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ECOLOGICAL AND SECURE ELECTRICITY MICROGRIDS - MONITORING AND FORECASTING CHALLENGES

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Abstract: *Reliable, low-carbon power systems depend on high-granularity, short-horizon forecasting, especially within islandable microgrids where consumers and prosumers shape real-time balance. Ultra-short-term (15-minute) forecasts support storage scheduling, demand response, and secure operation amid renewable intermittency and growing cyber risk. Forecasting approaches are classified into black-box, gray-box, and white-box methods, highlighting trade-offs in accuracy, explainability, and deployability. Operational use-cases are aligned with forecasting time scales, and current literature shows notable gaps: limited 15-minute multi-step studies, inconsistent evaluation protocols, insufficient attention to explainability, and restricted access to representative datasets. Design principles are outlined for deployable forecasting and control: standardised metrics and horizons, privacy-preserving data pipelines, explainability-first modelling, and transferable domain-specific hyperparameters. Addressing these gaps can increase renewable penetration, lower imbalance costs, strengthen cybersecurity compliance, and enhance resilience, delivering cleaner energy at reduced cost with higher quality of service. Researchers who want to support effective energy management technologies with their research should be aware of the current challenges.*

Keywords: *energy, anomaly detection, forecast, modelling, microgrids, cybersecurity*

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INTRODUCTION

Problem Statement

Electricity has become a critical resource with profound effects on economic growth and household living costs. Rising demand, combined with the imperative to reduce greenhouse gas emissions, has driven a steady expansion of renewable generation. Yet renewables are inherently intermittent because output depends heavily on weather and other exogenous factors. At the same time, the threat of cyberattacks on energy infrastructure is increasing, making secure and efficient system operation particularly challenging. Climate policy has introduced a range of regulations that influence both energy prices and the composition of generation (the energy mix). The tight coupling between weather-dependent renewables and traditional thermal sources, whose ramping capabilities are limited, creates persistent difficulties in balancing supply and demand across time and location. These pressures heighten the need for grid flexibility, including storage, demand response, and high-resolution forecasting, so that operators can anticipate short-term fluctuations and maintain reliability at reasonable cost.

The balance of supply and demand in a country-level power system ultimately aggregates the behavior of individual consumers and prosumers, yet it shapes the entire delivery chain. Effective microgrid management, ideally with the capability to operate in islanded (off-grid) mode when needed, can reduce the need for macro-scale interventions by absorbing local disturbances. Such off-grid operation demands agile, data-driven adjustments to both supply and demand, which in practice are only feasible with high-quality operational forecasting and planning. Management efficiency enabled by forecasting is reflected both in a higher feasible share of renewable generation and in the avoidance of critical events (overloads, voltage excursions, unserved energy). Importantly, different prediction horizons serve different purposes: second-to-minute horizons support protection and fast controls; 15-minute to intraday horizons enable dispatch, storage scheduling, and demand response; day-ahead and multi-day horizons inform procurement, maintenance, and market participation. In all cases, short- and medium-term, high-granularity forecasts are the backbone of reliable control and automation.

Accurate energy-consumption forecasting has operational, financial, and technological implications. On the operational side, it underpins continuity of service and system stability by aligning demand with available supply and flexibility resources. Financially, it improves procurement and bidding, reduces imbalance penalties, and guides investment in storage and efficiency. Technologically, it enables process control, grid diagnostics (e.g., anomaly detection that affects system stability), and quantification of energy-saving potential. Together, these capabilities translate directly into cost reduction while enhancing security and resilience of national power systems (Vasylieva et al., 2025; Mukhtarov et al., 2023).

Energy forecasts approaches

While long-term forecasts are adequate for strategic planning, short-term forecasts pose tactical challenges and are essential for stable system operation. For example, in April 2025 the Iberian Peninsula experienced a blackout linked to a local imbalance in an already overloaded grid, an event that underscores the critical role of timely, high-resolution forecasting.

Forecasting models are commonly grouped into three categories:

- Black-box models: classic top-down approaches that use only inputs and outputs to learn system behaviour.
- Gray-box models: systems are decomposed into logically separate components (e.g., PV, HVAC), each treated as a black box but differentiated at component level.
- White-box models: bottom-up, physics-based approaches that build detailed component models and aggregate them into a system representation.

A well-known paradox is that white-box models, while invaluable at the design stage, often diverge from operational reality due to construction tolerances, ageing, maintenance practices, and unforeseen interactions. Black-box models therefore dominate operations because they require little prior knowledge; however, the trade-off is reduced explainability and potentially limited accuracy outside the training domain. Against this backdrop, gray-box methods strike a pragmatic middle ground, offering manageable complexity with improved interpretability and reliability.

System scale matters: forecasting a single building is difficult due to non-stationary and highly variable demand patterns. Aggregation at city or metropolitan scales yields smoother, more cyclic trends - but large interconnected grids can be vulnerable to cascading effects triggered by local disturbances. This makes stability at the level of islandable microgrids (off-grids) especially important: local stability supports global stability.

These considerations highlight the need for ultra-short-term operational forecasting, predicting demand and supply shifts before they escalate into widespread disruptions. Such forecasts are foundational for real-time IT/OT operations (SCADA/EMS/DMS). The literature typically classifies time horizons as: (i) ultra-short-term/operational: minutes to tens of minutes, (ii) short-term: one hour to one week, (iii) medium-term: one week to one year, (iv) long-term: beyond one year.

Granularity is equally important: operational decisions are often taken at intervals of a few to several minutes. Despite widespread minute-level metering and settlement in 15-minute blocks across much of Europe, there is a shortage of studies that actually forecast at 15-minute resolution or that push multi-step forecasts 2, 12, or 24 hours ahead at that granularity (e.g., Somu et al., 2021). Most research still targets hourly (or coarser) horizons and sampling (e.g., Olu-Ajay et al., 2023; Demir & Gunal, 2025). Short-term and operational forecasts underpin demand management and storage scheduling. Regional systems and microgrids - particularly those serving large consumers such as hotels, public buildings, and industrial facilities - depend on operational planning for stability (Klyuev et al., 2022). Exogenous drivers are critical: common predictors include calendar/time features, building operations, macroeconomic indicators, occupancy, building parameters, weather, and historical consumption. Weather variables appear in about 80% of studies, while occupancy features are considered in roughly 20% and others even less frequently (Olu-Ajay et al., 2023). Incorporating space-use signals (e.g., motion detectors) can materially improve operational forecasts by capturing real utilisation patterns.

Prediction reliability and explainability are increasingly important amid rising cybersecurity requirements. The EU's NIS 2 Directive (European Parliament & Council, 2022) mandates robust monitoring and incident reporting, including anomaly detection, while the

Cyber Resilience Act (European Commission, 2023) obliges manufacturers to ensure cybersecurity across the product lifecycle. Reliable operational forecasting enhances observability and risk mitigation, supporting compliance. Nevertheless, few academic studies explicitly address these regulatory dimensions.

Model transparency and robustness also matter in practice. Deep neural networks, though powerful, can lack explainability, complicating causal interpretation and operator trust. A viable alternative is decomposition with interpretable models (gray-box): separate, instrumented models for air-handling units, heat pumps, thermal loops, machinery, and other subsystems. In parallel, classical machine-learning methods, e.g., decision trees and random forests, offer greater transparency, lower resource requirements, and improved robustness to adversarial risks (e.g., poisoned data, tampered models). Explainability is a prerequisite for safe autonomous control, and without it, confidence in automated decision-making will remain limited.

Methodological consistency and data availability. The literature varies widely in datasets, treatment of time-series structure, and evaluation metrics. Although MAE, MAPE, MSE, RMSE, and R^2 are common, they are often used in isolation without domain-aware interpretation. Normalised measures (e.g., N-MSE, N-RMSE) offer a path toward comparability but remain underused. Data scarcity is another constraint: even popular repositories (e.g., Kaggle) lack representative, comprehensive datasets for benchmarking. Sparse or fragmented data encourages overfitting and weak generalisation. Because energy data are strategic - and, in the context of ongoing hybrid warfare in Eastern Europe, unlikely to be broadly shared - there is a need for universal, adaptable control frameworks that can be rapidly tailored to specific microgrids without disclosing sensitive datasets. It is also worth defining domain-specific hyperparameters and protocols that standardise model configuration, measurement granularity, and evaluation, enabling fair comparison and safer deployment prior to real-world operation.

CONCLUSIONS

Scientific work on electricity monitoring and modelling is strategically important, particularly in the current geopolitical context, because reliable energy systems underpin the functioning of entire societies and economies. Despite notable progress, critical gaps remain, especially in ultra-short-term, high-granularity forecasting; reproducible evaluation protocols; explainability; and access to secure, representative datasets.

Meeting these challenges requires more than algorithmic advances. It calls for regulatory harmonisation, rigorous and transparent methodology (including standardised metrics and time-scale definitions), and trustworthy data pipelines that protect confidentiality while enabling learning, e.g., through privacy-preserving or federated approaches. At the system level, a balance between black-box performance and gray/white-box interpretability is essential to support operator trust, cybersecurity, and safe automation.

By closing these gaps, the community can deliver technologies that increase grid resilience, raise the feasible share of renewables, and lower operational and capital costs. The payoff is significant: cleaner energy, reduced volatility, and tangible improvements in quality of life.

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