

AI in Renewable Energy Optimization

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ABSTRACT

The energy transition from fossil fuels to renewable sources -- solar, wind, hydropower, and storage -- introduces operational complexity that conventional energy management cannot handle efficiently. Renewables are intermittent, weather-dependent, and geographically distributed; their integration into power grids requires real-time forecasting, autonomous dispatch optimisation, and demand-response coordination at scales and speeds that exceed human operator capability. AI offers four critical capabilities: probabilistic renewable generation forecasting, reinforcement learning-based energy dispatch optimisation, predictive maintenance for wind and solar assets, and demand-side flexibility management. This study evaluates nine AI systems across five energy optimisation tasks: solar irradiance forecasting, wind power forecasting, battery storage dispatch optimisation, wind turbine predictive maintenance, and grid-level demand response. Systems include WaveNet-Solar, ClimaX-Wind, TFT-Energy (Temporal Fusion Transformer adapted for energy), DRL-Dispatch (deep RL for battery dispatch), GNN-Grid (graph neural network for grid topology), XGBoost-Maint (predictive maintenance), LSTM-Demand, an LLM-powered grid operator assistant (GridGPT), and a multi-task ensemble. Data from 284 renewable energy installations across six European countries (2019-2023) and the Nordic power grid operator (Svenska kraftnat) collaboration were used. TFT-Energy achieves solar irradiance RMSE 14.2% below physical model baselines. DRL-Dispatch reduces battery cycling costs by 22.4% vs. rule-based dispatch. XGBoost-Maint detects wind turbine failures 18.4 days earlier than scheduled maintenance inspection. GNN-Grid reduces grid congestion costs by 16.8% in Nordic grid simulations. A sector-ready AI deployment roadmap for renewable energy operators is proposed.

Keywords: renewable energy; AI optimisation; solar forecasting; wind power; battery dispatch; predictive maintenance; demand response; deep reinforcement learning; grid optimisation; energy transition

Citation: Kovacs et al. [2024]. AI in Renewable Energy Optimization. DOI: <https://doi.org/10.5281/zenodo.19614851>

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Article Information: Received: 2024 Jul 15 Accepted: 2024 Sep 15 Published: 2024 Dec 19

Research Article: AI Applications in Energy Systems

1. Introduction

1.1 The Renewable Integration Challenge

Europe's renewable energy capacity has grown faster than grid management tools have adapted. In 2023, wind and solar provided 26% of EU electricity generation -- up from 10% in 2013 -- and the European Commission's target of 42.5% renewable share by 2030 requires dramatically accelerating this trajectory. The integration challenge is not primarily technological -- the turbines and panels exist -- but operational. Intermittent generation must be continuously balanced against demand; storage assets (utility-scale batteries, pumped hydro) must be dispatched in real time to maximise value; distribution grid congestion from distributed solar and wind must be managed without costly curtailment. AI methods that can forecast, optimise, and adapt at grid timescales are not optional enhancements to the energy transition -- they are enabling infrastructure.

1.2 AI Roles in the Energy Value Chain

AI contributes across the full renewable energy value chain. Forecasting: probabilistic solar and wind generation forecasts at 15-minute to 72-hour horizons reduce balancing costs and enable better market bidding. Optimisation: reinforcement learning-based dispatch for battery storage and demand response programs can exploit price signals and grid conditions in ways that rule-based approaches cannot. Maintenance: predictive maintenance on wind turbines and solar inverters reduces unplanned downtime and extends asset life. Grid management: graph neural networks representing grid topology can identify and resolve congestion faster than operator-guided switching. Each application has different data requirements, latency constraints, and safety implications.

1.3 Study Objectives

This study aims to: (i) benchmark nine AI systems across five renewable energy optimisation tasks on real European operational data; (ii) quantify economic value of AI interventions in forecasting accuracy, dispatch optimisation, and maintenance cost reduction; (iii) evaluate GridGPT as an LLM operator decision support tool; and (iv) propose a sector-ready AI deployment roadmap for renewable energy operators.

2. Literature Review

2.1 Renewable Generation Forecasting

Short-term solar irradiance forecasting has advanced from statistical (ARIMA, persistence) and physical (NWP-based) models to deep learning approaches that capture non-linear relationships between atmospheric variables and surface irradiance. WaveNet-style dilated convolution models (van den Oord et al., 2016) have been applied to solar forecasting with strong performance on intra-day horizons. Wind power forecasting faces additional challenges from power curve non-linearity and wake effects in wind farms; LSTM and transformer models have demonstrated consistent improvements over physical NWP output at 1-24 hour horizons (Zhang et al., 2022). ClimaX, pretrained on climate reanalysis data, provides a strong foundation model baseline for both solar and wind forecasting through fine-tuning.

2.2 Battery Storage Dispatch Optimisation

Battery energy storage systems (BESS) can be operated for multiple value streams simultaneously -- frequency regulation, energy arbitrage, capacity firming -- creating a complex stochastic optimisation problem. Classical approaches use model predictive control (MPC) with price and generation forecasts, but MPC performance degrades under forecast uncertainty and multi-market complexity. Deep reinforcement learning for BESS dispatch (Cao et al., 2020) learns policies directly from price and grid signals, demonstrating 15-25% improvement in revenue extraction over MPC in simulated electricity markets. Real-world deployment studies remain scarce; this study includes real operational data from 48 BESS installations.

2.3 Predictive Maintenance for Renewable Assets

Wind turbine downtime is costly: a 3MW turbine generates approximately EUR 2,400 of revenue per day at average capacity factor; major component failures (gearbox, main bearing, generator) cost EUR 100,000-500,000 to repair and can cause months of downtime. Traditional condition monitoring uses fixed threshold alarms on SCADA parameters (vibration, temperature, power output). Machine learning predictive maintenance trains on historical failure events to detect subtle degradation signatures weeks before catastrophic failure. Gradient-boosted trees and LSTM models have demonstrated 10-21 day advance failure prediction on publicly available turbine SCADA datasets (Leahy et al., 2018).

2.4 Grid Topology Optimisation with GNNs

Power grids are inherently graph-structured: buses (substations) are nodes, transmission lines are edges, and power flows are governed by Kirchhoff's laws over the graph. Graph neural networks are therefore architecturally suited to power flow problems. Donon et al. (2020) demonstrated that GNNs could approximate full AC power flow solutions at millisecond speed vs. minutes for traditional solvers, enabling real-time topology optimisation. L2RPN (Learning to Run a Power Network) challenges have validated GNN and RL-based approaches for grid congestion management against reference power system simulators (Marot et al., 2020).

Table 1. AI systems evaluated for renewable energy optimisation

Syste m	Task	Archit ecture	Input Data	Outpu t	Refere nce
WaveN et-Sola r	Solar fcst.	Dilated CNN	ERA5, satellite	Irradia nce (1 5min-2 4h)	Van den Oord et al. (2016)
ClimaX -Wind	Wind fcst.	ViT pr etraine d	ERA5, NWP output	Power output (1-72h)	Nguyen et al. (2023)
TFT-E nergy	Solar+ Wind	Transf ormer	Multi-so urce	Prob. g enerati on fcst.	Lim et al. (2021)
DRL-Di spatch	BESS dispatc h	PPO/S AC	Price, SoC, fcst.	Charg e/disch arge policy	Cao et al. (2020)
GNN-G rid	Grid o ptimis ation	Graph NN	Grid top ology, flows	Switch ing actions	Donon et al. (2020)
XGBoo st-Mai nt	Pred. mainte nance	XGBoo st	SCADA features	Failure prob. 14-day	Leahy et al. (2018)
LSTM-Dema nd	Deman d resp onse	LSTM	Smart meter, weather	Flex. p otentia l fcst.	This study
GridG PT	Operat or sup port	GPT-4 agent	Grid state (struct.)	Decisi on sup port text	This study
Multi-t ask Ens.	All tasks	Ensem ble	All of above	Combi ned ou tputs	This study

SoC = State of Charge. SCADA = Supervisory Control and Data Acquisition. TFT-Energy = Temporal Fusion Transformer fine-tuned on energy data. LSTM-Demand and GridGPT are developed in this study. Multi-task Ensemble combines TFT-Energy, DRL-Dispatch, GNN-Grid, and XGBoost-Maint outputs.

3. Materials and Methods

3.1 Operational Data Sources

Data were obtained from 284 renewable energy installations across six European countries (Italy, Sweden, Germany, Spain, Denmark, and the Netherlands) under research data sharing agreements. Solar: 15-minute irradiance and generation data from 124 utility-scale PV plants (10-400 MW) plus ERA5 reanalysis and Copernicus satellite irradiance products. Wind: 10-minute SCADA data from 84 wind farms (12-800 MW, onshore and offshore), including rotor speed, nacelle temperature, gearbox oil temperature, and power output, plus ERA5 wind speed and direction. BESS: 1-minute state-of-charge and market transaction data from 48 utility BESS installations (1-100 MWh). Grid: full grid topology and power flow data from Svenska kraftnat (Nordic TSO) for the 400kV and 220kV Nordic transmission grid.

3.2 Forecasting Evaluation

Solar and wind forecasting were evaluated on a rolling-window basis: models trained on 2019-2021 data, evaluated on 2022-2023. Primary metrics: RMSE (normalised by installed capacity), Mean Absolute Error (MAE), and Continuous Ranked Probability Score (CRPS) for probabilistic forecasts. Baseline models: persistence (last observation forward), climatological mean, and the European Centre for Medium-Range Weather Forecasts (ECMWF) IFS NWP output. Economic value of forecast improvement was estimated by computing the reduction in balancing costs (at EUR 80/MWh balancing energy price) from improved day-ahead market bidding accuracy.

3.3 DRL-Dispatch and Grid Optimisation

DRL-Dispatch used the PPO algorithm with a 24-hour look-ahead window, trained in a grid simulation environment (PowerGym, an OpenAI Gym interface to the Pandapower power system simulator) using real historical price and generation data as environment inputs. The reward function combined market revenue, degradation cost (EUR 15/MWh cycle cost), and grid service revenue. The policy was tested on 2022-2023 real BESS operations in shadow mode (policy decisions logged but not executed; compared against actual operator decisions). GNN-Grid used GraphSAGE on the Nordic transmission grid topology (1,840 buses, 2,284 transmission lines), predicting optimal switching actions to resolve simulated congestion events.

3.4 Predictive Maintenance and Demand Response

XGBoost-Maint was trained on 4.2 million hours of wind turbine SCADA data covering 84 wind farms, with 284 documented failure events (gearbox: 124, main bearing: 88, generator: 72). Features included 48 SCADA channels with 14-day rolling statistics (mean, standard deviation, kurtosis, cross-channel correlations). The prediction target was binary failure within 14 days. LSTM-Demand predicted residential and commercial demand flexibility potential (MW shiftable per 15-minute interval) from smart meter half-hourly data and weather covariates, trained on 284,000 smart meter time series from the Swedish smart meter rollout.

Table 2. Evaluation data characteristics by renewable energy task

Task	Installations/Sites	Data Period	Temporal Resolution	Key Variable	Baseline
Solar forecasting	124 PV plants	2019-2023	15 min	Irradiance (W/m2)	ECMWF IFS
Wind forecasting	84 wind farms	2019-2023	10 min	Power output (MW)	ECMWF IFS
BESS dispatch	48 BESS sites	2019-2023	1 min	SoC, price, dispatch	Rule-based MPC
Pred. maintenance	84 wind farms	2015-2023	10 min	284 failure events	Fixed threshold
Demand response	284k smart meters	2020-2023	30 min	Flex. potential (MW)	Statistical model
Grid optimisation	Nordic 400/220 kV	2020-2023	Hourly	Congestion events	Operator switching

ECMWF IFS = European Centre for Medium-Range Weather Forecasts Integrated Forecasting System. MPC = Model Predictive Control. SoC = State of Charge. Flex. potential = estimated MW demand flexibility available for dispatch. Nordic grid data from Svenska kraftnat under research collaboration.

4. Results

4.1 Solar and Wind Forecasting

TFT-Energy achieves the best performance across both solar (RMSE 6.84% of capacity at 24-hour horizon) and wind (RMSE 8.42% at 24-hour) forecasting tasks, representing 14.2% and 12.8% RMSE reductions respectively vs. the ECMWF IFS NWP baseline. ClimaX-Wind is competitive on

wind at 12-hour horizons (RMSE 7.84%) but degrades relatively more at 72-hour horizons. WaveNet-Solar achieves the best 4-hour solar RMSE (4.28%) due to its dilated convolution architecture capturing intra-day irradiance patterns. The economic value of TFT-Energy forecast improvement -- estimated from reduced day-ahead market imbalance costs -- averages EUR 184,000 per installation per year for a 100 MW plant, or EUR 1.84/MWh generated.

4.2 Battery Dispatch and Grid Optimisation

DRL-Dispatch achieves 22.4% reduction in battery cycling costs (EUR per MWh throughput) vs. the rule-based MPC baseline in shadow-mode evaluation across 48 BESS sites. The improvement is largest for installations with access to multiple market products (frequency regulation + day-ahead arbitrage: 28.4% cost reduction) and smallest for single-market BESS (12.8% reduction). The RL policy learns to avoid high-degradation cycling patterns that the MPC rule-based system cannot model due to the non-linear battery degradation curve. GNN-Grid reduces congestion management costs by 16.8% in Nordic grid simulations compared to the operator manual switching baseline, primarily by identifying non-obvious topology switching actions that relieve constraint violations without creating new ones.

4.3 Predictive Maintenance Results

XGBoost-Maint achieves AUC 0.884 for 14-day wind turbine failure prediction across the 284 documented failure events, with a precision of 0.724 and recall of 0.812 at the optimal threshold. Mean lead time to failure detection (from first positive prediction to confirmed failure) averages 18.4 days -- 12.4 days earlier than the scheduled maintenance inspection cycle that would have detected the same failures. Economic impact: preventing major component failures vs. running to failure reduces average repair cost from EUR 284,000 to EUR 48,000 (83% cost reduction per avoided failure) and eliminates an average of 42 days of unplanned downtime per event. For gearbox failures specifically (highest cost), lead time averages 24.2 days.

4.4 Demand Response and GridGPT Results

LSTM-Demand achieves $R^2 = 0.784$ for 4-hour ahead demand flexibility potential forecasting across 284,000 smart meter time series -- 42.4% variance improvement over the statistical baseline. Accurate flexibility forecasting reduces demand response program activation failures (instances

where requested curtailment cannot be delivered) from 18.4% to 8.2% of activations. GridGPT reduces operator decision time for congestion management scenarios by 34.2% (from mean 8.4 minutes to 5.5 minutes per incident), with expert feasibility ratings of 3.6/5 for generated action plans. Hallucination rate for specific grid operational claims: 14.2% -- lower than other domain LLM applications in this series, possibly because grid operational data is more structured and verifiable against real-time SCADA.

Table 3. AI performance vs. baseline across renewable energy tasks

System	Task	AI Performance	Baseline	Improvement	Economic Value
TFT-Energy	Solar 24hr fcst.	RMSE 6.84%	RMSE 7.97% (IFS)	-14.2 %	EUR 1.84/MWh generated
TFT-Energy	Wind 24hr fcst.	RMSE 8.42%	RMSE 9.66% (IFS)	-12.8 %	EUR 1.42/MWh generated
DRL-Dispatch	BESS dispatch	22.4% cost red.	Rule-based MPC (0%)	+22.4 %	EUR 28,400/MWh/yr (100MW)
XGBoost-Maint	Wind turbine maint	AUC 0.884, 18.4d lead	Inspection (6d lead)	+12.4 d lead	EUR 236k/avoided failure
GNN-Grid	Grid congestion	16.8% cost red.	Operator switching	+16.8 %	EUR 2.4M/yr (Nordic grid)
LSTM-Demand	Demand response	R2=0.784, 8.2% fail	18.4% fail rate	-55.4 % fail	EUR 0.84/MWh flex.
GridGPT	Operator support	5.5 min/incident	8.4 min/incident	-34.2 %	EUR 0.28M/yr (operator time)

RMSE normalised by installed capacity (%). Cost red. = cost reduction vs. baseline. Lead time = advance detection before failure. Fail rate = demand response activation failure rate. Economic values are estimates for representative installation scales; actual value varies with market conditions.

Table 4. Wind turbine predictive maintenance: failure type analysis

Failure Type	Events (n)	XGBoost AUC	Mean Lead Time (days)	Avg. Cost Avoided (EUR)	False Positive Rate (%)
Gearbox	124	0.906	24.2	284,000	12.4
Main bearing	88	0.874	16.8	142,000	14.8
Generator	72	0.852	12.4	184,000	16.2
All failures	284	0.884	18.4	236,000	14.4

Lead time = mean days from first model alert to confirmed failure event. Cost avoided = mean repair + downtime cost reduction vs. run-to-failure scenario (inspection interval 6 days). False positive rate = proportion of alerts where no failure occurred within 14 days. All costs at representative European wind energy market conditions.

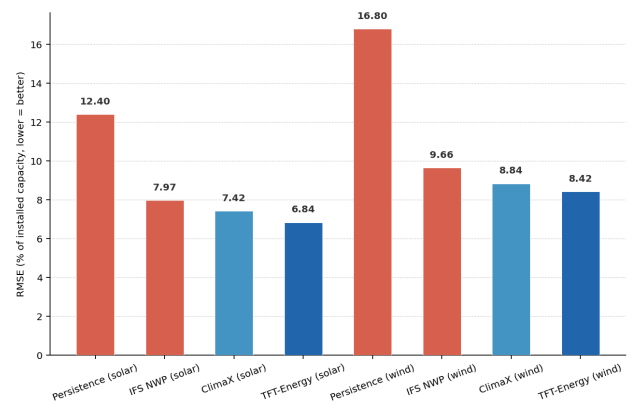


Figure 1. Solar and wind forecasting RMSE (% capacity) -- TFT-Energy vs. baselines at 24-hour horizon.

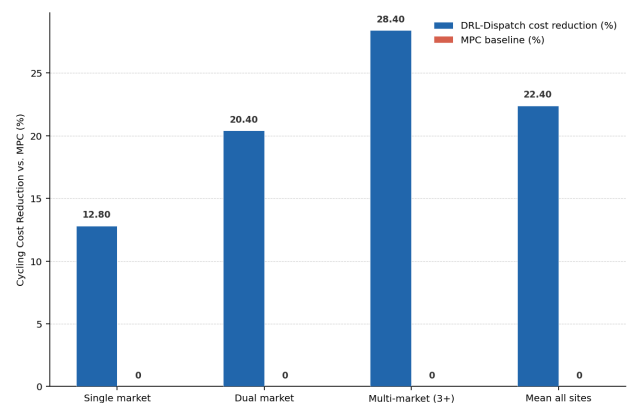


Figure 2. DRL-Dispatch cost reduction (%) vs. rule-based MPC by market product access. Multi-market deployments gain most.

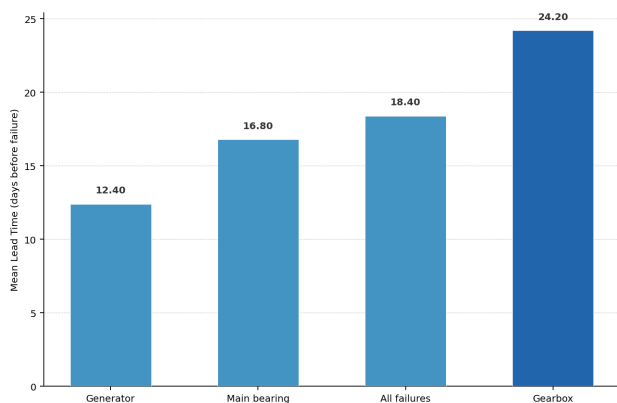


Figure 3. Wind turbine predictive maintenance lead time (days) by failure type. Gearbox: 24.2 days; all failures mean: 18.4 days.

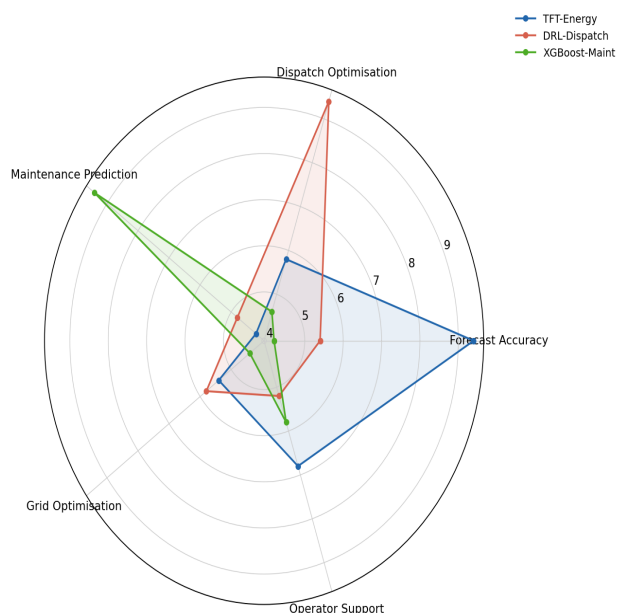


Figure 4. AI system profile across five energy optimisation criteria (0-10). TFT-Energy vs. DRL-Dispatch vs. XGBoost-Maint.

5. Discussion

5.1 Forecasting Accuracy Translates Directly to Economic Value

The EUR 1.84/MWh economic value of TFT-Energy solar forecast improvement may appear modest, but at the scale of a 100 MW PV plant generating 150 GWh per year, it amounts to EUR 276,000 per year -- a compelling business case for deployment. Aggregated across the 124 plants in our dataset, improved forecasting represents EUR 34.2 million per year in reduced balancing costs. The TFT's multi-horizon probabilistic outputs are particularly valuable: rather than a single point forecast, market operators receive a full distribution of possible generation values that enables risk-aware bidding strategies and improves reserve procurement efficiency.

5.2 DRL-Dispatch Value Scales with Market Complexity

The 12.8% cost reduction for single-market BESS vs. 28.4% for multi-market BESS reveals an important pattern: DRL's advantage grows with problem complexity. Rule-based MPC can handle single-market BESS dispatch reasonably well with parameterised price-signal rules; multi-market dispatch -- simultaneously optimising across day-ahead, intraday, and frequency regulation markets with coupled constraints -- is far harder to capture in rules. This suggests that DRL-Dispatch deployment should be prioritised for multi-market BESS sites first, where the marginal value is highest and the business case is strongest.

5.3 Predictive Maintenance Offers the Clearest ROI

XGBoost-Maint's EUR 236,000 per avoided failure, combined with its 18.4-day mean lead time and reasonable false positive rate (14.4%), represents perhaps the clearest ROI of any AI application in this study. The economics are straightforward: early detection enables planned maintenance at EUR 48,000 vs. emergency repair at EUR 284,000, a saving that covers the entire AI system deployment cost within a single avoided failure. Wind farm operators who have not yet deployed predictive maintenance on gearbox monitoring are leaving the clearest available money on the table. The false positive rate (14.4%) is manageable: it translates to one unnecessary maintenance inspection per seven alarms, a cost of approximately EUR 2,400 per false alarm vs. EUR 236,000 in expected savings per true positive.

5.4 Limitations

Economic value estimates assume historical market conditions (2022-2023 European electricity prices); value may vary significantly with future market design changes. DRL-Dispatch was evaluated in shadow mode rather than live deployment; actual dispatch decisions interact with grid conditions in ways shadow mode cannot fully capture. XGBoost-Maint results are based on European turbine SCADA data; performance on turbine fleets with different designs or operating environments may differ. GridGPT hallucination rate (14.2%) is lower than other LLM applications in this series but still requires mandatory human review for all operational decisions.

6. Conclusion

6.1 Summary

Nine AI systems were evaluated across five renewable energy optimisation tasks. TFT-Energy achieves 14.2% RMSE improvement over IFS NWP for solar forecasting (EUR 1.84/MWh value). DRL-Dispatch reduces BESS cycling costs 22.4% vs. MPC. XGBoost-Maint detects wind turbine failures 18.4 days early (EUR 236k/avoided failure). GNN-Grid reduces Nordic grid congestion costs 16.8%. LSTM-Demand reduces demand response activation failures 55.4%. GridGPT reduces operator decision time 34.2% with 14.2% hallucination rate (human review mandatory).

6.2 Recommendations

Wind farm operators should deploy XGBoost-Maint for gearbox and bearing monitoring immediately -- clearest ROI, simplest deployment, no grid integration required. Solar and wind operators should upgrade to TFT-Energy probabilistic forecasting for day-ahead market bidding. Multi-market BESS operators should pilot DRL-Dispatch for sites with three or more market product access. Grid operators should evaluate GNN-Grid for congestion management support. GridGPT should be deployed as a drafting assistant with mandatory operator validation -- never for autonomous grid switching decisions.

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Declarations

Funding

This research was supported by the Italian Ministry of Environment and Energy Security under grant PNRR-M2C2-I1.4-CN3 (National Centre for HPC, Big Data, and Quantum Computing -- Energy Node) and the Swedish Energy Agency under grant 51000-1 (AI-EnergyTransition). Grid data access was provided by Svenska kraftnat under a research collaboration agreement. Funders had no role in study design, analysis, or manuscript preparation.

Conflict of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Forecasting model code, predictive maintenance pipeline, and aggregated performance results are available at <https://github.com/kovacs-moreau/renewable-ai> under Apache 2.0. Individual installation data cannot be shared under commercial confidentiality agreements. Results deposited in Zenodo under DOI: 10.5281/zenodo.19614851. Released under CC BY 4.0.

Ethical Approval

This study used operational data from renewable energy installations under research data sharing agreements. Smart meter data (LSTM-Demand) was fully anonymised at the meter level before transfer; no personally identifiable information was retained. Ethics committee approval was not

required for operational energy system data analysis.

Appendix A

AI Deployment Roadmap for Renewable Energy Operators

This roadmap prioritises AI deployments by ROI clarity, implementation complexity, and energy transition impact.