe and reliable deployment of FMs in critical infrastructure domains [85].

B. Neuro-symbolic AI and Compound AI

Operational and long-term planning of power systems is supported by decades of accumulated knowledge, derived from modeling various assets and systems, as well as the practical experience of human operators and planners. This body of knowledge has been formalized through model-driven approaches (e.g., OPF, analytical sensitivity indices), encoded into rule-based expert systems (e.g., protection systems), and embedded in the mental models of human operators.

In parallel, digitalization efforts—notably the deployment of advanced data collection devices such as smart meters, smart sensors, wide-area monitoring systems, and 5G communication technologies—enable the massive data flows necessary for modern AI applications, as noted in Section I. Creating digital twins further enhances this ecosystem by generating high-fidelity synthetic data.

However, there is a need for AI methods that do not merely replace existing knowledge with purely data-driven solutions, which often demand large volumes of training data. These are usually perceived by decision-makers as "black-box" models with limited interpretability and transparency (potentially aggravating human algorithm aversion) and may struggle to comply with emerging regulatory frameworks such as the European Union AI Act [60], as discussed in Section IV.

A promising paradigm to address these challenges is knowledge-assisted learning, also commonly referred to as neuro-symbolic learning in the AI literature [85], [86]. In this framework, prior knowledge, including expert system rules, differential equations, conservation laws, and human cognitive models, can be ① integrated into the training process and architecture of ML models [87], and ② used to evolve or augment expert systems that learn from data through interaction with a (digital) environment [88]. The resulting systems can be purely data-driven models (e.g., NNs), rule-based expert systems, or a hybrid architecture combining rule-based, model-driven, and data-driven components optimally.

The symbolic structure of these models can be significantly enhanced by the semantic reasoning capabilities offered by recent advances in LLMs and large concept models (LCMs) [89]. LLMs and LCMs can continuously evolve hybrid AI systems by incorporating feedback (e.g., via reward functions) obtained either directly from the environment or human experts [90].

A promising direction of evolution is the development of compound AI systems [91], where multiple components, including physics-based models, LLMs, statistically-driven models, and traditional controllers (e.g., proportional-integral-derivative (PID) controllers), interact in a coordinated and optimal manner. This approach is particularly appealing in contexts such as control rooms, where AI components must coexist and interoperate with conventional power system analysis tools, including power flow analysis and state estimation, and function as reliable assistants to human operators within a workflow of tools that need to be optimized.

Finally, the semantic reasoning capabilities of small language and concept models that can be deployed at edge devices can be further explored by agentic models [4], [92], leveraging the neuro-symbolic architectures discussed above. These models can operate autonomously, perceiving their environment (e.g., grid state) and making context-aware decisions (e.g., active power set-point for a distributed energy resource). By leveraging the semantic processing power of language models, agentic systems can pursue goal-oriented actions while maintaining self-reflection and adaptability, capabilities essential for operating effectively in complex and dynamic environments.

C. Human–AI Co-working Interfaces

The compound AI concept can be extended beyond technical components to encompass the whole socio-technical system, integrating human operators as essential elements [85]. For instance, this extension aims to optimize the bi-directional information exchange between AI-based decision systems and human agents, explicitly considering aspects such as uncertainty quantification (e.g., by alerting human agents when recommended actions have low confidence levels), co-learning between humans and AI, and key human dimensions. The key human dimensions include: ① exploration, enabling humans to learn and investigate domain-specific knowledge, e.g., by providing a protected environment to test decisions, their effects, and AI capabilities and limits; ② animation, prompting human reflection and active contribution, e.g., by triggering the human to formulate hypotheses that explain observed phenomena; and ③ mirroring, whereby the AI reflects individualized patterns in human behavior to foster awareness of personal biases and variabilities in decision-making, e. g., the tendency to make riskier decisions at the end of a shift.

Advanced human−machine interfaces may also be necessary to facilitate the seamless integration of AI functionalities into existing legacy systems. Within the European project AI4REALNET [85], the InteractiveAI platform was developed as a prototype graphical interface for human−AI interactions, supporting a bi-directional virtual assistant for power grids [93]. This platform is designed as an open and extensible framework for industrial applications, enabling seamless integration with existing utility tools and operational workflows. Within this environment, human operators and AI agents engage in continuous two-way learning, where the AI system updates its internal models based on streaming operational data and the observed decisions, corrections, and preferences expressed by human experts, while the operator receives context-aware recommendations grounded in both data-driven insights and codified operational knowledge. This prototype demonstrates how collaborative decision systems can support operators in managing complex real-time operations, including disturbance analysis, incident resolution, and fault management, by combining explainable AI reasoning with visual, conversational, and actionable interfaces.

InteractiveAI platform leverages modular cognitive components such as scenario analysis, natural language-based explanation modules, and recommendation engines to enable transparent human−machine collaboration. For event and notification management, the platform integrates the OperatorFabric system [94] developed by RTE, which provides structured alerting, workflow orchestration, and real-time cross-team information sharing in grid operations following the hypervision concept.

Adequate evaluation workflows for human−AI interactions are also essential. A relevant real-world example from the AI4EALNET is a first trial conducted by TenneT, in which the joint control framework was applied to assess user experience in a control-room setting [95]. This framework enabled a structured cognitive analysis of human−AI interactions while evaluating an AI-based congestion management system. The evaluation considered key human dimensions, including operator acceptance, trust, cognitive workload, and overall decision-making performance.

Finally, the interaction between human operators and the multitude of grid management tools could be facilitated through an LCM, acting as a unified interface to mediate knowledge exchange. Such an interface would enable the capture of new human knowledge (e.g., sequence of actions to solve a congestion problem) and data (e. g., grid state), translating them into neuro-symbolic representations used to update and evolve the underlying knowledge-assisted AI models.

VI. Prospective Developments and Conclusions

The future of AI in power systems might evolve along two interdependent trajectories: the rapid development of large FMs and the continued refinement of small, task-specific models. While the former will have the deepest long-term impact, as their general-purpose reasoning and cross-domain transfer capabilities can fundamentally reshape how power systems are planned and operated, the latter remains indispensable for safety-critical functions requiring strict guarantees, particularly in control and protection domains. We anticipate three key thematic directions for prospective applications: ① trustworthiness, ② LLM and FM integration, and ③ intelligent decision-making.

Trustworthy AI represents the most urgent research priority in power systems, as no level of AI capability will translate into real-world deployment without rigorous guarantees. In particular, stability analysis and constraint embedding will become more dynamic, data-driven, and integrated into real-time operation loops, possibly involving physics-informed ML. It is also expected that emerging regulatory frameworks such as the European Union AI Act will accelerate the need for certifiable AI pipelines, making progress and standardization in this area unavoidable in the short term to medium term. Future advances will likely involve hybrid mechanisms where interpretable rules are continuously updated from streaming data and embedded into optimization in tractable and certifiable ways. Faster inference and simulation tools based on physics-informed neural operators can facilitate rapid fault analysis and contingency screening across a wide range of scenarios. Interpretability, robustness to distributional shifts, and resilience to adversarial inputs will be key areas of continued research and system-level validation.

Large models, especially FMs and multimodal LLMs, offer a transformative path for reshaping how humans interact with power system data, knowledge, and operational decisions. Among emerging AI paradigms, FMs are the most strategically promising due to their scalability, generality, and potential for shared development across utilities. FMs provide a unifying architecture capable of capturing cross-domain patterns and delivering rapid, scalable inference, enabling, together with LLM, not only document analysis and knowledge retrieval but also accelerated simulation, decision support, and tool integration across diverse tasks. These models can function as intelligent agents with deep reasoning abilities for scheduling, operational planning, and real-time assistance, while benefiting from significantly faster inference time compared to traditional numerical methods. LLMs are expected to expand toward interactive system monitoring, semi-automated dispatch, and operator training. In our view, establishing domain-adapted FMs should become a community-wide effort, as isolated one-off models are unlikely to deliver the robustness, interoperability, and reliability required by system operators. However, the practical deployment of both FMs and LLMs will depend on advances in domain adaptation, tighter integration with structured power system data (e.g., via RAG mechanisms), and robust safeguards to mitigate hallucinations, distributional shifts, and potential misuse.

AI for intelligent decision-making continues to address long-standing challenges in solving high-dimensional, nonlinear, and combinatorial optimization problems in long-term planning, operation, and control. Future developments will likely focus on deep integration between model-based solvers and AI-based components that provide structure-aware approximations, warm-starts, and real-time adaptation. We anticipate that hybrid solver-AI architectures will emerge as the dominant paradigm, given that purely data-driven controllers remain difficult to certify for safety-critical use. RL and surrogate modeling will continue to support real-time control and fast-response applications, including serving as predictive approaches to accelerate time-domain simulations. At the same time, data-driven decomposition and learning-to-optimize frameworks will push the limits of tractable large-scale decision-making under uncertainty. We therefore identify decision-focused learning as a particularly promising area where breakthroughs could materially influence operational practice.

In conclusion, AI will continue to play a transformative role in the evolution of power systems. Their successful deployment will require technical innovation, trustworthiness, interpretability, and alignment with physical principles. By advancing hybrid and compound AI paradigms that combine data, models, and domain knowledge, future power systems can become more intelligent, resilient, and responsive to emerging challenges. We encourage academia and industry to prioritize high-fidelity synthetic data generation (e. g., for FM training), secure pre-trained model and data sharing frameworks (e. g., data spaces and analytics marketplaces), transparent evaluation protocols, and certifiable AI components, as these are essential to strengthening trustworthiness and enabling future progress.

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Ricardo J. Bessa received the Licenciado (5-years) degree, the M.Sc. degree, and the Ph.D. degree from the University of Porto, Porto, Portugal, in 2006, 2008, and 2013, respectively. He is the Coordinator of the Center for Power and Energy Systems at the Institute for Systems and Computer Engineering, Technology and Science (INESC TEC), Porto, Portugal. He currently serves as an Associate Editor for the Journal of Modern Power Systems and Clean Energy, the IEEE Data Descriptions, and the International Journal of Forecasting. His research interests include renewable energy, energy analytics, smart grid, and electricity market.

Spyros Chatzivasileiadis received the Diploma in electrical and computer engineering from the National Technical University of Athens, Athens, Greece, in 2007, and the Ph.D. degree from ETH Zurich, Zurich, Switzerland, in 2013. Until 2025, he served as the Head of Section for Power Systems at Technical University of Denmark, Kgs. Lyngby, Denmark. He is currently a Professor at the Technical University of Denmark, Kgs. Lyngby, Denmark, and serves as a Senior Editor for IEEE Transactions on Power Systems. He is currently working on trustworthy machine learning and quantum computing for power systems.

Ning Zhang received the B.S. and Ph.D. degrees from Tsinghua University, Beijing, China, in 2007 and 2012, respectively. He is now an Associate Professor at the same university. His research interests include renewable energy, power system planning and operation, and integration of multiple energy systems.

Chongqing Kang received the Ph.D. degree in engineering from Tsinghua University, Beijing, China, in 1997. He is currently a Professor at the same university. His research interests include power system planning, power system operation, renewable energy, low-carbon electricity technology, and load forecasting.

Nikos Hatziargyriou is a Professor Emeritus of power systems with the Electrical and Computer Engineering School, National Technical University of Athens, Athens, Greece, and a part-time Professor at the School of Technology and Innovations, University of Vaasa, Vaasa, Finland. From 2015 to 2019, he served as both the Chair and the CEO of the Hellenic Distribution Network Operator, Athens, Greece. From 2007 to 2012, he served as Executive Vice-Chair and Deputy CEO of the Public Power Corporation, Athens, Greece, with responsibility for the transmission and distribution and island division. His research interests include power system stability, dynamic security assessment, distributed energy resource, and microgrid.