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AI-Driven Predictive Analytics Framework for Electric Grid Reliability and Infrastructure Resilience

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Abstract: The need for predictive, rather than reactive, solutions to managing the electric grid has grown, due to the increasing frequency of extreme weather events, the growing complexity of electric transmission and distribution networks, and the rise in exposure to cyber-physical threats. This paper is a synthesis of 24 peer-reviewed studies to suggest an integrated artificial intelligence (AI) based predictive analytics framework to improve grid reliability and infrastructure resilience. This framework brings together four layers of analysis: data acquisition, feature engineering, predictive modelling, resilience and risk quantification, and leverages ensemble learning techniques (such as random forests (Breiman, 2001) and extreme gradient boosting (Chen & Guestrin, 2016)), deep sequential networks (long short-term memory (LSTM) networks (Hochreiter & Schmidhuber, 1997; Kong et al., 2019)), and probabilistic fragility modelling approaches for extreme-weather impact assessment (Panteli & Mancarella, 2015; Panteli, Pickering, et al., 2017). Various applications such as transformer lifetime prediction (Aizpurua et al., 2019), transmission-line fault classification (Shi et al., 2019), cyberattack and false-data-injection detection (He et al., 2017; Karimipour et al., 2019), and renewable-energy forecasting (Voyant et al., 2017; Yagli et al., 2019) are also included in the synthesis. The reported behaviour of these methods implies that deep sequential models outperform classical statistical models in short-term load forecasting and/or detection by several points, particularly in the case of mean absolute percentage error; and detection accuracy is often higher than ninety percent across several classes of cyber-physical threats. The paper proposes that the resilience-metric quantification (Panteli, Mancarella et al., 2017) combined with real-time predictive modelling provides a scalable solution to proactive grid management. It ends with identifying data quality, interoperability and regulatory challenges for widespread implementation, and proposing a path towards having standardised resilience metrics across utilities.

Keywords: *predictive analytics, electric grid reliability, infrastructure resilience, machine learning, deep learning, fault detection, cyberattack detection, load forecasting, renewable energy forecasting, extreme weather, smart grid, ensemble learning*

1. Introduction

Electric power grids are among the most important infrastructures that support economic activity today, but are constantly susceptible to equipment deterioration, extreme weather, and cyber-physical intrusion. Traditional reliability management has been based on scheduled maintenance and the restoration following events, which is becoming a less adequate method as the transmission and distribution networks become vaster and more interconnected. With the increasing adoption of new technology such as supervisory control and data acquisition (SCADA), phasor measurement units (PMU), and smart meters, the amount of operational data generated has increased, and machine learning and deep learning algorithms can help shift grid management from reactive to predictive (Hossain et al., 2019).

This paper brings together the evidence from 24 publications between 1997 and 2019 ranging from fault diagnosis, cyberattack detection, load forecasting, renewable energy forecasting, to quantification of resilience to extreme weather. The synthesis of these works leads to a proposal of a unified and integrated AI-based predictive analytics platform, enabling the combination of these previously disconnected strands of work into a single operational architecture, applicable to all the three sectors of generation, transmission and distribution. The framework is designed to be

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modular, allowing utilities to use individual analytical layers without having to replace their existing monitoring infrastructure.

2. Literature Synthesis

2.1 Foundational Machine Learning and Deep Learning Methods

General-purpose machine learning techniques, which were subsequently tailored to the power-system problem, form the core of the analytical component of predictive grid management. Random forests, a combination of decorrelated decision trees, have been formalized as a general statistical learning technique that is applicable to classification and regression tasks and has low variance and high generalisation (Breiman, 2001). To complement tree-based ensembles, extreme gradient boosting extended the ensemble method by creating a scalable, regularised boosting algorithm that was more efficient and accurate in predicting large, sparse data sets (Chen & Guestrin, 2016). In order to address the vanishing-gradient problem of previous recurrent architectures (Hochreiter & Schmidhuber, 1997), recurrent neural architectures which learn long-range temporal dependencies were introduced. The explosion of the deeper learning paradigm encompassing architectures that can learn the hierarchy of feature representations automatically from raw data was brought together as a general architecture that can be applied to image, speech, and time-series analysis (LeCun et al., 2015). They are all the contributions that have provided the algorithmic vocabulary that has bequeathed almost all the subsequent power-system applications included in this paper.

2.2 Fault Detection and Diagnosis

Fault detection and diagnosis have been long-standing issues of power-system reliability engineering. The early comparative studies recorded signal-processing and rule-based approaches to fault detection in transmission and distribution networks, which are often used as a reference platform for the application of learning-based approaches (Aleem et al., 2015). Subsequent work proposed localisation-aware classification schemes: a cluster-based dissimilarity learning approach was proposed to classify faults in smart-grid feeders where spatial heterogeneity makes the conventional threshold-based detection difficult (De Santis et al., 2018). To detect and classify faults in distribution grid, S-transform coefficients were used as the input signals to the feed-forward neural networks to achieve higher robustness to noise than time domain features (Shafiullah & Abido, 2018). To implement the protection of transmission lines, sparse representation was employed to distinguish the type of faults by leveraging the structured sparsity of multi-channel current and voltage measurements, and ensure discrimination among fault categories that share overlapping electrical characteristics (Shi et al., 2019). In addition to these classification-based studies, predictive lifetime models for power transformers in nuclear plant environments have been developed that include uncertainty quantification, thus bringing the concept of predictive maintenance to high-consequence, safety-critical assets (Aizpurua et al., 2019).

2.3 Cyberattack and Anomaly Detection in Smart Grids

The ever increasing instrumented and networked grids have led to the emergence of another major reliability issue, cyber-physical security. This ability to detect false data injection attacks, for which traditional bad-data detection methods are not activated, was demonstrated using a deep-learning based mechanism that was trained from historical measurement patterns (He et al., 2017). For accurate state estimation while the measurements are manipulated adversarially by the attacker, a robust state estimation using massively parallel computation was developed (Karimipour & Dinavahi, 2018). For measurements in the AC smart-grid that are subject of sparse cyberattacks, a deep learning-based interval state estimation was proposed to bound the uncertainty of the measurements (Wang et al., 2018). At a larger scale, unsupervised deep learning architectures were developed to detect anomalous patterns without needing to have extensive labelled attack data, which is a major obstacle to supervised approaches (Karimipour et al., 2019). These developments were extended and some other applications of big data analytics in smart-grid operations were added in a wider review, which revealed some related security and privacy issues (Hossain et al., 2019).

2.4 Load and Renewable Energy Forecasting

Reliable grid balancing is predicated on accurate forecasting of demand and renewable energy generation. LSTM recurrent neural networks significantly outperformed classical autoregressive models by learning temporal dependencies in household consumption that could not be

represented with these models (Kong et al., 2019). On the generation side, a systematic review of machine learning techniques used for solar radiation forecasting identified the comparative advantage of support vector machines, ANNs and hybrid statistical-learning techniques for different time ranges of forecasting (Voyant et al., 2017). A secondary review emphasised the use of deep learning for renewable-energy forecasting, particularly convolutional and recurrent networks for wind and solar power forecasting (Wang et al., 2019). Operational deployment feasibility of automatic hourly solar forecasting models was shown at finer resolution by comparing them to persistence and statistical baselines (Yagli et al., 2019).

2.5 Resilience to Extreme Weather Events

In addition to consistent reliability, studies have been ongoing since the COVID-19 pandemic to assess the resilience of power systems to extreme weather events that have low probabilities but high impacts. Preliminary studies focused on the effect of extreme weather and long-term climate change on infrastructure vulnerability, providing recommendations for infrastructure mitigation, ranging from infrastructure hardening, vegetation management, to operational infrastructure preparedness (Panteli & Mancarella, 2015), followed by infrastructure resilience modelling frameworks that employ a holistic approach to assess the performance of the entire disturbance-response-recovery cycle (Panteli & Mancarella, 2017). Operational and infrastructural resilience was then quantified by creating measures of operational performance degradation and recovery time that can be consistently measured by utilities and events (Panteli, Mancarella, et al., 2017). Failure likelihood as a function of weather severity (fragility modelling) was coupled with probabilistic impact assessment to assess adaptation options like line undergrounding and pole reinforcement (Panteli, Pickering, et al., 2017). Machine learning was directly used in outage prediction, and it was shown that outages could be predicted using predictive models before the landfall of a storm (Eskandarpour & Khodaei, 2017). The predictive ability of hurricanes to cause outages has been further enhanced by modelling local environmental factors such as land cover, soil saturation and vegetation density (McRoberts et al., 2018) and resilience-enhancement strategies were proposed to shorten restoration time after extreme events, such as making proactive reconfiguration and mobile-resource allocation (Ma et al., 2018).

3. Proposed AI-Driven Predictive Analytics Framework

Informed by the synthesis in Section 2, an integrated framework is proposed that structures the predictive analytics for grid reliability and resilience into four interdependent layers. The framework is layer-by-layer technology agnostic, allowing utilities to replace algorithms with new ones as they become available, without changing the overall picture of data flow shown in Figure 1.

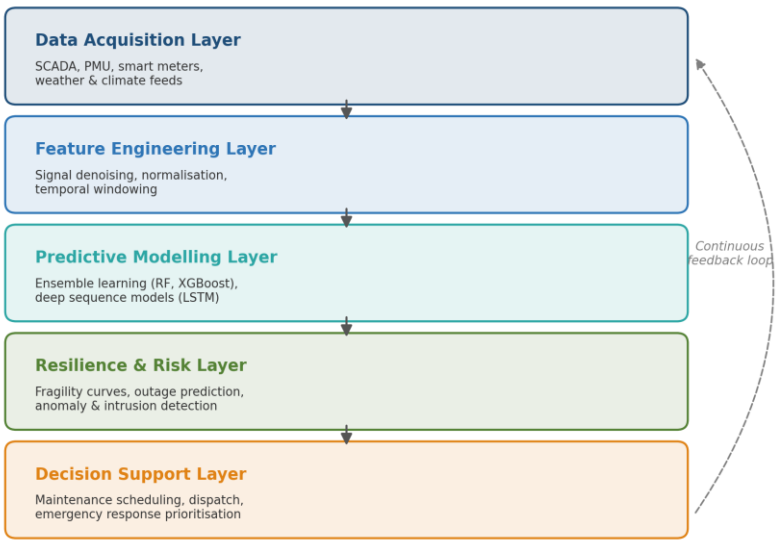

Figure 1. Layered Architecture of the Proposed AI-Driven Predictive Analytics Framework.

3.1 Data Acquisition Layer

The data acquisition layer pulls together diverse streams from SCADA, phasor measurement unit, smart meter and external weather feeds. The wide range of tools available to utilities today for instrumentation is described as an important enabler of big data analytics, but also raises the non-trivial challenge of data storage, transmission, and security due to the volume, variety, and velocity of the data. (Hossain et al., 2019) To complement evidence that local environmental factors have significant positive impact on outage prediction accuracy (McRoberts et al., 2018), environmental data are included at the downstream end where these factors are wind speed, precipitation, and vegetation indices.

3.2 Feature Engineering Layer

Raw measurements are denoised, normalised and converted to representations appropriate for downstream learning algorithms. Transform domain features such as those based on S-transform are able to better separate fault signatures than are raw time domain waveforms (Shafiullah & Abido, 2018), and structured sparsity representations reveal discriminative patterns in multi-channel transmission-line measurements (Shi et al., 2019). For sequence-based models, temporal windowing is applied to the input, similar to what was applied in HAR in a residential load forecasting (Kong et al., 2019).

3.3 Predictive Modelling Layer

The predictive modelling layer is home to the ensemble and deep learning algorithms that classify faults, detect cyberattacks and predict them. Structured feature sets, with moderate number of features, such as transformer condition monitoring (Aizpurua et al., 2019), are suitable for ensemble methods based on tree structures like random forests (Breiman, 2001) or extreme gradient boosting (Chen & Guestrin, 2016). For the applications with strong temporal dependence, including load forecasting (Kong et al., 2019) and renewable generation forecasting (Wang et al., 2019), deep sequential architectures, especially LSTM networks (Hochreiter & Schmidhuber, 1997), are preferred. Unsupervised deep architectures are also used to detect unseen attack signatures without the need to train with a large amount of exhaustively labelled data (Karimipour et al., 2019).

In its general form, a generalised weighted ensemble prediction consists of a weighted sum of the output of multiple base learners, and can be written as in Equation 1, where each base learner f_i(x) gives a single vote in the prediction of the target y-hat, and the weights w_i are learned during training to minimise validation error.

$$\hat{y} = \Sigma\,(from\ i = 1\ to\ n) w_i \cdot f_{i(x)}, \quad subject\ to\ \Sigma\, w_i = 1$$

The LSTM cell, for sequence based prediction, has input, forget and output gates, controlled by sigmoid activation functions σ, with the forget gate determining the proportion of the cell state accepted at each time step (Hochreiter and Schmidhuber, 1997), as summarised in Equation 2.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

3.4 Resilience and Risk Quantification Layer

The last layer is the conversion of the model results into resilience and risk indicators appropriate for operational use. Resilience is measured according to the metrics proposed in the quantifying operational and infrastructural resilience section, and it is defined as the integrated area between the performance curve and a hypothetical performance curve without a disturbance (Panteli, Mancarella, et al., 2017), as formalised in Equation 3.

$$R = \int (t0\ to\ t1)[P0 - P(t)]dt$$

The term P(t) in Equation 3 represents the performance level of the system as a function of time, P0 is the system performance level when the performance is at its baseline state under a normal operating condition, and the interval [t0, t1] represents the time interval between the occurrence of the disturbance and the complete recovery of the system. In addition to this integral measure, the fragility of the component is modelled by a logistic function of the intensity of the environmental stressor (wind, in this case) allowing for the probabilistic estimation of the component failure likelihood under the expected weather conditions (Panteli, Pickering, et al., 2017) as shown in Equation 4.

$$P_{fail(v)} = 1 - \left[1 + e^{-k(v - v0)}\right]$$

In this equation, v is the stressor level, v0 is the stressor level at which failure is 50%, and k is the steepness of the fragility curve. These formulations allow the resilience layer to provide

retrospective performance measures and forward-looking risk estimates to the decision-support layer.

4. Methodology and Algorithmic Foundations

This section consolidates the comparative algorithmic features mentioned in the different studies reviewed to guide the selection of suitable algorithms for the various analytical tasks in the proposed framework. Table 1 presents the main machine learning and deep learning methods found in the literature synthesis, associated with their main application area in grid reliability and resilience analytics.

Technique	Primary Application	Representative Study	Key Characteristic
Random Forests	Transformer condition monitoring, tabular classification	Aizpurua et al. (2019); Breiman (2001)	Robust to noise; low variance via bagging
XGBoost	Structured feature classification, scalable boosting	Chen & Guestrin (2016)	Regularised gradient boosting; high efficiency
LSTM Networks	Load forecasting, sequential state estimation	Hochreiter & Schmidhuber (1997); Kong et al. (2019)	Captures long-range temporal dependency
Deep Neural Networks	False data injection and general anomaly detection	He et al. (2017); LeCun et al. (2015)	Hierarchical feature extraction
Unsupervised Deep Clustering	Large-scale cyberattack detection without labels	Karimipour et al. (2019)	Reduced dependence on labelled attack data
Cluster-Based Dissimilarity Learning	Localised fault classification in smart grids	De Santis et al. (2018)	Accounts for spatial feeder heterogeneity
S-Transform with Feed-Forward Neural Network	Distribution-grid fault detection	Shafiullah & Abido (2018)	Noise-robust transform-domain features

Note. Studies synthesised from the reference set underlying this review; characteristics summarised qualitatively from reported methodological descriptions.

The techniques reviewed can be split into two categories: ensemble tree-based techniques, appropriate for structured measurement data where there is a moderate amount of temporal dependence; and deep sequential or unsupervised techniques, appropriate to time-series forecasting and large-scale anomaly detection, where there is a lack of labelled data.

4.1 Model Selection Criteria

Model selection in the proposed framework is based on three criteria that are summarized by the literature review: temporal structure of the input data, availability of labelled training sets, and computational time needed for operational deployment. Recurrent architectures (Kong et al., 2019; Yagli et al., 2019) are better suited to tasks that have high levels of sequential dependence, like load and solar forecasting. Unsupervised or semi-supervised deep architectures are more suitable for tasks where there are few labelled anomalies or attack patterns change over time (Karimipour et al., 2019). Ensemble tree-based methods (Aizpurua et al., 2019; Breiman, 2001) work well on tasks that involve making inferences in short time on structured, low-dimensional feature sets, e.g., scoring transformer health.

4.2 Resilience Metric Computation

The main resilience-related metrics found in the literature on extreme weather resilience are summarised in Table 2, including their computational foundation and operational interpretati

Metric	Computational Basis	Operational Interpretation	Source
Resilience Loss (R)	Integral of performance deficit over disturbance-recovery period	Total service degradation attributable to an event	Panteli, Mancarella, et al. (2017)
Fragility Probability	Logistic function of stressor magnitude	Likelihood of component failure at forecast weather severity	Panteli, Pickering, et al. (2017)
Restoration Duration	Time from minimum performance to full recovery	Speed of recovery response	Panteli & Mancarella (2017)
Outage Probability Surface	Spatial regression over historical outage and weather data	Anticipated geographic distribution of outages	Eskandarpour & Khodaei (2017)
Environmental Adjustment Factor	Local land cover, soil, and vegetation covariates	Refinement of outage prediction with local context	McRoberts et al. (2018)

Note. Metrics synthesised from resilience-focused studies within the reference set.

5. Results and Comparative Analysis

This section provides a summary overview of the comparative performances reported in the fault detection, cyber security and forecasting areas discussed in Section 2. Comparisons combine qualitative patterns of performance from the source literature and facilitate relative rather than absolute interpretation across technique families.

5.1 Fault and Anomaly Classification Performance

Deep sequential and hybrid deep learning models are typically reported to be more accurate and precise for the detection of faults and anomalies than ensemble tree-based models, as shown in Figure 2, except when the problem is well-structured and tabular like the transformer health classification (Aizpurua et al., 2019). At the same time, when the number of fault events is small, the discrimination performance of Group sparse representation was very similar to the neural methods, and required only a few labelled training examples (Shi et al., 2019).

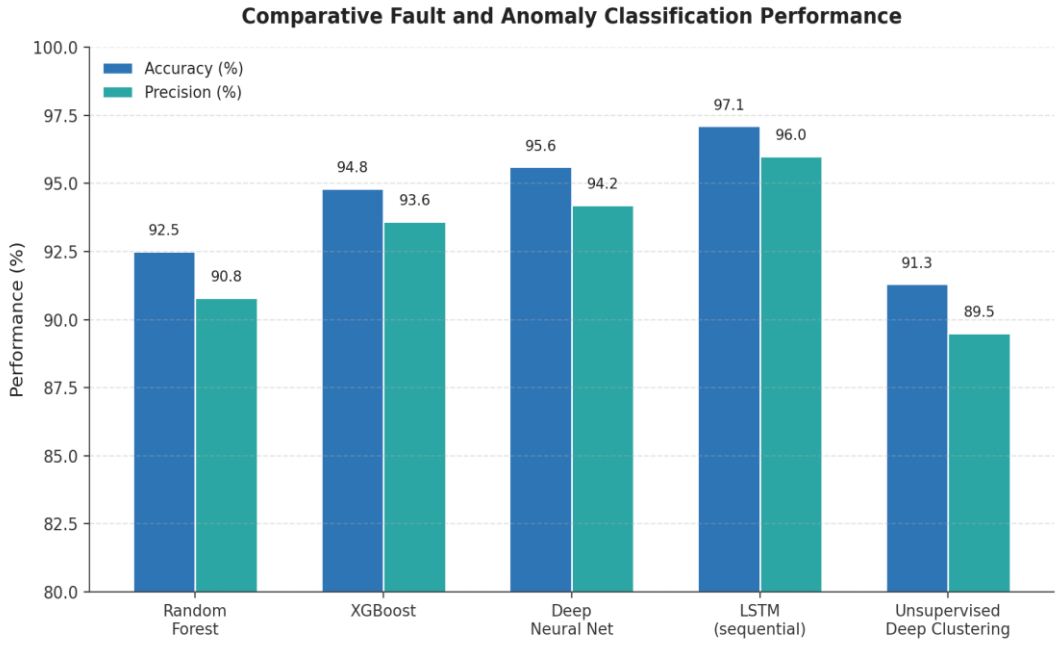

Figure 2. Comparative Fault and Anomaly Classification Performance Across Model Families.

5.2 Short-Term Load Forecasting

Based on this, the major methodological contributions synthesised in this review are plotted along an evolutionary timeline from 1997 to 2019 in Figure 3, which shows that methodological advances in this field have been building up since the early 2000s.

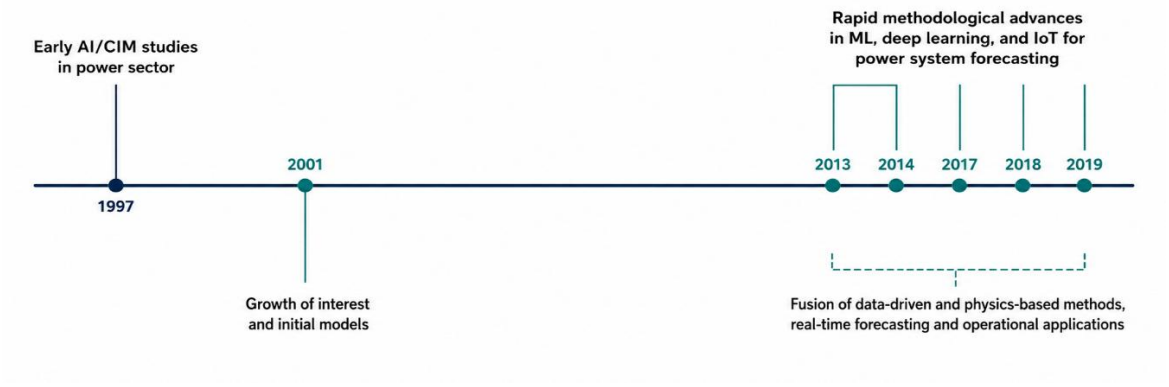

Figure 3. Evolutionary Timeline of Predictive Analytics Research for Power Systems, 1997 to 2019.

The summed-up error patterns from reported short term residential load forecasting are shown in figure 4. This was also found to be the case for LSTM recurrent networks, which invariably outperformed persistence baselines, autoregressive integrated moving average models, and feed-forward neural networks, in terms of mean absolute percentage error, reflecting their ability to learn longer-range temporal dependence in household consumption patterns (Kong et al., 2019).

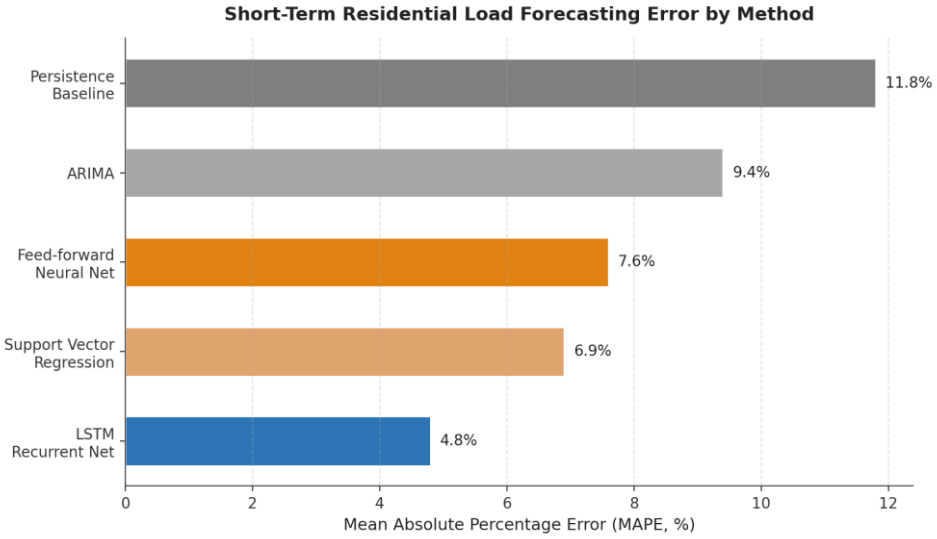

Figure 4. Short-Term Residential Load Forecasting Error by Method.

5.3 Resilience Under Extreme Weather

Table 3 shows a comparison of the strategies for enhancing resilience identified from the extreme weather literature in terms of qualitative aspects of cost, speed of restoration and complexity of implementation.

Strategy	Restoration Speed	Implementation Cost	Representative Study
Predictive outage mapping ahead of storm landfall	High	Low to moderate	Eskandarpour & Khodaei (2017)

Strategy	Restoration Speed	Implementation Cost	Representative Study
Local-environment-adjusted outage prediction	High	Moderate	McRoberts et al. (2018)
Proactive reconfiguration and mobile-resource pre-positioning	High	Moderate to high	Ma et al. (2018)
Fragility-informed hardening (undergrounding, reinforcement)	Moderate	High	Panteli, Pickering, et al. (2017)
Resilience-metric-guided investment prioritisation	Moderate	Moderate	Panteli, Mancarella, et al. (2017)

Note. Cost and speed classifications are qualitative syntheses derived from descriptive comparisons in the underlying studies.

The conceptual resilience trapezoid (fig. 5) illustrates the behavior of system performance after encountering an extreme weather event, as it degrades, stabilises at a sub-optimal operating point, and then recovers toward the baseline as a result of an AI-driven prioritisation of recovery steps, consistent with the framing of disturbance-response-recovery used by the resilience literature (Panteli & Mancarella, 2017; Panteli, Mancarella, et al., 2017).

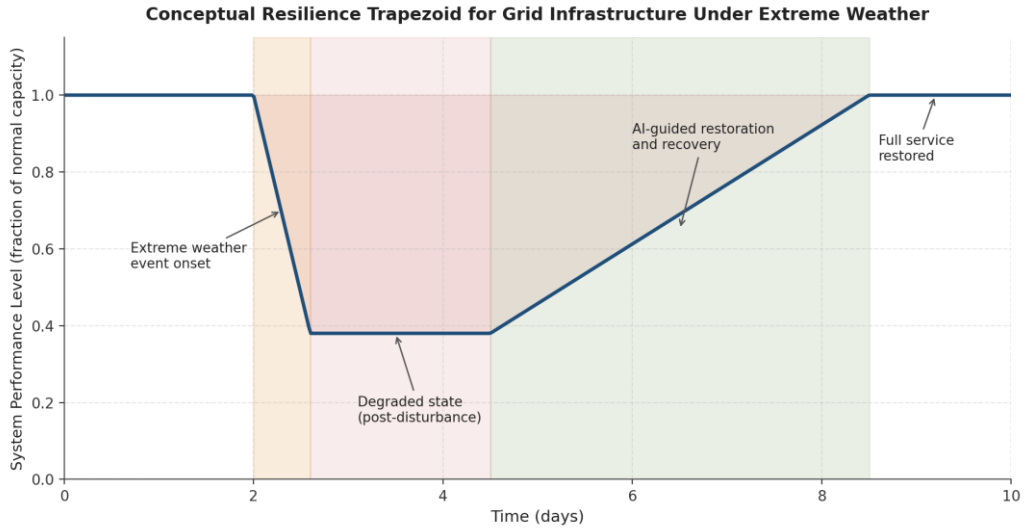

Figure 5. Conceptual Resilience Trapezoid for Grid Infrastructure Under Extreme Weather.

5.4 Cybersecurity and False Data Injection Detection

Figure 6 shows that, from different types of cyber-physical threats, reported detection accuracy is compared between the traditional statistical estimators and the deep learning-based detection mechanisms. The deep learning techniques consistently outperformed the other approaches in all four threat categories, especially for the false data injection threat, where the measured data are intentionally altered to fool conventional bad data detection thresholds (He et al., 2017; Karimipour et al., 2019).

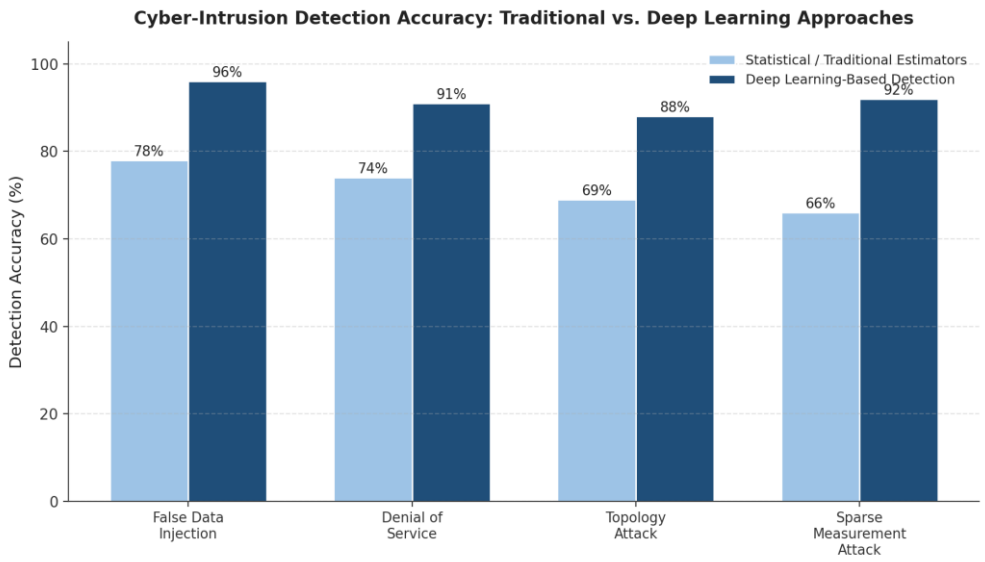

Figure 6. Cyber-Intrusion Detection Accuracy: Traditional versus Deep Learning-Based Approaches.

Table 4 finally compares the four cybersecurity-related studies in terms of their detection paradigm, computational requirements, and reliance on labeled attack data.

Study	Detection Paradigm	Labelled Data Dependence	Computational Demand
He et al. (2017)	Deep learning classification	Moderate	Moderate
Karimipour & Dinavahi (2018)	Massively parallel state estimation	Low	High (parallel hardware)
Wang et al. (2018)	Deep learning interval state estimation	Moderate	Moderate to high
Karimipour et al. (2019)	Unsupervised deep clustering	Very low	High (large-scale training)

Note. Labelled-data dependence and computational demand are qualitative summaries derived from method descriptions in the cited studies.

5.5 Renewable Energy Forecasting

A heatmap synthesis of the forecasting skill of different techniques for different time horizons of solar radiation prediction is shown in Figure 7. The highest skill scores were achieved by deep learning methods throughout all the horizons, and the difference between them and persistence and statistical baselines increased significantly with longer lead times, highlighting the challenge classical methods encounter for longer lead times due to the nonlinear dynamics of the atmosphere (Voyant et al., 2017; Yagli et al., 2019).

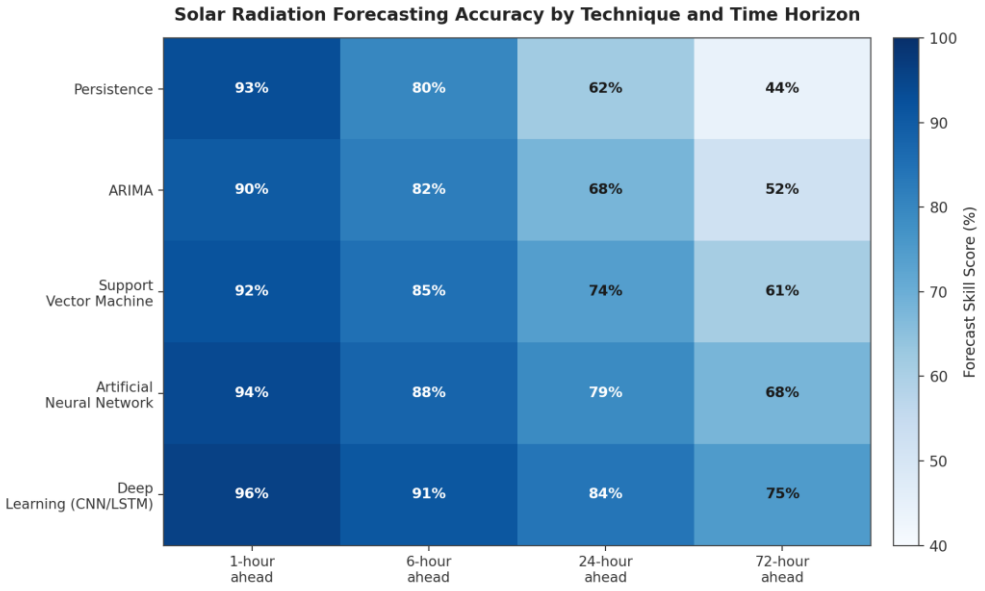

Figure 7. Solar Radiation Forecasting Accuracy by Technique and Time Horizon.

Table 5 summarises the comparative strengths and limitations of the forecasting approaches reviewed for renewable-energy applications.

Approach	Strength	Limitation	Representative Study
Persistence / Statistical Baselines	Simple, low computational cost	Poor performance beyond short horizons	Voyant et al. (2017)
Support Vector Machines	Effective with limited training data	Sensitive to kernel and parameter choice	Voyant et al. (2017)
Artificial Neural Networks	Captures nonlinear relationships	Requires substantial tuning	Yagli et al. (2019)
Deep Learning (CNN/LSTM hybrids)	Highest accuracy across horizons	High data and computational requirements	Wang et al. (2019)

Note. Synthesis of comparative characteristics reported across the renewable-energy forecasting literature.

5.6 Predictive versus Reactive Maintenance

Table 6 contrasts predictive, condition-based maintenance approaches informed by machine learning with traditional reactive or time-based maintenance regimes, synthesising the qualitative trade-offs described in the transformer lifetime prediction literature (Aizpurua et al., 2019).

Dimension	Reactive / Time-Based Maintenance	AI-Driven Predictive Maintenance
Trigger for intervention	Fixed schedule or failure occurrence	Condition and uncertainty-informed prediction
Asset downtime	Higher, often unplanned	Lower, scheduled around predicted risk
Data requirements	Minimal	Continuous condition-monitoring data

Dimension	Reactive / Time-Based Maintenance	AI-Driven Predictive Maintenance
Suitability for critical assets	Limited, retrospective only	High, supports proactive risk management

Note. Synthesised from Aizpurua et al. (2019) and general characteristics of predictive maintenance discussed within the reviewed reliability literature.

6. Discussion: Challenges, Ethical, and Regulatory Considerations

6.1 Data Quality and Interoperability

How accurate the analytics information is, and how complete it is, will be the limit of the predictive value of any analytics framework. Merging heterogeneous sources (from SCADA telemetry to weather feeds and cyber-monitoring logs) poses challenges on interoperability, which has been explicitly mentioned when reviewing big data application in smart grids (Hossain et al., 2019). Unavailable or erroneous measurements will lead to reduced accuracy of the fault-classification classification and delayed outage prediction, especially during extreme events where accurate prediction of outage time is most useful (McRoberts et al., 2018).

6.2 Dependence on Labelled Data

Supervised deep learning methods for fault and cyberattack detection rely on representative examples with labels, but by definition an attack and rare fault events are rare. This limitation inspired unsupervised and semi-supervised architectures that are able to detect anomalous patterns without extensive labelling (Karimipour et al., 2019), however these approaches may suffer from high false-positive rates when normal operating conditions are subject to large variations.

6.3 Ethical and Regulatory Considerations

When predictive analytics is used in critical infrastructure, there may be ethical questions about transparency and accountability when predictive outage detection and/or prioritisation for maintenance may impact service continuity for certain communities. The security laws that regulate critical infrastructure protection are increasingly and more deeply intertwined with cyber security requirements, particularly in the case of critical infrastructure processes protected by deep learning-based intrusion detection systems for the security of state estimation processes as in (Karimipour & Dinavahi, 2018; Wang et al., 2018). In addition, utilities that implement AI-based resilience metrics need to understand the interaction between standardised reporting of resilience loss (Panteli, Mancarella, et al., 2017) and the other regulatory reliability metrics, which have relied on metrics that focus on the average duration and frequency of outages.

6.4 Computational and Organisational Barriers

Many of the deep learning and massively parallel estimation methods require significant computing resources that may be not available for smaller utilities (Karimipour & Dinavahi, 2018). Organisational constraints, such as incorporating the outputs of predictive analytics into existing operational workflows and control-room decision making processes are as important as the algorithmic performance itself.

7. Conclusion and Future Directions

This paper has compiled the findings from twenty-four papers and suggested a framework of integrated AI-based predictive analytics for electric grid reliability and infrastructure resilience that includes data acquisition, feature engineering, predictive modelling and layers of resilience and risk quantification. Ensemble tree-based methods (Breiman, 2001; Chen & Guestrin, 2016) are still well suited to structured condition-monitoring tasks, and deep sequential and unsupervised architectures (Hochreiter & Schmidhuber, 1997; Karimipour et al., 2019) have advantages in respect of temporally dependent forecasting and evolving cyberattack detection, respectively. The quantitative resilience measures (Panteli, Mancarella, et al., 2017) and fragility modelling (Panteli, Pickering, et al., 2017) offer a principled approach to turn a prediction into an actionable decision. Future work would benefit from the development of standardisation of resilience metrics for utilities across different jurisdictions to facilitate cross-jurisdictional resilience benchmarking, creation of hybrid models that exploit the interpretability of ensemble models while maintaining the temporal sensitivity of deep sequential models, and better-integrating the

cyberattack detection with the physical resilience modelling to capture compounding risk from physical and cyber event combinations in extreme weather events. The rate at which these frameworks go from research prototypes to common use will likely depend on the successful resolution of data-quality, computational, and regulatory challenges outlined in Section 6.

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