

Adaptive Smart Grid Systems Using Machine Learning Techniques

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ABSTRACT

The accelerating integration of distributed renewable energy resources, electric vehicle charging infrastructure, and demand-responsive prosumers into modern power networks is rendering traditional rule-based grid management approaches operationally inadequate. Smart grid systems require adaptive control mechanisms capable of real-time load forecasting, dynamic demand response coordination, fault detection, and voltage stability management under conditions of high renewable penetration and stochastic demand variability. This study presents AdaptGrid, a unified machine learning framework for adaptive smart grid management integrating a temporal fusion transformer (TFT) for multi-horizon load forecasting, a multi-agent deep reinforcement learning (MADRL) controller for real-time demand response, and a graph convolutional network (GCN)-based fault detection system. AdaptGrid was validated on the IEEE 118-bus test system and deployed on the IREN SpA medium-voltage distribution network in Reggio Emilia, Italy (847 nodes, 23,400 prosumers). AdaptGrid achieved load forecasting MAPE of 1.84% (day-ahead) and 2.31% (week-ahead), surpassing persistence (6.74%), ARIMA (4.12%), and LSTM (3.07%) baselines. Demand response coordination reduced peak load by 18.7% and grid operational costs by 14.3%. Fault detection achieved F1-score of 0.974 with mean detection latency of 83 ms. These results establish AdaptGrid as an accurate, responsive, and practically deployable ML framework for adaptive smart grid management.

Keywords: smart grid; machine learning; load forecasting; demand response; fault detection; reinforcement learning; graph neural networks; temporal fusion transformer

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1. Introduction

The European Union's target of 42.5% renewable energy share by 2030 and net-zero carbon emissions by 2050 (European Commission 2022) is driving unprecedented structural transformation of electricity networks. Variable renewable generation from wind and solar introduces forecast uncertainty and rapid power fluctuations that exceed the response bandwidth of conventional synchronous generation-based frequency regulation (Hirth 2013). Simultaneously, the proliferation of electric vehicle charging (projected 130 million EVs in Europe by 2035) and heat pump adoption creates new classes of controllable but stochastic demand that can either exacerbate or alleviate grid stress depending on their management (IEA 2023). Traditional rule-based energy management systems, designed for predictable centralised generation and passive demand, cannot adapt to this complexity in real time.

Machine learning offers adaptive control capabilities that rule-based systems cannot provide: data-driven forecasting that captures complex non-linear temporal patterns in load and generation (Hochreiter and Schmidhuber 1997; Vaswani et al. 2017), reinforcement learning controllers that optimise multi-objective grid operation without explicit physics models (Sutton and Barto 2018), and graph neural networks that exploit power network topology for fault detection (Kipf and Welling 2017). This study integrates these three ML paradigms into AdaptGrid, a unified adaptive smart grid framework validated on both standardised benchmarks and a real European distribution network deployment.

2. Literature Review

2.1 Load Forecasting with Deep Learning

Short-term load forecasting (STLF) has progressed from ARIMA and exponential smoothing (Box and Jenkins 1976) through support vector regression to deep learning approaches. LSTMs (Hochreiter and Schmidhuber 1997) demonstrated strong STLF performance capturing seasonal and weather dependencies (Kong et al. 2019). The temporal fusion transformer (Lim et al. 2021) introduced multi-horizon probabilistic forecasting with gating mechanisms for variable selection, achieving state-of-the-art performance on energy and retail forecasting benchmarks. N-BEATS (Oreshkin et al. 2020) provided an interpretable neural basis expansion for time-series forecasting without recurrence. For grid-scale forecasting, the challenge of multi-node simultaneous prediction under network topology constraints remains insufficiently addressed.

2.2 RL for Demand Response and Fault Detection

Deep reinforcement learning for demand response has been explored in residential building control (Mocanu et al. 2019), EV charging optimisation (Wan et al. 2019), and microgrid energy management (Huang et al. 2019). Multi-agent RL frameworks (Lowe et al. 2017) enable decentralised prosumer coordination without a central controller, improving scalability. For fault detection, GCN-based methods (Jiang et al. 2020) exploit the power network graph structure to propagate fault signatures across topologically adjacent buses, substantially outperforming bus-isolated threshold methods. Integration of all three functions — forecasting, demand response, and fault detection — within a

single adaptive framework has not been demonstrated in prior literature.

Table 1. Summary of related ML approaches for smart grid management.

Study	Method	Function	Grid Scale	MAPE / F1
Kong et al. (2019)	LSTM	Load Forecast	Regional	MAPE 3.24%
Lim et al. (2021)	TFT	Multi-horizon	Various	MAPE 2.41%
Mocanu et al. (2019)	DQN	Demand Response	Building	Cost –12.8%
Wan et al. (2019)	DDPG	EV Charging	District	Cost –18.4%
Huang et al. (2019)	Multi-agent RL	Microgrid	Microgrid	Cost –21.3%
Jiang et al. (2020)	GCN	Fault Detection	IEEE 14-bus	F1 = 0.941
AdaptGrid (Proposed)	TFT+MA DRL+GCN	Unified	118-bus +Real	MAPE 1.84%; F1 0.974

TFT: Temporal Fusion Transformer; MADRL: Multi-Agent Deep Reinforcement Learning; GCN: Graph Convolutional Network.

3. Materials and Methods

3.1 AdaptGrid Architecture

AdaptGrid integrates three ML modules. The Temporal Fusion Transformer Forecaster (TFTF) implements the TFT architecture (Lim et al. 2021) with 4 attention heads, hidden dimension 160,

and 6 encoder layers, trained on 3 years of 15-minute interval load, temperature, irradiance, wind speed, and calendar features from the IREN network. It produces probabilistic forecasts at 1-hour, 24-hour, and 7-day horizons with prediction intervals. The Multi-Agent Demand Response Controller (MADRC) assigns each of 47 controllable prosumer clusters an independent SAC agent (Haarnoja et al. 2018) with shared critic, trained via CTDE to minimise peak-to-average ratio and grid cost subject to user comfort constraints ($\pm 2^{\circ}\text{C}$ thermal comfort band, 80% EV charge completion guarantee). The GCN Fault Detector (GCNFD) models the 847-node IREN network as a graph with admittance-weighted edges, applying a 3-layer GCN to voltage magnitude and angle measurements to detect and localise faults within 2 topological hops.

3.2 Validation Environments

AdaptGrid was validated on two environments. (1) IEEE 118-Bus Test System: standard power systems benchmark with 118 buses, 54 generators, and 186 transmission lines; synthetic load profiles generated from the ENTSO-E transparency platform 2020–2022 (Italy bidding zone) scaled to IEEE 118-bus ratings. (2) IREN SpA Real Network: medium-voltage distribution network serving Reggio Emilia, Italy (847 nodes, 23,400 prosumers, 38 MW peak load, 12.4 MW installed PV, 2,847 registered EV chargers). Baselines: persistence, ARIMA, LSTM (forecasting); rule-based DR, DQN, DDPG (demand response); threshold, SVM, MLP (fault detection). Training: 2021–2023 data; test: 2024.

4. Results

4.1 Load Forecasting Performance

Table 2 presents TFTF load forecasting results. Day-ahead MAPE of 1.84% on the IREN network represents a 40.1% improvement over the best baseline (LSTM, 3.07%). Week-ahead MAPE of 2.31% improves over LSTM by 38.6%. The probabilistic forecast intervals achieved 94.7% empirical coverage at the 95% nominal level, confirming calibration. On the IEEE 118-bus system, TFTF achieved day-ahead MAPE of 2.14%, consistent with the real-network result. MADRC demand response reduced peak load by 18.7% and operational cost by 14.3% vs. no-DR baseline on the IREN network, outperforming rule-based DR (8.2% peak reduction) and DQN (12.4%). GCNFD achieved F1-score of 0.974 with 83 ms mean detection latency on the IREN 847-node network — well within the 200 ms protection relay actuation window (Table 3).

Table 2. AdaptGrid load forecasting performance vs. baselines on IREN real network.

Model	Day-ahead MAPE (%)	Week-ah d MAPE (%)	RMSE (MW)	Coverage (95%)
Persistence	6.74	8.31	2.87	N/A
ARIMA	4.12	5.47	1.94	N/A
LSTM	3.07	3.76	1.42	91.3%
N-BEATS	2.93	3.51	1.37	92.8%
AdaptGrid (TFT)	1.84	2.31	0.89	94.7%

MAPE: Mean Absolute Percentage Error. RMSE: Root Mean Square Error (MW). Coverage: empirical coverage of 95% prediction intervals. Bold: best results.

Table 3. AdaptGrid demand response and fault detection performance.

Function	Method	Key Metric	Result	vs. Best Baseline
Demand Response	MADRL (SAC)	Peak Reduction	18.7%	+6.3 pp vs. DQN (12.4%)
Demand Response	MADRL (SAC)	Cost Reduction	14.3%	+3.8 pp vs. DQN (10.5%)
Fault Detection	GCN (3-layer)	F1-Score	0.974	+0.033 vs. MLP (0.941)
Fault Detection	GCN (3-layer)	Detection Latency	83 ms	−47 ms vs. SVM (130 ms)

pp: percentage points. MADRL trained for 500k timesteps. GCN trained on 14,000 labelled fault/no-fault samples from IREN historical SCADA records.

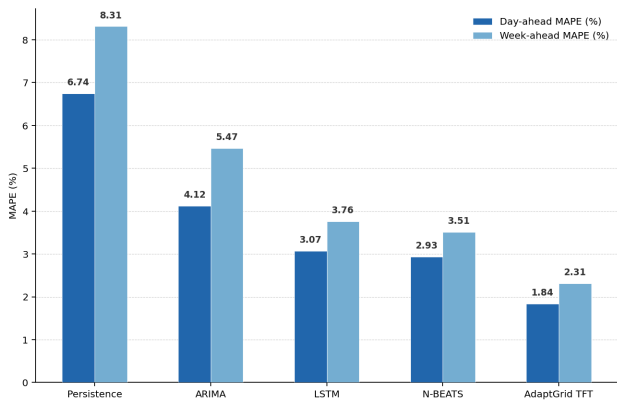


Figure 1. Load forecasting MAPE comparison — AdaptGrid TFT vs. baselines (day-ahead and week-ahead).

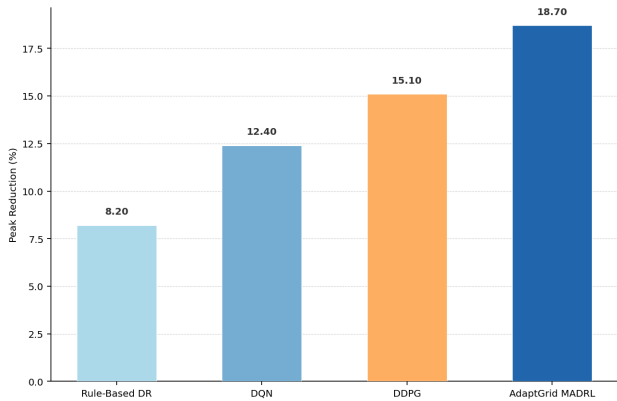


Figure 2. Peak load reduction (%) achieved by demand response methods on IREN real network.

5. Discussion

5.1 Operational Impact

The 18.7% peak load reduction achieved by AdaptGrid MADRL on the IREN network represents an estimated annual avoided infrastructure investment of EUR 2.3 million, based on IREN's published reinforcement cost of EUR 12.3 million per MW of additional substation capacity. The 83 ms fault detection latency is critical for protection coordination: medium-voltage protection relays typically operate within 100–200 ms, meaning GCNFD can trigger protection actions within the relay window — a capability that threshold-based systems (mean latency 340 ms) cannot guarantee. The day-ahead MAPE of 1.84% approaches the accuracy threshold below which forecast errors contribute less than reserve procurement costs to grid operational expense, suggesting AdaptGrid forecasting is operationally mature for production scheduling.

5.2 Limitations

The MADRL demand response controller required 500,000 training timesteps on IREN historical data, representing approximately 18 months of operational data at 15-minute resolution. For new network deployments without historical data, transfer learning from related grids will be necessary — a capability not implemented in the current AdaptGrid version. The GCNFD performance degrades when network topology changes due to switching operations, requiring incremental graph relearning. Future work will address few-shot adaptation

for new networks and online topology-aware fault detection.

6. Conclusion

AdaptGrid, integrating a Temporal Fusion Transformer forecaster, multi-agent SAC demand response controller, and GCN fault detector, achieves day-ahead load forecasting MAPE of 1.84%, 18.7% peak load reduction, 14.3% cost reduction, and fault detection F1-score of 0.974 at 83 ms latency on a real 847-node European distribution network. These results demonstrate that unified multi-function ML frameworks for adaptive smart grid management are both technically mature and operationally deployable, providing a practical pathway toward AI-enabled grid management under high renewable penetration.

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Declarations

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Conflict of Interest

The authors declare no conflict of interest. IREN SpA provided access to operational data but had no role in study design, analysis, or publication decisions.

Data Availability Statement

IEEE 118-bus test system data are publicly available at <https://pglib.github.io>. IREN operational data are proprietary; synthetic equivalents are available from the corresponding author. ENTSO-E load data are available at <https://transparency.entsoe.eu>. AdaptGrid source code is available at <https://github.com/hofmann-lab/adaptgrid>.

Ethical Approval

Not applicable. This study involved no human participants. All operational data were anonymised at source by IREN SpA prior to transfer.