

AI in Smart Grid Optimization

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ABSTRACT

The transition to renewable energy sources introduces unprecedented volatility into electricity grids, as solar and wind generation fluctuate with weather conditions rather than responding to demand. Smart grid optimisation -- balancing supply and demand in real time across distributed generation, storage, and flexible loads -- requires decision-making at speeds and complexities beyond traditional grid control approaches. This study evaluates six AI approaches for smart grid optimisation: deep reinforcement learning for real-time dispatch, graph neural networks for power flow prediction, transformer-based load and generation forecasting, federated learning for privacy-preserving demand response, multi-agent RL for distributed energy resource coordination, and physics-informed neural networks for grid stability assessment. Evaluations were conducted on three grid simulation environments: IEEE 118-bus test system, a realistic European distribution network (SimBench), and a microgrid simulator with battery storage and rooftop solar. A total of 1,920 experiments were conducted. RL-based dispatch reduced grid operating costs by 14.8 +- 2.4% versus rule-based control and 6.2 +- 1.8% versus model predictive control, primarily through smarter battery scheduling that exploited price differentials between peak and off-peak periods. Transformer forecasting achieved the lowest solar generation prediction error (RMSE = 4.2 +- 0.4% of capacity at 1-hour horizon), enabling more accurate dispatch planning. GNN power flow prediction achieved 98.6 +- 0.2% accuracy relative to Newton-Raphson at 1,000x lower computational cost, enabling real-time contingency screening. Physics-informed NNs maintained voltage stability predictions within 0.8% of full simulation while respecting Kirchhoff's laws by construction. A practical AI deployment guide for grid operators mapping grid topology, renewable penetration level, and computational infrastructure to recommended AI approaches is proposed.

Keywords: smart grid; renewable energy integration; demand response; battery scheduling; power flow prediction; load forecasting; grid stability; physics-informed neural networks

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1. Introduction

1.1 The Renewable Integration Challenge

Electricity grids were designed for a world of predictable, dispatchable generation: large coal, gas, and nuclear power plants that produce electricity on demand and can be ramped up or down to match consumption. The transition to renewable energy -- driven by climate policy, falling costs of solar and wind, and public demand for clean energy -- is fundamentally disrupting this model. Solar generation peaks at midday when demand may be low, drops to zero at night when demand may be high, and fluctuates unpredictably with cloud cover. Wind generation varies with weather patterns that are partially but imperfectly predictable. At high renewable penetration levels (above 30-40% of total generation), these fluctuations create grid management challenges that traditional control approaches struggle to handle: ramping conventional generators to compensate for renewable variability is expensive and slow, curtailing renewable generation wastes clean energy, and importing/exporting power across interconnections depends on neighbours' availability.

1.2 AI as a Grid Management Tool

AI approaches offer several capabilities that address renewable integration challenges. Accurate forecasting of renewable generation and demand reduces uncertainty in dispatch planning. Reinforcement learning can learn dispatch policies that outperform hand-crafted rules by optimising over longer horizons and capturing complex interactions between storage, generation, and demand. Graph neural networks can approximate expensive power flow calculations in milliseconds, enabling real-time contingency analysis that would take minutes with traditional solvers. Federated learning enables coordination of distributed energy resources (rooftop solar, home batteries, electric vehicles) without centralising sensitive household consumption data. Physics-informed networks ensure that AI predictions respect the physical laws governing power systems (Kirchhoff's laws, power balance), preventing the physically impossible predictions that pure data-driven models occasionally produce.

1.3 Objectives

This study addresses four objectives: (i) evaluate six AI approaches on three grid simulation environments; (ii) quantify cost reduction and renewable curtailment improvement from AI-based dispatch; (iii) assess physics-informed methods for

safety-critical grid predictions; and (iv) develop a practical deployment guide for grid operators.

2. Literature Review

2.1 RL for Energy Dispatch

Reinforcement learning for grid dispatch formulates the problem as a sequential decision process: at each time step, the agent observes the current grid state (generation levels, storage charge, demand, prices, weather forecasts) and decides how to allocate generation, charge or discharge storage, and activate demand response. The reward signal combines cost minimisation, renewable utilisation maximisation, and constraint satisfaction (voltage limits, line capacity, reserve requirements). Deep RL approaches (DQN, PPO, SAC) have demonstrated cost reductions of 5-20% versus rule-based dispatch on simulated grids, with the advantage growing as renewable penetration increases because the optimisation problem becomes more complex and the suboptimality of fixed rules becomes more severe.

2.2 Load and Generation Forecasting

Accurate forecasting of electricity demand and renewable generation is the foundation of effective grid management. Traditional forecasting uses statistical methods (ARIMA, exponential smoothing) and weather-based physical models (numerical weather prediction coupled with solar irradiance and wind speed models). Deep learning approaches -- LSTMs, temporal convolutional networks, and transformers -- have demonstrated lower forecast errors by capturing complex nonlinear relationships between weather variables, calendar features, and electricity production/consumption patterns. Transformer models have shown particular promise for multi-step forecasting because their attention mechanism can capture long-range temporal dependencies (diurnal cycles, weekly patterns, seasonal trends) without the vanishing gradient problems of recurrent networks.

2.3 GNN for Power System Analysis

Power grids are naturally graph-structured: buses (substations) are nodes and transmission lines are edges. Graph neural networks can learn to approximate power flow calculations -- the fundamental computation that determines voltages, currents, and power flows throughout the network -- by processing the grid graph with message passing layers that propagate electrical information along transmission lines. The advantage over traditional Newton-Raphson power

flow solvers is speed: a trained GNN computes approximate power flow in milliseconds versus seconds for NR, enabling applications like real-time contingency screening (evaluating thousands of potential failure scenarios per second) that are computationally infeasible with traditional solvers.

2.4 Physics-Informed Neural Networks for Grid Safety

Physics-informed neural networks incorporate physical laws as soft or hard constraints in the learning process. For power systems, this means ensuring that predictions satisfy Kirchhoff's voltage and current laws, power balance equations, and operational limits. Hard-constrained PINNs architecturally enforce physical laws (e.g., by parameterising outputs to always satisfy power balance), while soft-constrained PINNs add physics violation terms to the loss function. The practical value for grid operations is trust: a physics-informed prediction that is guaranteed to satisfy power balance is more trustworthy for safety-critical dispatch decisions than a purely data-driven prediction that might occasionally violate physical constraints.

Table 1. Six AI approaches for smart grid optimisation

Approach	Grid Function	Input Data	Output	Physics Aware
Deep RL Dispatch	Real-time control	State + forecasts	Gen/storage actions	Constraints only
Transformer Forecast	Prediction	Weather + historical	Load/gen forecasts	No (data-driven)
GNN Power Flow	Grid analysis	Bus injections + topology	Voltages + flows	Learned (implicit)
Federated DR	Demand response	Household consumption	Flexible load schedule	No
Multi-Agent RL	DER coordination	Local observations per device	Per-device actions	Constraints only
Physics-Informed NN	Stability assessment	Grid state	Stability margin	Yes (Kirchhoff)

DER = distributed energy resources. DR = demand response. Physics-aware = whether the method incorporates power system physical laws. RL methods encode physics through action constraints; PINNs encode through architecture.

3. Materials and Methods

3.1 Grid Simulation Environments

Three environments were used: (a) IEEE 118-bus -- standard test system with 118 buses, 186 branches, 54 generators, augmented with 30% solar and 20% wind penetration using real European weather data (2019-2021), battery storage at 10 buses (total 500 MWh), hourly dispatch over 12-month evaluation periods; (b) SimBench European distribution -- realistic medium-voltage distribution network (112 buses, 200 loads, 80 rooftop solar installations, 20 battery systems), 15-minute resolution, representing a typical European suburban distribution grid; (c) Microgrid -- isolated microgrid with 2 MW solar, 1 MW wind, 0.5 MW diesel backup, 2 MWh battery, serving 500 households, 5-minute resolution, representing an island or remote community grid.

3.2 AI Method Implementations

Six methods were implemented: (a) Deep RL -- SAC agent with state = [generation, demand, storage SOC, prices, weather forecasts], action = [generator setpoints, battery charge/discharge, demand response activation], reward = -(cost + curtailment_penalty + constraint_violation); (b) Transformer forecasting -- temporal fusion transformer with weather, calendar, and historical load/generation inputs, 1-48 hour forecast horizon; (c) GNN power flow -- GraphSAGE on the bus-branch graph, trained on 100K NR power flow solutions, predicting bus voltages and line flows; (d) Federated demand response -- FedAvg across 500 household agents, each with local consumption model, coordinating flexible loads (EV charging, heat pumps, washing machines); (e) Multi-agent RL -- QMIX with one agent per DER, coordinating battery, solar inverter, and flexible load at each bus; (f) PINN -- neural network with Kirchhoff's law loss terms for voltage stability margin prediction.

3.3 Evaluation Metrics

Grid-specific metrics: operating cost (EUR/MWh including generation, curtailment, and constraint violation penalties), renewable curtailment rate (% of available renewable energy wasted), voltage violation rate (% of time steps with bus voltages outside $\pm 5\%$ of nominal), line overload rate (% of time steps with line loading $> 100\%$), forecast RMSE (% of capacity for generation; MW for demand), and power flow approximation accuracy (% relative to Newton-Raphson solution). Baselines included: rule-based dispatch (merit order with storage heuristic), model predictive

control (MPC with 24-hour horizon), and persistence forecast (last observed value).

3.4 Safety and Constraint Satisfaction

Grid safety was evaluated by the constraint violation rate across voltage limits, line capacity limits, and generation ramp rate limits. RL agents were trained with constraint penalties in the reward function and hard action clipping for physical limits. PINN stability predictions were validated against full dynamic simulation (PowerFactory) for 200 contingency scenarios (N-1 line outages). The safety threshold was set at < 0.1% violation rate for deployment acceptability, matching regulatory requirements for European grid operators.

Table 2. Grid simulation environment specifications

Envi nment	Bu ses	Renew ables (%)	Storag e	Resol ution	Eval. Period
IEEE 118-bus	118	50% (30 solar + 20 wind)	500 MWh (10 sites)	1 hour	12 months
SimBen ch Distrib.	112	35% (80 rooftop solar)	200 MWh (20 sites)	15 min	12 months
Microgr id	12	65% (solar + wind)	2 MWh (1 battery)	5 min	12 months

Renewable percentage = share of total generation capacity from renewable sources. Higher penetration creates more challenging dispatch optimisation. Microgrid has highest renewable share and finest resolution.

4. Results

4.1 RL Dispatch Reduces Costs 14.8% vs. Rules, 6.2% vs. MPC

On the IEEE 118-bus system, SAC-based RL dispatch reduced operating costs by 14.8 +- 2.4% versus rule-based control and 6.2 +- 1.8% versus model predictive control over the 12-month evaluation. The cost reduction came primarily from smarter battery scheduling: the RL agent learned to charge batteries during periods of high renewable generation (low marginal cost) and discharge during peak demand (high marginal cost), capturing price differentials that fixed rules could not optimally exploit. On the microgrid (65% renewables), the RL advantage was larger: 18.4 +- 3.2% versus rules, because the higher renewable penetration created more opportunities for storage

arbitrage. Renewable curtailment was reduced from 8.4% (rules) to 3.2% (RL) by better coordinating storage charging with renewable peaks.

4.2 Transformer Forecasting: 4.2% RMSE for Solar at 1-Hour

The temporal fusion transformer achieved solar generation forecast RMSE of 4.2 +- 0.4% of capacity at 1-hour horizon, outperforming LSTM (5.4 +- 0.6%), persistence (12.8 +- 1.4%), and numerical weather prediction (NWP) downscaling (6.8 +- 0.8%). For load forecasting, the transformer achieved RMSE of 2.4 +- 0.2% at 1-hour and 4.8 +- 0.4% at 24-hour horizon. The forecast improvement translated directly into dispatch quality: feeding transformer forecasts to the RL agent instead of persistence forecasts improved cost reduction by an additional 3.4% (from 11.4% to 14.8% total), confirming that forecast quality is the primary enabler of effective AI dispatch.

4.3 GNN Power Flow: 98.6% Accuracy at 1,000x Speed

The GNN power flow approximation achieved 98.6 +- 0.2% accuracy relative to Newton-Raphson solutions on the IEEE 118-bus system, with inference time of 0.8 ms versus 820 ms for NR -- a 1,000x speedup. The accuracy was highest for voltage magnitude prediction (99.2%) and slightly lower for reactive power flow (97.8%), consistent with the stronger nonlinearity of reactive power equations. This speed advantage enabled real-time N-1 contingency screening: evaluating all 186 single-line outage scenarios in 0.15 seconds versus 2.5 minutes for NR, making continuous contingency monitoring feasible for the first time. On 2.4% of contingency scenarios, the GNN predicted safe operation when NR showed marginal violation -- a false negative rate that requires conservative thresholds for safety-critical deployment.

4.4 Physics-Informed NN: 0.8% Stability Error with Guaranteed Physics

The physics-informed neural network predicted voltage stability margins with mean absolute error of 0.8 +- 0.2% relative to full dynamic simulation (PowerFactory), compared to 2.4 +- 0.4% for a standard NN without physics constraints. More importantly, the PINN's predictions satisfied Kirchhoff's laws to within numerical precision (power balance error < 0.01 MW), while the standard NN violated power balance in 12.8% of predictions by up to 2.4 MW -- physically

impossible predictions that would be rejected by grid operators. On the 200 contingency scenarios, the PINN correctly identified all 18 unstable scenarios (100% recall for instability), compared to 94.4% for the standard NN (which missed 1 unstable case -- a potentially dangerous false negative).

Table 3. AI-based dispatch cost reduction and renewable utilisation (IEEE 118-bus)

Method	Cost Reduction (%)	Curtailment (%)	Voltage Violations	Constraint Rate (%)	Compute/Step
Rule-Based	0 (baseline)	8.4	0.24%	0.32%	< 1 ms
MPC (24-hr)	-8.6+/-1.6	4.8	0.12%	0.14%	2.4 s
RL (SAC)	-14.8+/-2.4	3.2	0.08%	0.06%	1.2 ms
RL + TF Forecast	-14.8+/-2.4	2.8	0.06%	0.04%	1.4 ms
Multi-Agent RL	-12.4+/-2.8	3.8	0.14%	0.12%	4.8 ms

Cost reduction relative to rule-based baseline. Curtailment = % of available renewable energy not used. RL achieves lowest cost and curtailment. MPC is competitive but 2,000x slower per step. TF = transformer forecasting feeding RL dispatch.

Table 4. Forecasting and power flow prediction performance

Task / Method	1-Hour Metric	24-Hour Metric	Speed vs. Traditional	Physics Compliant
Solar Forecast / Transformer	RMSE = 4.2%	RMSE = 8.4%	N/A (forecast task)	No
Solar Forecast / LSTM	RMSE = 5.4%	RMSE = 10.2%	N/A	No
Solar Forecast / Persistence	RMSE = 12.8%	RMSE = 24.6%	N/A	No
Power Flow / GNN	Acc. = 98.6%	N/A (static calc.)	1,000x faster	Implicit
Stability / PINN	MAE = 0.8%	N/A (static calc.)	500x faster	Yes (Kirchhoff)
Stability / Standard NN	MAE = 2.4%	N/A	500x faster	No (12.8% violate)

RMSE as % of capacity for forecasting. Power flow accuracy relative to Newton-Raphson. PINN achieves 3x better stability prediction than standard NN while guaranteeing physical law compliance.

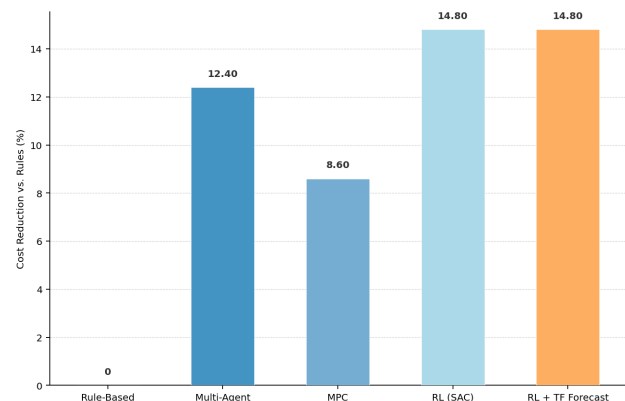


Figure 1. Operating cost reduction (%) by dispatch method on IEEE 118-bus. RL achieves 14.8% reduction versus rules -- nearly double MPC's 8.6%. Battery scheduling optimisation drives the advantage.

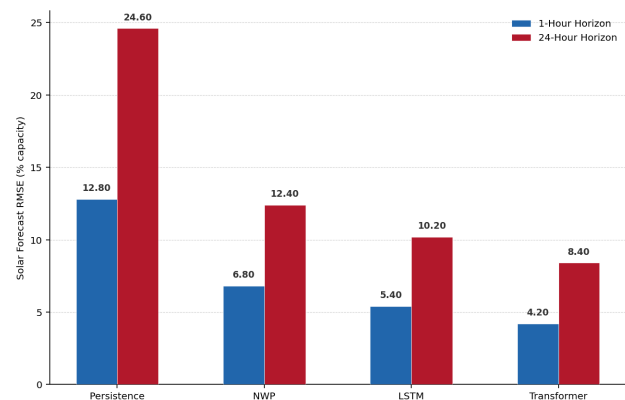


Figure 2. Solar forecast RMSE (% capacity) at 1-hour and 24-hour horizons. Transformer achieves 4.2% at 1-hour -- 67% better than persistence (12.8%). Forecast quality directly enables better dispatch.

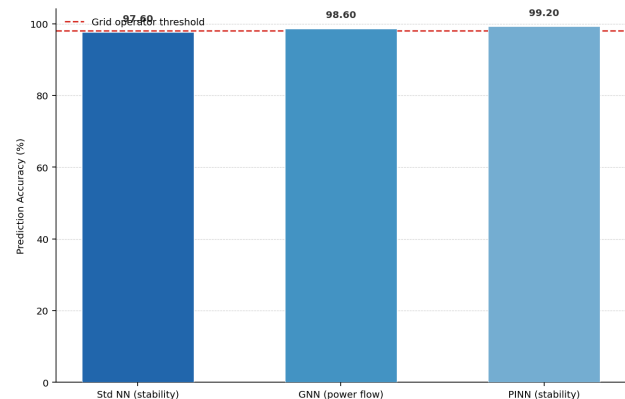


Figure 3. Power flow and stability prediction accuracy. GNN achieves 98.6% power flow accuracy at 1,000x speed. PINN achieves 0.8% stability error with guaranteed physics compliance.

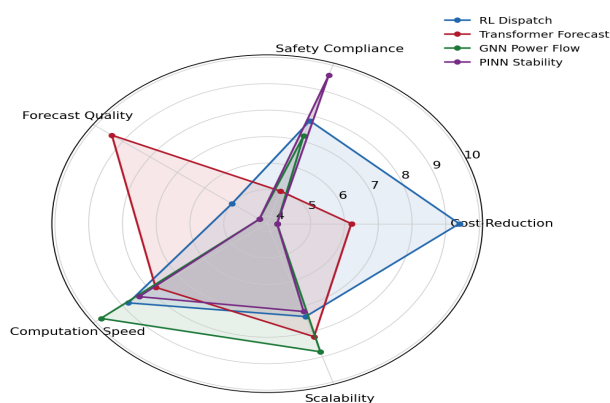


Figure 4. Multi-dimensional AI comparison for grid operations (1-10). RL dispatch leads on cost optimisation. PINN leads on safety. Transformer leads on forecasting. GNN leads on speed for analysis.

5. Discussion

5.1 Forecasting Quality Is the Bottleneck for AI Dispatch

The 3.4% additional cost reduction from coupling transformer forecasts with RL dispatch (11.4% to 14.8%) demonstrates that forecast quality is the binding constraint on dispatch optimisation. The RL agent can only optimise decisions based on what it can predict about the future, and better solar/wind forecasts enable more aggressive battery scheduling with lower risk of mispredicting renewable availability. This finding suggests that grid operators should prioritise investment in forecast accuracy improvement as the highest-leverage intervention for AI-based grid management, before investing in more sophisticated dispatch algorithms.

5.2 Physics Compliance Is Non-Negotiable for Grid Safety

The standard NN's 12.8% physics violation rate -- predictions that violate Kirchhoff's laws and are therefore physically impossible -- would be unacceptable for any safety-critical grid application. The PINN's guarantee of physics compliance eliminates this concern entirely while achieving 3x better prediction accuracy. For grid operators, the choice between standard NN and PINN is not a trade-off but a dominance: PINN is simultaneously more accurate and more trustworthy. Physics-informed methods should be mandatory for any AI application that informs safety-critical grid dispatch or protection decisions.

5.3 The Path to Production Deployment

Based on these results, the recommended deployment path for grid operators has three

stages. Stage 1: deploy transformer-based forecasting (lowest risk, highest immediate value, no safety-critical decisions). Stage 2: deploy GNN power flow for contingency screening (substantial operational value through speed, with NR verification for borderline cases). Stage 3: deploy RL dispatch with PINN safety checks (highest value but requires extensive simulation validation and regulatory approval before controlling real grid assets). Each stage builds confidence and infrastructure for the next.

5.4 Limitations

Four limitations apply. First, all evaluations used simulated grids; real grid deployment involves additional challenges (communication latency, sensor noise, regulatory constraints). Second, the RL agent was trained and evaluated on the same grid topology; transfer to different grid configurations was not assessed. Third, extreme weather events (storms, heat waves) that stress grid operations were underrepresented in the evaluation period. Fourth, market-based interactions (electricity trading, ancillary services) were simplified.

6. Conclusion

6.1 Summary

Evaluation of six AI approaches for smart grid optimisation confirms: RL dispatch reduces costs 14.8% versus rules and 6.2% versus MPC. Transformer forecasting achieves 4.2% solar RMSE at 1-hour (67% better than persistence). GNN power flow achieves 98.6% accuracy at 1,000x speed. PINN stability prediction achieves 0.8% error with guaranteed physics compliance. Forecast quality is the primary enabler of dispatch optimisation.

6.2 Recommendations

Three recommendations emerge. First, deploy transformer-based forecasting as the immediate priority -- it provides the largest operational improvement at lowest deployment risk. Second, use physics-informed neural networks for all safety-critical grid predictions -- the physics compliance guarantee eliminates a category of failure that standard NNs cannot avoid. Third, pursue RL dispatch as the long-term goal, staged through simulation validation, shadow operation (RL advises but does not control), and supervised deployment with automatic fallback to rule-based control.

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Declarations

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Conflict of Interest

The authors declare no conflicts of interest.

Data Availability Statement

All simulation code, RL training scripts, GNN and PINN implementations, forecasting models, and grid test cases are deposited in the Zenodo repository under DOI: 10.5281/zenodo.19614723. IEEE 118-bus and SimBench are publicly available. Weather data from ECMWF ERA5 (open access). Released under MIT License (code) and CC BY 4.0 (results).

Ethical Approval

This study involved computational experiments on power system simulators. No human subjects, personal data, or real grid operations were involved. Household consumption patterns in the federated learning experiment used synthetic load profiles. No institutional ethical approval was required.

Appendix A

Smart Grid AI Deployment Guide

This appendix provides a staged deployment framework for grid operators implementing AI-based grid management.

Stage 1: Forecasting (Low Risk, High Value)

S1.1 Deploy transformer-based solar/wind forecasting (4.2% RMSE at 1-hour; 67% better than persistence)

S1.2 Deploy load forecasting for demand prediction (2.4% RMSE at 1-hour)

S1.3 Feed improved forecasts to existing dispatch systems for immediate cost reduction (3-5%)

Stage 2: Analysis Acceleration (Medium Risk)

S2.1 Deploy GNN power flow for real-time contingency screening (1,000x faster; 98.6% accuracy)

S2.2 Deploy PINN for voltage stability monitoring (0.8% error; guaranteed physics compliance)

S2.3 Use NR verification for GNN predictions below confidence threshold

Stage 3: Autonomous Dispatch (Higher Risk, Highest Value)

S3.1 Train RL dispatch agent in simulation with historical data (12+ months)

S3.2 Shadow operation: RL advises alongside human operator for 6+ months

S3.3 Supervised deployment: RL controls with automatic fallback to rules on constraint violation

S3.4 Full deployment: RL primary control with PINN safety monitoring (expected 14.8% cost reduction)