Role of Machine Learning in Power Systems: A Review

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Abstract

The rapid digitalization and decarbonization of electric power systems have created vast, high-velocity data streams and complex decision problems. Machine learning (ML)—spanning supervised, unsupervised, reinforcement, and physics-informed paradigms—has emerged as a core toolkit for forecasting, monitoring, control, optimization, and cybersecurity across grid planning, operations, and markets. This review synthesizes recent advances with an application-oriented taxonomy: (i) forecasting and situational awareness; (ii) protection, fault diagnosis, and resilience; (iii) security assessment and state estimation; (iv) optimization and control (including learning-assisted optimal power flow); and (v) emerging graph-, physics-, and reinforcement-learning approaches. We discuss data and model lifecycle issues (labels, drift, uncertainty, explainability, and MLOps), benchmarking needs, and pathways for trustworthy deployment. We conclude with a research agenda for grid-aligned, auditable ML at scale.

Keywords: Deep Learning, Forecasting, Graph Neural Networks, Machine Learning, Optimal Power Flow, Physics-Informed Learning, Power Systems, State Estimation, Reinforcement Learning.

1. INTRODUCTION

Electrification, inverter-based resources, and sensor proliferation (AMI, PMUs, UAV inspections) are transforming system dynamics and observability. Traditional physics-driven tools remain indispensable but face limits under high uncertainty and topology variability. ML complements these tools by learning patterns from historical and streaming data, enabling probabilistic predictions, anomaly detection, and fast approximate optimization subject to physical constraints [1]–[3].

2. TAXONOMY OF ML IN POWER SYSTEMS

Applications can be classified as:

- **Forecasting & situational awareness:** load, price, renewable energy forecasting, inertia estimation, PMU-based event detection [1], [4]–[7].

- **Protection & resilience:** fault detection/classification, component inspection, resilience analytics [8], [9].
- **Security assessment & state estimation:** stability/security margin estimation, hybrid SE, cyber considerations [10]–[13].
- **Optimization & control:** OPF approximations, RL for control [14]–[17], [21], [22].
- **Modeling paradigms:** graph neural networks (GNNs), physics-informed ML [18]–[20].

3. DATA FOUNDATIONS AND EVALUATION

Data sources include SCADA, AMI, PMUs, weather data, UAV imagery, and market telemetry. Data issues such as missing values, noise, and drift demand robust preprocessing. Public benchmarks are rare; RL2Grid is a recent initiative standardizing tasks for reproducibility [25].

Metrics must align with operational needs: probabilistic scores for forecasting [1], [4], classification metrics for imbalanced data, and feasibility/optimality gaps for OPF surrogates.

4. FORECASTING AND SITUATIONAL AWARENESS

4.1 Load and Renewable Forecasting

Probabilistic load forecasting evolved from regression to deep sequence models [1], [4]. Surveys demonstrate advances in wind forecasting via ML [5], [6], while transformer-based architectures offer state-of-the-art performance [7].

4.2 Inertia and Frequency Dynamics

Physics-informed ML improves data-driven estimation of inertia and frequency dynamics [12].

4.3 Event Detection with PMUs

Deep models trained on PMU data classify line trips, oscillations, and load ramps, even under noisy or missing data [13].

5. PROTECTION, INSPECTION, AND RESILIENCE

Deep learning supports intelligent fault detection, e.g., attention-GRU and CNNs [8]. Reviews further document ML-driven condition monitoring and resilience applications [9].

6. SECURITY ASSESSMENT AND STATE ESTIMATION

ML accelerates stability and security assessments [10]. Hybrid estimators defend against FDI attacks [11]. Foundational research revealed SE vulnerabilities [12], and physics-informed neural networks enhance resilience [13].

7. LEARNING-ASSISTED OPTIMIZATION AND CONTROL

7.1 Optimal Power Flow (OPF)

ML surrogates provide fast, approximate OPF. DeepOPF introduced feasibility-aware predictors for DC [14] and AC-OPF [15], extended by augmented learning [16]. Warm-start tree-based methods improved explainability [17]. Reviews summarize these trends [21], [22].

7.2 Reinforcement Learning (RL)

RL optimizes switching, voltage control, and restoration. Surveys highlight DRL applications [23], [24]. RL2Grid offers benchmarks for reproducibility [25].

8. EMERGING PARADIGMS

8.1 Graph Neural Networks (GNNs)

GNNs leverage network topology for tasks like reliability assessment and forecasting [18], [19].

8.2 Physics-Informed ML (PIML)

PIML embeds physical constraints into ML. Reviews [20] and case studies on frequency [12] and state estimation [13] illustrate benefits.

9. CHALLENGES AND BEST PRACTICES

- **Data drift & quality:** require continual learning [13].
- **Uncertainty:** probabilistic methods align predictions with risk [1].
- **Explainability:** tree-based warm starts improve interpretability [17].
- **Security:** models must withstand cyberattacks [11], [12].
- **Reproducibility:** benchmarks like RL2Grid are essential [25].

10. OUTLOOK

Future research should integrate physics-informed ML with certified optimization, develop safe RL for operator-in-the-loop control, explore multimodal data, and advance benchmarking for trustworthy deployment.

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