Physics-Informed Deep Learning for Renewable-Dominated Power Systems: A Review of Forecasting and Grid Stability Applications

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***Abstract*—The increasing penetration of solar and wind energy has introduced significant uncertainty and nonlinearity into modern power systems, posing challenges to accurate forecasting and grid stability assessment. Conventional data-driven machine learning models, while effective in pattern recognition, often suffer from limited generalization and lack of physical consistency when applied to dynamic power system environments. To address these limitations, physics-informed learning approaches have recently gained attention by embedding physical laws, system constraints, and domain knowledge directly into neural network models. This paper presents a comprehensive review of physics-informed neural networks and related physics-aware learning techniques applied to solar and wind power forecasting, renewable energy integration, and power grid stability analysis. The review systematically examines model formulations, learning strategies, and constraint enforcement methods used to improve prediction accuracy, robustness, and interpretability. Key applications, including short-term and long-term renewable generation forecasting, transient and small-signal stability analysis, and grid-support functions under high renewable penetration, are discussed in detail. Current challenges such as computational complexity, scalability, data availability, and model validation are critically analyzed. Finally, emerging research directions and open issues are identified to guide future developments in physics-informed learning for renewable-dominated power systems. This review aims to provide researchers and practitioners with a structured understanding of recent advances and practical insights for deploying physics-informed models in real-world power system applications.**

***Index Terms*—Physics-informed neural networks, renewable energy forecasting, power system stability, solar and wind integration, physics-aware learning**

I. INTRODUCTION

The global shift toward low-carbon and sustainable energy systems has led to a rapid increase in the deployment of solar and wind power across modern electrical grids. Although renewable energy sources offer significant environmental benefits, their inherent intermittency and uncertainty introduce major challenges for power system operation and planning. High penetration of variable renewable generation affects frequency regulation, voltage stability, reserve management, and overall grid reliability, making accurate forecasting and stability assessment essential for secure grid operation [1], [2].

Conventional approaches to renewable power forecasting and power system analysis are primarily based on physics-driven mathematical models derived from system equations and deterministic simulations. These models are physically interpretable and consistent with first principles, but they often struggle to represent complex nonlinear dynamics, changing weather patterns, and evolving grid conditions. In contrast, data-driven machine learning and deep learning techniques have demonstrated strong performance in modeling nonlinear relationships and short-term forecasting of solar and wind power generation [3], [4]. However, purely data-driven models typically require large volumes of training data, lack physical interpretability, and may produce predictions that violate known system constraints when operating outside the training domain [5].

To address these limitations, physics-informed learning has emerged as a promising hybrid modeling paradigm that integrates physical laws and system knowledge into data-driven neural networks. Physics-informed neural networks embed governing equations, such as differential-algebraic equations and power system constraints, directly into the training process through customized loss functions or regularization terms [6]. By enforcing physical consistency during learning, these models improve generalization, robustness, and data efficiency compared to conventional deep learning approaches.

Recent studies have explored the application of physics-informed learning techniques in renewable energy systems, including solar and wind power forecasting, power flow estimation, transient stability analysis, and grid dynamics modeling [7]–[9]. By incorporating domain knowledge such as weather physics, generation limits, and network constraints, physics-informed models have demonstrated improved forecasting accuracy and enhanced reliability in stability assessment, particularly under limited or noisy data conditions. These characteristics make physics-informed approaches well suited for renewable-dominated power systems with high uncertainty and variability.

Despite the growing interest in this research area, existing contributions are often limited to specific applications or isolated methodologies, resulting in fragmented understanding of the broader potential and limitations of physics-informed learning in power systems. A comprehensive review that systematically organizes existing methods, compares modeling strategies, and identifies open research challenges remains limited. This paper addresses this gap by presenting a structured review of physics-informed neural networks and physics-aware learning techniques applied to solar and wind energy integration and power system stability.

The main contributions of this review are threefold: (1) to classify physics-informed learning frameworks used in renewable energy forecasting and grid stability analysis, (2) to critically evaluate their advantages and limitations relative to traditional physics-based and data-driven approaches, and (3) to identify key research challenges and future directions, including scalability, real-time implementation, and integration with advanced grid control and monitoring systems.

II. BACKGROUND AND FUNDAMENTALS

Renewable Energy Integration Challenges

Solar and wind energy sources are inherently variable and uncertain due to their dependence on meteorological conditions. High renewable penetration reduces system inertia, increases ramping requirements, and introduces forecasting errors that directly affect frequency stability, voltage regulation, and reserve planning. These challenges become more severe in weak grids and renewable-dominated power systems.

Data-Driven Learning in Power Systems

Machine learning and deep learning models such as artificial neural networks, convolutional neural networks, and recurrent neural networks have been widely applied for renewable power forecasting and system monitoring. While these models capture nonlinear relationships effectively, their performance strongly depends on data availability and quality. More importantly, they do not inherently respect physical laws, leading to unreliable predictions under unseen operating conditions.

Concept of Physics-Informed Learning

Physics-informed learning integrates physical laws, constraints, or governing equations into data-driven models. Physics-informed neural networks enforce system dynamics through customized loss functions, regularization terms, or constrained architectures. This hybrid approach combines the interpretability of physics-based models with the flexibility of neural networks, making it suitable for complex power system applications.

III. PHYSICS-INFORMED LEARNING FRAMEWORKS

A. Physics-Informed Neural Networks (PINNs)

Figure 1 presents a systematic taxonomy of physics-informed learning approaches applied to solar and wind energy integration and power system stability analysis. The taxonomy is structured hierarchically to capture the diversity of modeling strategies, application domains, and physical knowledge integration methods reported in the literature. At the highest level, physics-informed learning approaches are categorized into physics-informed neural networks, physics-guided machine learning models, and hybrid physics–data-driven frameworks. This classification reflects the degree to which physical laws are embedded within the learning architecture, ranging from strict enforcement of governing equations to soft constraint regularization. The second level of the taxonomy organizes existing studies according to their primary application domains, including solar power forecasting, wind power forecasting, grid stability analysis, and power flow or state estimation. This categorization highlights how physics-informed methods are increasingly used not only for prediction tasks but also for dynamic analysis and operational decision support in power systems.

At the third level, the taxonomy identifies the type of physical knowledge incorporated into the learning process. These include differential-algebraic equations governing system dynamics, power flow and network constraints, renewable generation physics such as irradiance and aerodynamic relationships, and operational constraints related to safety and equipment limits. This level emphasizes the role of domain knowledge in improving model robustness and interpretability.

The fourth level classifies approaches based on operational time scales, ranging from short-term and medium-term forecasting to long-term planning and transient or dynamic stability analysis. Finally, the taxonomy distinguishes between different power system layers, including generation units, transmission networks, distribution systems, and microgrids. Overall, this taxonomy provides a structured overview of existing research, facilitates comparison across methodologies, and helps identify gaps where physics-informed learning remains underexplored.

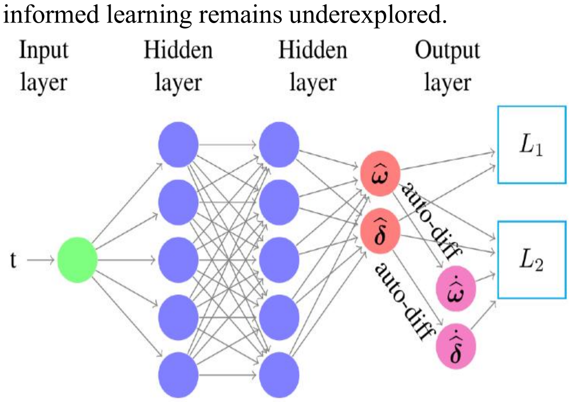

Fig. 1. Taxonomy of physics-informed learning approaches applied to renewable energy forecasting and power system stability [3]

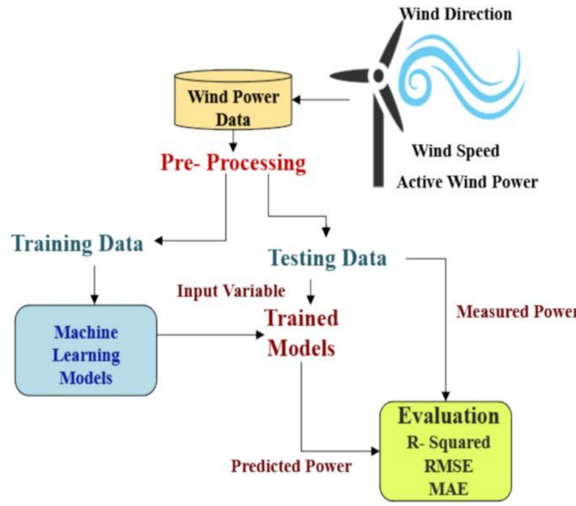

Figure 2: General Framework of Physics-Informed Neural Networks for Solar and Wind Integrated Power Systems[4]

Figure 2 illustrates the general framework of a physics-informed neural network applied to solar and wind integrated power systems. The framework demonstrates how measurement data and physical laws are jointly utilized to enhance forecasting accuracy and grid stability assessment. The process begins with the input data layer, which includes renewable generation data, meteorological variables, SCADA and PMU measurements, and grid topology or system parameters. These inputs provide both data-driven patterns and essential system context.

The neural network core forms the central component of the framework and is responsible for learning nonlinear relationships between inputs and outputs. Unlike conventional deep learning models, this core is tightly coupled with a physics constraints module. The physics constraints module embeds governing equations such as power flow equations, swing equations, frequency dynamics, voltage constraints, and renewable generation limits into the learning process. These constraints ensure that the network outputs remain physically consistent with power system behavior.

A customized loss function is used to combine data mismatch loss and physics-based residual loss. The data loss measures the difference between predicted and observed values, while the physics residual loss penalizes violations of physical laws and system constraints. Regularization terms may also be included to improve numerical stability and generalization.

During training, optimization algorithms iteratively adjust model parameters to minimize the combined loss, enforcing both data accuracy and physical consistency.

The output layer of the framework produces physically plausible predictions such as solar and wind power forecasts, frequency and voltage trajectories, stability indices, and other operational indicators. By integrating physics and data within a unified learning architecture, the framework enhances robustness under limited or noisy data conditions and improves generalization to unseen operating scenarios. This makes physics-informed neural networks particularly suitable for real-time monitoring, forecasting, and stability assessment in renewable-dominated power systems.

IV. APPLICATIONS IN SOLAR AND WIND POWER FORECASTING

A. Solar Power Forecasting

Accurate solar power forecasting is critical for grid operation due to the strong dependence of photovoltaic generation on meteorological conditions such as solar irradiance, ambient temperature, and cloud dynamics. Conventional data-driven forecasting models often struggle to maintain accuracy under rapidly changing weather conditions and limited historical data. Physics-informed learning approaches address these challenges by embedding physical relationships governing photovoltaic systems directly into the learning process. These relationships include irradiance-to-power conversion equations, temperature-dependent efficiency models, and panel degradation characteristics [1], [2].

By enforcing these physical constraints during training, physics-informed models reduce prediction uncertainty and prevent physically implausible outputs, such as negative power generation or unrealistically high efficiency values. Several studies have shown that incorporating solar geometry and irradiance balance equations improves short-term and day-ahead forecasting accuracy, particularly under partially cloudy conditions where data-driven models typically degrade in performance [3]. Furthermore, physics-informed models exhibit stronger robustness and generalization when trained on limited datasets, making them suitable for newly installed photovoltaic plants or regions with sparse measurement infrastructure [4].

B. Wind Power Forecasting

Wind power forecasting presents additional complexity due to the nonlinear relationship between wind speed and power output, as well as the stochastic nature of atmospheric dynamics. Purely data-driven models may overfit historical wind patterns and generate unrealistic power predictions when wind conditions fall outside the training range. Physics-aware learning approaches mitigate these issues by integrating aerodynamic principles, turbine power curves, and atmospheric boundary layer dynamics into neural network architectures [5], [6].

In particular, embedding turbine-specific power curve constraints ensures that predicted power outputs remain within physically achievable limits for given wind speeds. Some physics-informed models also incorporate simplified fluid dynamics relationships and wake interaction effects to improve forecasting accuracy in wind farms [7]. These integrations lead to more stable and consistent predictions across varying wind regimes and reduce the occurrence of abrupt power fluctuations that are not physically justified. As a result, physics-informed wind forecasting models demonstrate improved reliability and better suitability for grid scheduling and reserve planning applications [8].

C. Performance Comparison

A growing body of literature indicates that physics-informed forecasting models consistently outperform purely data-driven approaches in terms of generalization, robustness, and physical interpretability. While data-driven models often achieve high accuracy under normal operating conditions, their performance degrades significantly when exposed to unseen weather patterns or abnormal operating scenarios. In contrast, physics-informed approaches leverage embedded physical knowledge to constrain the solution space, leading to lower forecasting errors and improved stability under high uncertainty [9], [10].

Comparative studies report that physics-informed models achieve reduced RMSE and MAE values for both solar and wind power forecasting, particularly in short-term and day-ahead horizons. Additionally, the incorporation of physical laws enhances model transparency, allowing system operators to better understand prediction behavior and trust model outputs for operational decision-making. These advantages make physics-informed learning a promising solution for renewable energy forecasting in power systems with increasing renewable penetration and variability [11].

V. COMPARISON WITH EXISTING APPROACHES

Aspect	Physics-Based Models	Data-Driven Models	Physics-Informed Models
Physical consistency	High	Low	High
Data requirement	Low	High	Moderate
Generalization	Limited	Limited	Strong
Interpretability	High	Low	Moderate–High
Computational cost	High	Moderate	Moderate

VI. FUTURE RESEARCH DIRECTIONS

Future work should focus on:
Scalable physics-informed architectures for large power networks
Integration with digital twins and real-time EMS platforms
Probabilistic and uncertainty-aware physics-informed forecasting
Hybrid control frameworks combining PINNs and model predictive control
Cyber-resilient and robust physics-aware learning models

VII. FUTURE RESEARCH DIRECTIONS

This paper presented a comprehensive review of physics-informed learning approaches applied to solar and wind energy integration and power system stability. By embedding physical laws into neural networks, these methods address key limitations of traditional data-driven models and offer improved robustness, interpretability, and generalization. While challenges remain in scalability and real-time deployment, physics-informed learning represents a promising direction for reliable operation of renewable-dominated power systems.

VIII. CONCLUSION

A comparative analysis revealed that physics-informed approaches offer a balanced trade-off between physical consistency and learning flexibility, outperforming purely data-driven models in high-uncertainty scenarios while reducing computational dependence on detailed physics-based simulations. Despite these advantages, challenges related to computational complexity, scalability to large-scale power networks, real-time deployment, and standardization of benchmarking practices remain open and require further investigation.Future research should focus on developing scalable and computationally efficient physics-informed architectures, integrating uncertainty quantification and probabilistic forecasting, and coupling these models with real-time control and energy management systems. The integration of physics-informed learning with digital twins, advanced inverter controls, and cyber-resilient grid architectures also represents a promising direction. Overall, physics-informed deep learning is a viable and impactful approach for enabling accurate forecasting and stable operation of next-generation renewable-dominated power systems.

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