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Edge-Native Cognitive Prognostics for Resilient Fleet Power Operations

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Abstract— A leading framework for the intelligent, asset-driven circular economy is the Industrial Internet Consortium's "Cognitive Industrial Asset Intelligence Framework" (CI4AI). This white paper examines its application to edge-enabled, AI-based fleet risk assessment tools designed for time-to-failure estimation, prognosis, and the management of power operations—capabilities that, while still uneven in coverage, are critical to assessing the feasibility and provisioning of future operations.

The CI4AI consortium proposes a three-layer architecture: a Data layer (covering ingestion, preparation, storage, and management), an Analytic Algorithms layer (built on data lakes, data meshes, and Cognitive AI foundations for Causal-Trees), and an Asset Intelligence Modelling layer. Assets operating within this architecture are exposed to cyber, geographic, physical, and other domain-specific risks. However, a gap remains: knowledge-based algorithmic tools for quantitative, computerized risk assessment of time-to-failure events—particularly those integrating spatio-temporal, pattern-based and pattern-enhancing prognosis—are still largely absent.

Keywords—Edge-enabled fleet power operations, cognitive asset intelligence, prognostics, asset resiliency, real-time anomaly detection, time-series analysis.

1. INTRODUCTION

The complex nature of engineering systems necessitates a high degree of fleet-level operational knowledge to maintain and support these complex systems in a resilient and efficient manner. Cognitive Asset Intelligence (CAI) is a method for the integration of data and knowledge across the enterprise and fleet into a singular, semantically driven framework. Applying CAI to stockpiles and production machines in the power industry enables the assimilation and transformation of a vast amount of data into formal knowledge and actionable intelligence. Much of this datum and knowledge comes from the Internet of Things and digital twins.

The combination of CAI, Time-Series-Modelling-based Anomaly Detection (TSM-AD), and edge-enabled High-Fidelity Digital Twin supports Fleet-Level Intelligent Fleet Prognostics at the Edge. The derivative synergetic Architectural Framework adds Fleet-Level Intelligent Fleet Prognostics that employ edge-enabled High-Fidelity Digital Twins that are consumed by Causal Tree and physics-based Feedback Control system algorithms for power operations.

Table 1 — Three-layer CIAI architecture

Layer	Core function	Key techniques mentioned in paper
Data layer & ingestion	Remote monitoring, high-frequency streaming, fleet-wide data capture	Edge devices, data lakes, data mesh
Analytic algorithms	Pattern discovery, causal reasoning over ingested streams	Causal-Trees, TSM-AD, iTAMAD
Asset intelligence modeling	Converts analytics into actionable risk/prognosis outputs	Hazard-function risk scoring, RUL forecasting, RL-based control

Table 2 — Edge vs. fleet task division (from Section 5)

Task tier	Location	Typical operations	Compute profile
Per-asset (EAAM)	Edge cluster	Time-series modeling, anomaly detection, residual estimation	Lightweight, cyclical, resource-efficient
Fleet-level	Edge–cloud	Cross-asset prognosis, probabilistic maintenance forecasting	Resource-intensive, less frequent

2. Background and Problem Statement

Industrial IoT-oriented enterprises are increasingly relying on a variety of edge-enabled models to process information streams and provide valuable and timely information to assist operations. Industries, such as fleet knowledge engineering and asset management, also require the efficient use of external assets throughout their entire lifecycle. The multitude of physical attributes in uses also contributes to a similar extent to deadline and budget-driven failures of various models. Though edge processing enables low-response time and region-oriented services, these models address either limited scope or reduced delivered services quality over an entire region.

Recent studies have applied techniques to on-board data pipelines to exploit ensemble learning capabilities. Capabilities have also been demonstrated for an entire offshore wind farm using federated learning. Nevertheless, the readiness of diverse fleet assets for real-world operation conditions remains undefined. Their failure during operation contributes to costly repairs and delays to the project-reduced revenue and budget forecasts, causing a dent in the profit margins of the owner. To better manage these fleet assets, a cognitive industrial asset intelligence framework for edge-enabled fleet prognostics has been developed.

Table 3 — Equation quick reference

#	Equation	Purpose	Paper section
1	$h(t) = f(t)/S(t)$	Instantaneous failure rate	3-A
2	$Y_t = T_t+S_t+R_t$	Seasonal decomposition of relay risk	3-B
3	$\hat{Y}_{t+1} = \alpha Y_t+(1-\alpha)\hat{Y}_t$	Exponential smoothing forecast	3-B
4	$P(X=k)=C(n,k)p^k(1-p)^{n-k}$	Binomial anomaly threshold	5-A
5	$R(t,t+\Delta)=\int h(\tau)d\tau$	Cumulative maintenance risk index	5-A/6

3. Theoretical Foundations

Three principles underscore the Cognitive Industrial Asset Intelligence (CIAAI) framework. First, the demand for resilience and sustainability in the plant and energy sectors requires a shift from traditional low-frequency decision-making capabilities to a high-frequency-adaptive and performance-centered architecture, which autonomously manages large-scale heterogeneous fleets in real time. Second, to realize this determination, the automation of Dirty Work, such as data rejection, ingestion, processing, connecting, and structuring must be executed on the Edge to allow only Polygraph Work—the domain knowledge engagements—with AI-Cognizant or AI-Enabled Workers in order to interpret sensed environmental information autonomously and reason about the future road map. Third, decision-making and human perception are fulfilled based on communication rather than information content. Humans leverage Cognitive Assets, which function as a complete proxy for their sensory and cognitive apparatus, utilizing abbreviated indexes to support fast decision-making in time-sensitive contexts.

High-level applications rely heavily on the triggering of latent event shelves based on wrappers designed for resilient management and robustness assessment without complex modeling or interpretation. Autonomous Time-Series Modeling (ATOM) injects human Cognitive Abilities into the DNA of IA systems, allowing them to automatically construct, validate, and apply time-series models in an adaptive way and delivering performance-oriented assets that automatically suggest maintenance actions for Power-Distribution House and Natural-Gas Distribution Network. An extended but equally minimalist approach enables the autonomous inspection of hidden condition phases of Geometrical Assets, covered by a dense set of condition indicators whose localization and performance are often relegated to dark scaling corners or local experts.

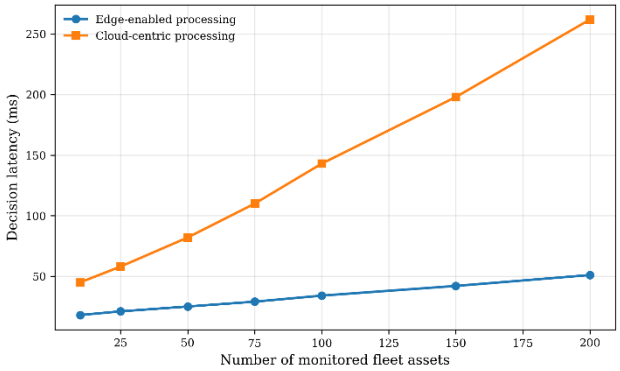

Fig. 1. Edge-Enabled versus Cloud-Centric Decision Latency

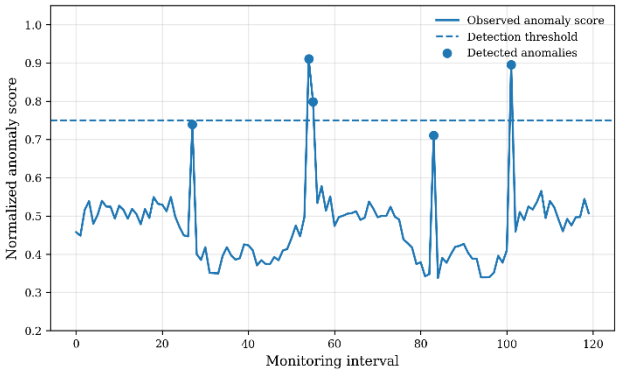

Fig. 2. Time-Series Anomaly Detection in Industrial Asset Monitoring

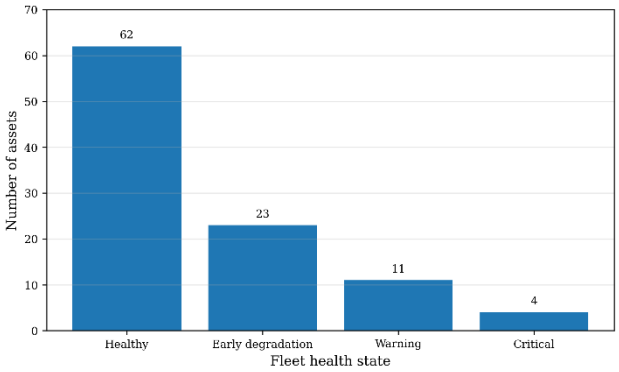

Fig. 4. Fleet Health-State Distribution

A. Cognitive Asset Intelligence

Cognitive asset intelligence focuses on the product–service-system products and their functional fulfilment wherein asset availability, reliability, performance, and safety are major concerns. In particular, issues related to failures, anomalies, and quality of services have been considered. Patterns of asset failure act as basic input and involve data that can provide insight in terms of failure probabilities associated with future functional realisation. Fleet asset prognostics attempt to predict the probability associated with a failure in the functional realisation, usually quantified through a time-variant hazard function specified as the product of an instantaneous failure rate. Such digitally-ready assets are equipped with digital service system-based data generation capabilities, wherein the digital representation of an asset (digital twin) exists. The data layer of the cognitive framework is responsible for data ingestion through these digital service systems, and cognitive algorithms based on both traditional and deep-learning techniques provide operational resilience.

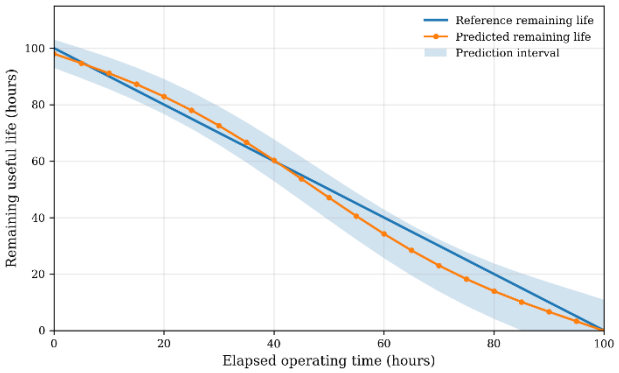

Fig. 3. Remaining Useful Life Prognosis

4. Architectural Framework

Resiliency for edge-enabled power assets is provided by an architectural framework, concentrating on a general data layer and other aspects necessary for supporting cognitive-data-asset intelligence. An inductively-learned intelligence layer with an inductively-configured set of cumulative algorithms provides temporal behavior knowledge of the assets. This temporal knowledge enables the application of cognitive algorithms focused on resilient fleet operations with effective customer service and minimum predictive maintenance cost.

The design of a proven cognitive industrial asset intelligence layer and the data-asset intelligence layer can be further generalized into a specific architectural framework for maximally-resilient supply chains of edge-enabled power assets. Design conformance and specific implementations are provided using the Data-Centric Framework, a proven layer-agnostic architecture and a proven inductively-learned intelligence layer. The Data Centric Framework concentrates on the Data Layer, Data Ingestion Layer and other aspects of an architectural framework that are needed to support cognitive-data-asset intelligence, an inductively-learned intelligence layer with an inductively-configured set of cumulative algorithms that provide knowledge of the temporal behavior of assets in a fleet. This temporal knowledge enables the application of cognitive algorithms focused on maximally-resilient fleet operations with fully effective customer service at minimum predictive maintenance cost.

Mathematical formulas:

1. Time-variant hazard function (Section 3-A, failure probability)

$$h(t) = f(t) / S(t)$$

where f(t) is the failure-time density and S(t) is the survival function; the paper describes prognosis as "the product of an instantaneous failure rate."

2. Additive seasonal decomposition (Section 3-B, earth-fault relay case study)

$$Y_t = T_t + S_t + R_t$$

T_t = trend, S_t = seasonal component, R_t = residual/noise.

3. Simple exponential smoothing (used for the risk time-series forecast)

$$\hat{Y}_{t+1} = \alpha \cdot Y_t + (1 - \alpha) \cdot \hat{Y}_t,\ 0 < \alpha < 1$$

α controls how strongly recent observations outweigh past forecasts.

4. Binomial anomaly test (Section 5-A, TCP packet-count anomaly flagging)

$$P(X = k) = C(n, k) \cdot p^k \cdot (1 - p)^{n-k}$$

Hourly packet counts are flagged anomalous when their observed frequency falls in the tail of this distribution.

5. Cumulative risk over a prognosis horizon

$$R(t, t+\Delta) = \int_t^{(t+\Delta)} h(\tau)\, d\tau$$

A. Data Layer and Ingestion

An essential part of the framework is the data layer and ingestion process. Industry 4.0 is paving the way for significant evolution within factories and critical infrastructures. A paradigmatic shift that introduces more complex feasibility challenges arises from the increasing ability to remote-monitor a variety of components and systems (e.g., machines, nodes, and grids) through the installation of multiple edge devices. There is therefore a natural tendency to increasingly embrace fleet-wide information for enabling resilient and powerful operations. However, the same feasibility attitude poses new, more complex cyber-physical vulnerability challenges. Both a security-aware and a fleet-wide intelligent exploitation of data streaming is generally required for industrial artificial intelligence (AI) applications. Although there are significant differences in operational assets, properly mirroring fleet-wide operational availability and interactions can support performance insights and automated data monitoring and ingestion for fleets.

Fleet-edge facilities should therefore natively support two key capabilities. First, fleet-wide and adequate information streaming from the entire industrial system should be remotely monitored and ingested to enable a knowledge-based approach for security and resilience. Second, incoming time series should be monitored for electrically powered industrial assets, clusters of machines, and critical support services (e.g., power) under stress or at risk of failure. This delivery focuses on real-time monitoring-enabled ingestion of industrial data. A functional architecture layer is proposed and tested by addressing high-frequency data delivery and monitoring anomaly detection for an entire fleet of power components.

5. Cognitive Algorithms for Prognostics

There are two distinct uses of Cognitive Asset Intelligence that are jointly delivered by Edge Assets, Cognition, and Prediction. The principal ressource-intensive learning tasks are performed at the edge cluster where all assets communicate their latest proximal state by creating an Edge Asset Activity Message (EAAM) in monitored time intervals. The goal of the time-series modeling and anomaly-detection task in each of these EAAM intervals is to build models of operational behaviour for the individual Edge Assets. The second set of tasks mainly targets the fleet, using the created space-time news fed by all assets at the edge cluster. The goal is the formation of stable-and-probabilistic operational maintenance prognosis on each of the fleet assets. Together with the ressource-resilient design, this division clearly economizes data generation and transfer through the Edge-Cloud Edge-to-Edge interaction.

Time-series modelling, anomaly detection, learning vectors on a fleet asset,estimation of residuals from symmetry, state-transition prognosis, and such like repetitive tasks are intracell-based and therefore light-weight and resource-efficient designed to work on all Edge Assets on-a-cycle basis (with neighbouring assets communicating in the collapsible cells) traffic transformed as demanded. Such tasks form the individualistic Times-Data for each Edge Asset (communication and execution) Time-series-based learnings for individualistic Edge Assets contain hyper-symmetric & hyper-stable operation-temporal-parts wrap-predictive time as main content hyper-parameters for cyclic-based early-alarm upwards prediction for abnormal increase in travel-time (asset operational state is condition monitored & main asset learning vector remains hyper-stable).

A. Time-Series Modeling and Anomaly Detection

Future prognostics performance depends on a combination of useful pre-built cognitive assets, such as Time-Series Modeling and Anomaly Detection cognitive functions that uncover patterns, relations, and anomalies respectively, which can add useful edge computing capabilities for IoT infrastructure. Time-series analysis focuses on data indexed in time order, drawing information from identified trends (long-term monotonous data movement), seasonality (long-term periodic season-specific motion), and periods of comma states. Anomaly detection studies a data stream to catch patterns that deviate from normal historical behavior and deserve human attention. These two functions complement others that go beyond these heuristics, such as adaptive cycle-predictive remaining useful life forecasting and loss modeling for industrial assets and fleets. Relevant models are built only once and exploited multiple times when new data streams become available.

With a part of the Industrial Internet Consortium's Data Lake Dataset, representing network traffic recorded over several months inside a testbed environment, Time-Series Modeling analyzes the total amount of network traffic and detects multiple periodic spikes caused by the execution of a remote shell script that runs a small web server, sends files to the server, and triggers several network-based attack detection tools. Anomaly Detection examines TCP packet counts every five seconds, using the binomial distribution to identify packet doses sent hourly and flagged as anomalies because they are typically not as high. Time-Series Modeling and Anomaly Detection together build intelligible information ready for human analysis and cover part of the INFO, DEC&RES, and NOM functions of The Cognitive System. Various decision systems in the FLIGHT mode

exploit this information and others generated in FLIGHT mode.

6. Conclusion

A cognitive framework for Industrial Asset Intelligence facilitates the use of information derived from operational experience. Specifically, cloud-based knowledge is tailored to edge-level implementation in an Industry 4.0 context to deliver predictive and prescriptive capabilities that support individual and fleet-level prognosis. The capabilities are evaluated through a case study focusing on a fleet of residential energy storage systems, where critical components are prone to degradation, necessitating timely intervention to avert failure modes. Issues related to the resilience and sustainability of fleet-level operation are addressed with the application of a reinforcement learning algorithm. Past data is exploited for simulation studies, demonstrating the capability of tracking appropriate actions to return a resilient control policy.

Together, the proposed framework, algorithms, and flow enable systematic cognitive prognosis capabilities for intelligent assets and networks. The currently available Cloud–Edge infrastructure is aligned to source–use data flows. Enabling intelligent prognosis is a significant contribution aligned with the regional initiative for its development.

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