



Predictive Maintenance and Power Continuity

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Abstract— Climate change is driving the need for investment in resilient power infrastructure. Digital twins offer a promising way to assess the power grid's ability to withstand and rapidly recover from disruptive events. Building such a digital twin requires combining an asset-prognostics framework—which uses prognostics to detect and predict asset condition—with edge computing to ensure low-latency, high-reliability responses. Automating the development and deployment of such an edge-driven asset-prognostics framework, however, remains an open challenge.

This work presents an industrial digital twin system that meets the requirements of low latency, high reliability, security, and scalability through an edge-driven asset-prognostics framework. These properties enable prediction of asset-indicator time series and of failures that could compromise power infrastructure. The main contribution is the design of the framework itself, encompassing the end-to-end pipeline of data ingestion, pre-processing, feature generation, sensor fusion, and supervised-model training and deployment. The framework supports statistical, machine-learning, deep-learning, and physics-informed methods. Following an applied-science approach, we define suitable metrics to evaluate the performance of each component.

Keywords—Resilience, Digital Twin, Edge Computing, Asset Prognostics, Wide Area Monitoring System, Power

Infrastructure, Digital Twins, Edge Computing, Industrial Internet of Things, Asset Prognostics, Predictive Maintenance, Remaining Useful Life, Condition Monitoring, Power Infrastructure Resilience, Edge Intelligence, Fault Diagnosis.

1. INTRODUCTION

Prognostics are essential for the resilience of power systems, where Digital Twins (DTs) are not only gaining popularity for asset management but also producing robust prediction models. Such models are typically huge and need to be located as close as possible to frequency and severity changes to ensure a timely response and to be easily and quickly integrated into the DTs. Furthermore, as with the DTs, it is important to ensure that the quality of the predictions is aligned with the provided resources for data pre-processing, sensor information fusion, decision feature generation, algorithm training and maintenance. A proposal for a distributed edge-assisted Industrial Twin system is presented to focus on those aspects. The underlying technology supporting the ability for timely responses is examined, with attention on the edge-driven data ingestion and pre-processing, feature generation, and prediction capability.

Timely power supply is increasingly questioned by new local loads that are sensitive to long interruptions, such as data centers and hydrogen production. In addition, the occurrence of major events, like the COVID-19 pandemic, is changing typical reliability and availability statistics. Such aspects demand growing attention, aiming for power supply tolerance to severe local demand and/or supply issues. To enhance resilience, the recently proposed concept of power web goes one step beyond active management and provides redundancy by supporting the usual service in abnormal conditions. This concept is also being used in industry, where local unexpected demands are mirrored in local supply capability by battery storage and/or local generation. As with power systems, these web-like structures need a proper set of



redundant and adequate-quality capabilities to guarantee service in adverse conditions.

A. Resilience in Power Infrastructure

Resilience to extreme weather events and environmental threats is critical for a sustainable future. Resilience is defined as the ability to anticipate hazards, adapt and prepare for extreme conditions, prevent and withstand disruption,

recover quickly from shocks, ensure acceptable levels of service and protect vulnerable clients and communities. Scientific investigations and industry focus on resilient Power Delivery Systems (PDS), and Resilient Smart Grid (RSG) concepts aim to understand and provide actionable solutions for improving PDS resilience within cyber-physical corridors.

The solutions include the development of Digital Twin (DT) systems for asset management, enabling real-time Infrastructure-as-a-Service (IaaS), and innovative Edge Computing-driven methodologies for real-time hazard monitoring, risk prediction, system integrity assessment and resilience-enhancing asset repair/replacement decision support systems. DT systems enable efficient management of physical assets by processing their condition and risk assessment in real time.

Resilience-increasing real-time prognostics remain open challenges, especially for Highly Hazard Purposed (HHP) assets such as transformers and substations at risk due to extreme weather events, environmental threats and major terrorism attempts. These assets experience high hazard exposure and the resulting risk prediction and system integrity assessment are essential to evidence-based resilience-enhancing decision support solutions; however, support for evidence-based decision making is still nascent. Hence, edge-driven signal processing and data fusion of continuous information from environmental sensors, risk control and external open-source risk/prediction models provide real-time predictions for these high hazard purposed (HHP) assets.

Mathematical Formulas:

A. End-to-End Latency Budget

Total round-trip latency at an edge-hosted prognostic node is the sum of sensing, transmission, preprocessing, feature-generation, and inference delays:

$$T_{total} = T_{sens} + T_{tx} + T_{pre} + T_{feat} + T_{inf}$$

(1) Total edge-to-decision latency.

Transmission latency itself depends on propagation distance d , link bandwidth B , payload length L , and any queuing delay, consistent with the paper's claim that distance and channel conditions jointly determine end-to-end delay:

$$T_{tx} = \frac{d}{v_{prop}} + \frac{L}{B} + T_{queue}$$

(2) Transmission-latency component.

B. Health Index and Remaining Useful Life

Sensor-fusion output is expressed as a weighted combination of normalized asset-indicator time series, matching the manuscript's description of combining condition indicators into a longer health-state vector:

$$HI(t) = \sum_{i=1}^n w_i \hat{x}_i(t), \quad \sum_{i=1}^n w_i = 1$$

(3) Weighted sensor-fusion health index.

Remaining useful life follows from the first future time at which the health index is predicted to cross a calibrated failure threshold:

$$\widehat{RUL}(t) = t_f - t, \quad t_f = \min\{\tau : HI(\tau) \leq HI_{thr}\}$$

(4) Threshold-crossing RUL estimator.



C. Statistical and Frequency-Domain Feature Extraction

Time-domain statistical features (e.g., for vibration or current signals) are computed as the root-mean-square amplitude over a sliding window of N samples:

$$x_{rms} = \sqrt{\frac{1}{N} \sum_{k=1}^N x_k^2}$$

(5) Root-mean-square time-domain feature.

Frequency-domain features are obtained from the discrete Fourier transform of the windowed signal, supporting the manuscript's frequency- and time-frequency-domain feature classes:

$$X(f) = \sum_{k=0}^{N-1} x_k e^{-j2\pi f k/N}$$

(6) Discrete Fourier transform.

D. Anomaly / Early-Warning Scoring

A simple standardized-residual score supports the anomaly-detection and early-warning task described for the fused feature set:

$$z_k = \frac{x_k - \mu_{ref}}{\sigma_{ref}}, \text{ anomaly if } |z_k| > z_{thr}$$

(7) Standardized anomaly score with detection threshold.

2. Background and Related Work

Significance of resilience in power infrastructure is discussed, followed by a concise overview of related work on digital twins, probabilistic prognostics, edge computing, and twin-centric analytics. The analysis reveals a lack of industrial digital twins designed for resilience-oriented asset prognostics, and consequently an absence of latency-sensitive edge-based data analytics enabling twin functionality to be offloaded deep within the grid.

Power system resilience encompasses the ability to withstand, adapt to, and rapidly recover from extreme conditions, and is driven by the probabilistic health status of the system's assets. A digital twin is a virtual representation of a physical asset that is synchronized with its physical counterpart through the continuum of data and information flows. Digital twins create a platform for asset prognostics by allowing an estimate of the current health status, predicting the dynamics of future degradation or failure, and providing guidance on suitable maintenance strategies. Such twin-centric predictive analytics are often resource-intensive and consequently unsuitable for deployment close to the grid assets. To address this, a terminal-probabilistic power grid twin is examined, whereby a limited number of resilience-critical parameters are continuously estimated and used to inform maintenance scheduling.

Condition indicators crucial to asset health prognostics are ingested at edge nodes, preprocessed to remove noise and outliers and combined into a longer vector of health states through a sensor fusion algorithm. A comprehensive family of data-driven models is deployed on servers at the edge of the grid. The models are context-aware, trained continuously, and offer a flexible vertical pipeline that can support statistics, machine learning, deep learning, and even physics-informed approaches. Model performance is evaluated with respect to established quality indicators via leave-one-out cross-validation.

Table I. Comparison of Prognostic Modeling Approaches

Approach	Representative Techniques	Edge Suitability
Statistical	Control charts, ARIMA, regression baselines	High (lightweight)
Machine Learning	KNN, random forest, SVM	Moderate-high
Deep Learning	CNN/RNN on 2-D/3-D transformed time series	Moderate (needs accelerators)
Physics-informed	Knowledge-based / simulation-constrained models	Moderate



Table II. Two-Layer Architecture Responsibilities

Layer	Twin Role	Key Functions	Placement Driver
Cloud ("over-simulation")	System-wide digital twin	Model governance, cross-asset analytics, Pub/Sub fusion	Compute intensity, non-latency-critical
Edge ("under-simulation")	Asset-local digital twin	Ingestion, preprocessing, sensor fusion, inference	Low latency, high reliability, security
Physical layer	Physical twin / assets	Sensing, actuation, data acquisition	Source of ground-truth signals

A. Digital Twins in Asset Prognostics

Security, technological maturity, and cyber-physical coupling motivate the adoption of digital twins in various verticals. As an interactive virtual model, the digital twin is sourced with data from a related physical twin in close proximity. Within a power system context, the digital twin is defined as an interactive virtual replica of an asset that incorporates real-time data from its physical counterpart in the Smart Grid network that allows it to mirror the behavior and condition of the physical asset (or a group of assets) over time. Through the continuous exchange of information between the Physical Twin and the digital twin, the Digital Twin is capable of providing many services, including Asset Condition Monitoring, Asset Prognostics, Asset Performance Optimization, Failure Prediction and Decision Support. Asset conditions can be monitored by comparing data between the digital twin and the physical twin. Specific algorithms can also be created to decide when maintenance should occur for the Physical Twin in order to prevent major faults. These services enable asset digital twins to produce substantial cost reductions through risk mitigation, maintenance optimization, and performance enhancement.

Edge devices located near the Physical Twin are capable of performing the data-driven analysis supported by the Digital Twin and its Data Lakes. Moving the computations

closer to the signal source reduces data transmission latency, avoids bandwidth footprint conflict amid thousands of devices connected to the Smart Grid, and diminishes the risk of data interception and cyber-attacks. Data contamination can also be developed on edge computing devices where data-driven attacks are evitable; Artificial Neural Networks (ANN) generating random switches on various sensors might be identified on edge devices and therefore avoided.

3. System Architecture and Design Principles

The system architecture relies on a two-layered diagram, illustrated in Fig. 1, where an "over-simulation" digital twin runs on an IT cloud platform while the "under-simulation" twin is composed of prognostic models distributed close or at the edge of grid asset devices. The latter interacts with the physical layer for data acquisition and other operational purposes. The two layers dialog via common messages. They accomplish formalized definitions, closures, and validation rules necessary to meet the overall proposed objective: an integrated system to support resilience in the power system grid, in particular for power transmission and distribution. The architecture should guarantee low-latency information delivery, reliability during delivery, and reliability at the devices along with suitable mechanisms for security and scalability. Distribution of an "over-simulation" twin mainly on a cloud infrastructure, while the "under-simulation" action is placed as close to the field as possible leads to the overall performance optimization.

Latencies and reliability drive such placement. Naturally, a longer distance in message travel means a larger latency, and both the distance and the condition of the communication channel should guarantee a low probability of transient errors. In edge computers or at devices, besides being ready to fulfil the mission of digital twins, the computing power should not be insufficient to avoid bottlenecks and should be reliable; in particular, the pre-processing, feature extraction modules, and model execution modules should represent the most critical points. Assigning part of the communication inside the edge or at the devices creates paths where messages are not stretched through a complete path but through a partial one, a direct-to-device one. Security and scalability have to be managed by the overall set of elements, while the other three characteristics respond locally, at the level of the edge and devices.



Table III. Candidate Evaluation Metrics

Metric	Formula / Definition	Applies To
Precision / Recall	$TP/(TP+FP)$; $TP/(TP+FN)$	Fault / anomaly classification
RMSE	$\sqrt{\text{mean squared error}}$	Health-index / RUL regression
MAPE	$\text{mean}(\text{actual} - \text{predicted} / \text{actual})$	RUL / time-series forecasting
Leave-one-out CV score	Held-out asset validation accuracy	Cross-asset generalization
Inference latency (ms)	Time from data arrival to model output	Edge deployment feasibility

Table IV. Statistical Feature Domains Used in Sensor Fusion

Domain	Example Features	Typical Source Signals
Time-domain	RMS, mean, kurtosis, crest factor	Vibration, current, voltage
Frequency-domain	Dominant frequency, spectral energy	Vibration, acoustic
Time-frequency	Wavelet coefficients, STFT bands	Vibration, transient events
Chaos features	Lyapunov exponent, entropy measures	Nonlinear degradation signals

A. Data Ingestion and Preprocessing

The data-driven approach requires tailored data sources, types, and targets. The method relies on three common phases: data ingestion and preprocessing, data-driven model development and validation, and model deployment on the edge. Data can come from dedicated sensors or existing supervisory systems, with increasing focus on physics-informed designs relying on simulation data or knowledge-based feature engineering.

Data ingestion should include everything needed to develop or validate a relevant model for the target prognostic capability. The system automatically collects data according to these requirements, performs preprocessing and sensor fusion at the edge, extracts relevant features, and notably offers timeline-aligned multi-table datasets ready for statistical analysis or modelling. Preprocessing relies on common best practices and includes data cleansing, transformation, and oversampling for class-imbalanced classification tasks.

General-purpose functionalities handle the main operations on tabular data, with the goal of supporting all required tasks and avoiding repetition when preparing datasets for model training. Timeline-based analysis leverages the temporal nature of most signals and is particularly useful for building datasets for time-series and temporal deep-learning algorithms.

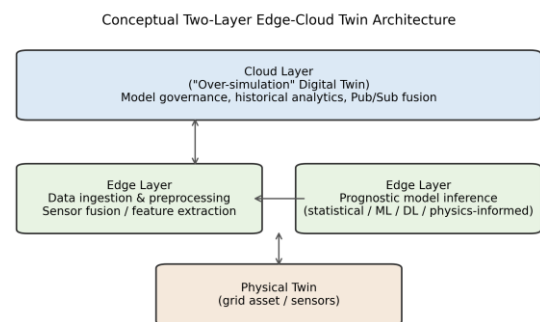


Fig. 1. Conceptual two-layer edge-cloud twin architecture, showing the over-simulation / under-simulation split described in Section III.

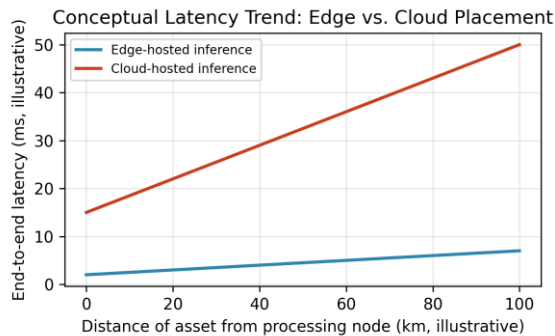


Fig. 2. Illustrative latency trend contrasting edge-hosted and cloud-hosted inference as a function of distance from the asset (schematic, not measured data).

4. Edge-Driven Prognostics Algorithms

Data processing and prognostics algorithms run at the edge, developed through a hybrid implementation approach. First, the microservices orchestrate data delivery to modules performing preprocessing and initial prognostics next to source devices. Subsequent modules—air quality, energy meter, and weather-data services—are hosted on general-purpose cloud resources. Finally, module outputs are sent through Pub/Sub networks and fused into an advanced prognostics model deployed on private cloud resources.

Reception of data streams on the edge microservices is managed by a combination of Python Flask APIs and application-agnostic sensor-cloud connections provided by Cumulocity, the device management platform used in the system. The first layer of the data ingestion pipeline is bespoke, processing sensor types unsupported by Cumulocity (e.g., external weather station). The supervision of the data streams is implemented using a combination of Google Cloud Functions and Pub/Sub elements that trigger data actions in a user- and management-defined way.

Main data-conditioning tasks include outlier identification and segmentation to trim unused period and high-outlier levels of the measured variables. The air-quality module checks the correlation between pollution levels and proximity to traffic infrastructure; if significant, pollution levels are scaled down according to the ratio of distance curvilinear of the grid segment and linear distance from the pollution source. Sensor data are proxied either on a full-scale or on a reduced-range basis for aggregation procedures

integrating grid-level energy, pollution, and weather-data information. Their fusion constitutes a training dataset for single-asset analysis using statistical-model approaches, machine-learning proxies, or deep-learning neural networks, with model appraisal focusing on prediction precision and the identification of possible causality links.

A. Sensor Fusion and Feature Extraction

To make full use of the accumulated data within the system, sensor data of different characteristics are fused to obtain multiple physical status features of the equipment. The mixed digit structure data are further fused with non-structured data such as images and sound waves. Data-driven features like vibration and heat sources can be extracted directly using data-driven models, while the remaining data based on physical statistics can be obtained based on the physical features observed in time sequences. At present, statistical features in time series are mainly taken as perspectives considered for detection. Statistical features such as time-domain features, frequency-domain features, time-frequency domain features, and chaos features are extracted from temperature, humidity, voltage current, sound and vibration data. Traditional statistical machine-learning models can be built based on these features, while deep learning models with the ability of automatic feature extraction can also be transformed by circularly overlapping the time series into image forms, such as 2D-plane images and 3D-volume images.

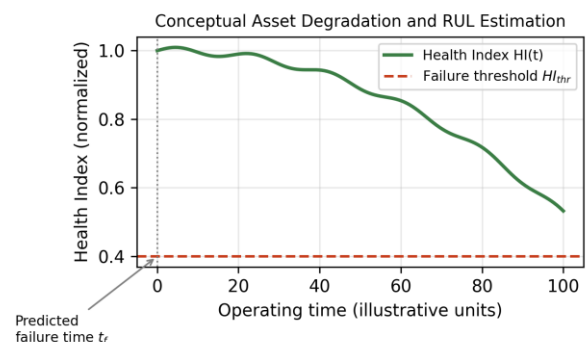


Fig. 3. Illustrative health-index degradation curve with threshold-crossing used for remaining-useful-life estimation (schematic, not measured data).

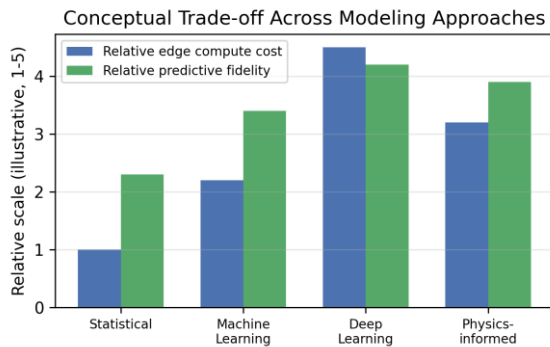


Fig. 4. Conceptual trade-off between relative edge compute cost and predictive fidelity across the four modeling families (schematic, not measured data).

5. Conclusion

The proposed edge-assisted industrial twin system enables the secure deployment of asset-relevant prognostics and augments the resilience assessment of the power infrastructure. Digital replicas of critical grid assets serve as the basis for the prognostics of their health and remaining useful life. The algorithms can run on the edge and leverage all data generated during their operational life. They combine fault- and non-fault-related Health and Usage Monitoring Systems data in a unified data structure, and extensive preprocessing and fusion phases shrink the data set size while covering a broader range of operational conditions. The computation of different classes of health indicators significantly reduces the operational burden and improves the training-fault coverage of final models. Various statistical, machine learning, and deep learning models, as well as engineering and physics-informed models and expert knowledge, can be implemented.

A set of evaluation metrics, both quantitative and qualitative, are defined according to the model's final purpose and the relevant application context. All procedures aimed at reducing overfitting and evaluating models for unseen operational conditions, such as cross-validation and k-fold validation, are followed. Despite the current implementation focus on the asset prognostics system, the overall architecture, with its champion-challenger approach, can be leveraged to facilitate and support the design and deployment of the resilience assessment module for the industrial twin system in the future.

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