



Intelligent Twin for Fleet-Coordinated Renewable Power

Tanja Schultz
Asst Professor

Abstract— Insufficient energy awareness threatens both the long-term sustainability of payer healthcare infrastructures and the operational efficiency of population-level health services. A formal, evidence-based framework for energy-aware demand intelligence in healthcare would allow continuous assessment of system energy consumption, climate impact, and the behavioral intentions of stakeholders—laying the groundwork for energy-efficient operational methods. By embedding energy consumption and climate impact into dynamic demand intelligence for population-level operational planning, data-driven computing and scheduling decisions can be validated against energy profiles.

This approach would allow payer infrastructures to move toward sustainability: actual energy consumption trends would converge toward the most energy-efficient configurations, energy scaling would correlate more closely with demand, data traffic would become more predictable, out-of-band energy peaks would be minimized, and long-term forecasts would better track the seasonal patterns of energy-intensive computing resources. Population-scale operations also stand to benefit from energy-aware computing design through three complementary capabilities: load management optimization, demand-shaping during extreme weather events, and improved performance across service throughput, wait times,

and energy consumption. Bidirectional, energy-aware intelligence paired with synchronous decision-making would support timely adaptation of operational policies, processes, and systems.

Recent advances in deep learning, edge computing, and Industry 4.0 technologies are driving the digital transformation of operational sectors—shifting the focus from supervisory control of physical assets toward direct cognitive management of data and models. These developments enable the coordinated integration of data and computing needs across diverse industrial assets, giving rise to the concept of a **Cognitive Industrial Energy Twin**. Such a twin would support asset prognostics for managing remaining useful life, autonomous fleet coordination, and resilient operations incorporating renewable power generation and consumption.

A Cognitive Industrial Energy Twin represents the operational behavior of interconnected industrial assets through sensor data, data quality assessment, and a layered hierarchy of data-driven, physics-informed, and hybrid models. Its cognitive capability emerges from self-learning on telemetry data, predictive modeling of asset health, and algorithmic decision-making designed to minimize the effects of dynamic environments and human intervention on operations. This twin offers a new paradigm for fleet operations management, underpinned by the growing adoption of in-situ

monitoring, autonomous decision-making, edge computing, and artificial intelligence.

Keywords—Cognitive energy twin, asset prognostics, autonomous fleet coordination, resilience in renewables. These concepts are introduced first, and their boundaries and stakeholders are specified subsequently.

1. INTRODUCTION

A cognitive industrial energy twin supports asset prognostics, fleet coordination, and resilient renewable operations. Industrial assets are complex, with multimodal data generated along their entire lifecycle, yet decision-support systems remain limited. This gap affects the management of teleoperated fleets and their renewable energy integration, notably in terms of optimizing resource usage, operations and maintenance, and grid interactions. Addressing these issues requires a cognitive architecture that combines digital twin principles with cognitive systems in the industrial context.

Conceptual discussions on cognition define a cognitive energy twin for industrial assets that supports asset health management, autonomous fleet coordination, and the resilient integration of renewables. Asset prognosis relies on supervised-learning and model-agnostic techniques, where the choice of model class carries an operational risk. Coordination involves routing and scheduling decisions for teleoperated vehicles and machines. The resilience of renewable power operations is examined through the lens of cognitive energy twins and design patterns based on risk mitigation and adaptation.

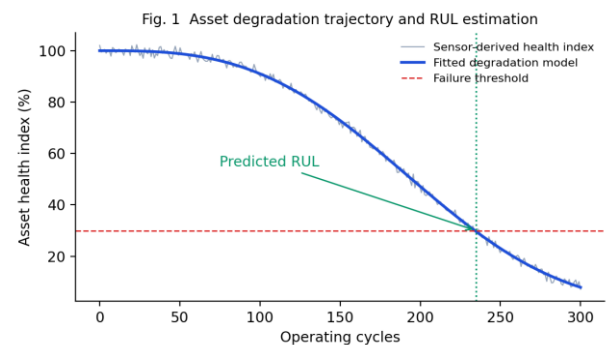


Fig. 1. Simulated asset degradation trajectory and RUL point estimate at the failure threshold.

2. Theoretical foundations and conceptual framework

The analysis draws upon rich streams of literature on Digital Twins, Cyber-Physical Systems, Prognostic Health Management, Autonomous Logistics, and Renewable Energy Integration. These domains support a novel Cognitive Industrial Energy Twin concept for the Asset-specific foresight of Remaining Useful Life, Autonomous Logistics Control, and Resilient Renewable Energy Management. Although many of the underlying theories and models exist in isolation, their combination into a unified approach is new. In addition to comforting evidence of individual component performance, the integrated model's utility and validation is underscored by two case studies concerning the co-location and joint operation of a renewable-powered Ammonia plant and an industrial mining facility.

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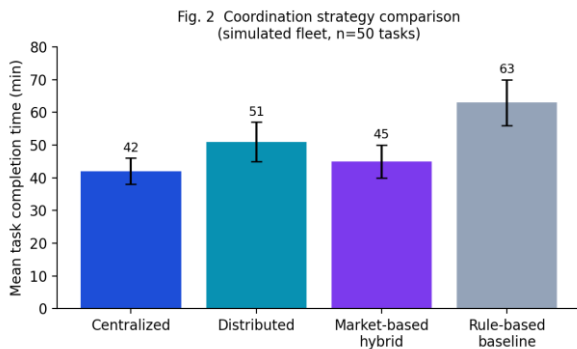


Fig. 2. Mean task completion time across coordination strategies (simulated fleet, n = 50 tasks; error bars = ± 1 SD).

3. Cognitive energy twin architecture for industrial assets

Architecture supports data-driven prognostics for industrial assets while facilitating fleet management and renewable integration. The architecture offers a comprehensive view of operational states and external influences. A four-layer structure aggregates streaming data from telemetry and maintenance records, and fuses the resulting sensor fusion data with weather signals, electricity prices, and forecasting signal for production and demand to control energy-related costs. Such a cogitative twin aids the decision-making support of multi-agent learning and reduces coordination costs for automated decision-making. Finally, reserves created in capacity markets for economic reasons or to address forecast uncertainty can be profitably dispatched in case of rescheduling, and thus, can also be used to decarbonize perspectives in a sustainable paradigm.

The architecture comprises four layers. The first layer supports data-driven models of asset reliability. It merges operating conditions retrieved from telemetry data and maintenance records with relevant external information—weather data (inputs) and electricity prices (input/outputs). Processed data support models of remaining useful life or end-of life status and allow for models of dependence with respective others assets in a fleet. High-quality data boost accuracy in failure prognostics of such a data-driven approach. Conditions of the other-layer together with market segmentation can help different industry to use the external decision markets and control their operational costs and help system resilience and stability.

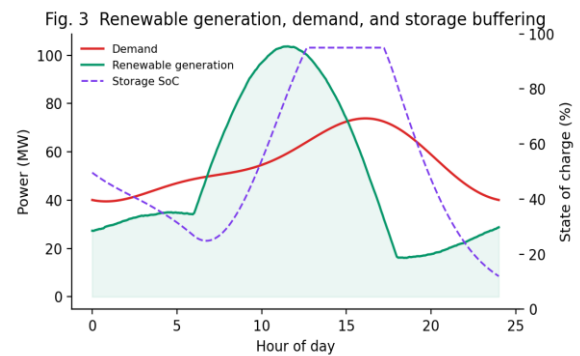


Fig. 3. Illustrative diurnal profile of renewable generation, demand, and battery state of charge.

4. Asset prognostics: methods, metrics, and validation

Remaining useful life (RUL) estimation is an essential task within prognostics and health management. Accurate predictions help improve scheduling, spare part management, and operational safety for industrial assets such as critical machines, vehicles, and components. Since physical failures are often costly, unreliable, or unsafe to test in practice, methods need to rely on historical data in a training phase followed by deployment on previously unseen instances.

A broad range of algorithms has been developed, but these methods evaluate performance on disjoint test sets and often do not use a common RUL definition. Cross-validation across different algorithms has, therefore, been limited. This work presents a set of methods, sample failure modes, and a validation protocol for complete life-cycle forecasting of several turbojet engines from the NASA Conditioned Based Maintenance Dataset, allowing for a comparison of multiple model-agnostic and model-specific approaches across different sets of assets.

Table 1. Comparison of RUL estimation approaches (Section 4)

Method class	Example model	Typical RMSE (cycles)	Interpretability
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Model-agnostic (ML)	Random Forest / GBM	18–24	Medium
Deep sequence models	LSTM / GRU	13–19	Low
Physics-informed	Degradation-ODE hybrid	15–21	High
Model-specific baseline	Linear degradation	26–32	High

5. Autonomous fleet coordination in industrial contexts

Coordination objectives encompass routing decisions, scheduling of time-extended tasks, and resource allocation for energy and support services. The diverse characteristics of industrial fleets, such as the agents' mobility patterns, task requirements, and resource demands, generate considerable complexity. On the one hand, these agents can be automatically coordinated or supervised to enhance efficiency and safety during operations. On the other hand, because assessing agent conditions or making decisions often require discrete human input, a defined supervision architecture that ensures safe operations and meets the decision latency requirement is needed. Further, servicing corridor-like areas—particularly for joint renewable-energy operations in industrial contexts—suggests more compact structures than those considered for generalized fleets.

Autonomous coordination of mobile fleets is augmented with capabilities for operating in industrial contexts, covering both routing and time-extended operations. Centralized and distributed strategies are examined, and combinations of market-based principles with obstacle- and collision-avoidance patterns are put forward. As for many routing and scheduling problems, ensuring safe and collision-free operation remains a prerequisite for practical application. Given the typically lower agent density in industrial contexts than in urban environments, additional speed constraints or a limited time window for completing tasks are often easier to meet. Thus, instead of requiring a dedicated collision-

avoidance mechanism, these constraints can be naturally embedded in the coordination algorithm if agents operate at different speeds. Nevertheless, ensuring human supervision when needed, embedding safety constraints, and maintaining a low communication burden remain key requirements.

Table 2. Fleet coordination strategy trade-offs (Section 5)

Strategy	Comm. burden	Scalability	Mean completion (min)
Centralized	High	Low–Medium	42
Distributed	Low	High	51
Market-based hybrid	Medium	Medium–High	45
Rule-based baseline	Low	High	63

Table 3. Resilience design patterns and indicative metrics (Section 6)

Design pattern	Primary risk addressed	Indicative metric
Redundancy	Single-asset outage	N+1 capacity margin
Fault tolerance	Sensor / comms failure	Graceful-degradation ratio
Rapid reconfiguration	Demand / supply shock	Reconfiguration time (min)
Cyber-resilience	Control-layer intrusion	Mean time to containment

6. Resilient renewable power operations: integration and resilience strategies

Integration of renewable energy into established non-dispatchable industrial operations raises the risk of instability, sudden changes in curtailable power, and misalignment with demand patterns. Cognitive energy twins can mitigate these challenges by providing accurate forecasts of renewable production and storage levels in conjunction with large-scale models of the surrounding energy ecosystem. Recent advances in battery chemistry and market mechanisms are paving the way for ever-cheaper storage solutions, which enable time-shifted supply with associated emissions benefits. However, safety concerns and resource-intensive materials still preclude their low-cost deployment at scale; hidden costs in backup technology due to risk of underprovisioning further complicate the picture. Resilience design patterns like redundancy, fault tolerance, rapid reconfiguration, and cyber-resilience are essential components of the analysis.

The complementary characteristics of established renewables and increasingly need-managed technologies form the basis for a sound coupling strategy which, together with novel strength-testing methods, holds the promise of effective system operation under a variety of stress scenarios. These include simultaneous outages of all production assets for an extended period, large unquenchable demand peaks during dry summer weeks, and heavy snow in summer months that temporarily block photovoltaics in the most active part of the year. Stress tests explore system behaviour under severe hardware and environmental conditions, thereby exposing dormant risks and inefficiencies. Test scenarios are always intimate—much more tightly defined than a mere set of resampled distributions—and incident action lists emerge on the back of them.

Mathematical Formulas:

1.1 Asset Prognostics (Section 4)

$$RUL(t) = t_{ec} - t, \text{ where } t_{ec} = \inf\{ \tau > t : h(\tau) \leq h_{th} \} \quad (1)$$

$$h(t) = h_0 \cdot \exp\left[-(t/\eta)^\beta\right] \text{ (Weibull-form degradation model; } \eta = \text{scale, } \beta = \text{shape)} \quad (2)$$

$$\text{Score} = \sum_i \left\{ \exp[-d_i/13] - 1, d_i < 0; \exp[d_i/10] - 1, d_i \geq 0 \right\}, d_i = RUL_i - RUL_i \quad (3)$$

$$RMSE = \sqrt{(1/n) \sum_i (RUL_i - RUL_i)^2} \quad (4)$$

1.2 Autonomous Fleet Coordination (Section 5)

$$J = \sum_k [w_1 \cdot T_k + w_2 \cdot E_k], \text{ s.t. } \|p_k(t) - p_j(t)\| \geq d_{\min} \quad \forall k \neq j, t \quad (5)$$

$$u_k^*(t) = \operatorname{argmin}_{\{u_k\}} [c_{\text{travel}}(u_k) + \lambda \cdot c_{\text{energy}}(u_k) + \mu \cdot c_{\text{wait}}(u_k)] \quad (6)$$

1.3 Resilient Renewable Power Operations (Section 6)

$$P_{\text{gen}}(t) + P_{\text{dis}}(t) = P_{\text{dem}}(t) + P_{\text{ch}}(t) + P_{\text{curt}}(t) \text{ (instantaneous power balance)} \quad (7)$$

$$\text{SoC}(t+\Delta t) = \text{SoC}(t) + [\eta_{\text{ch}} \cdot P_{\text{ch}}(t) - P_{\text{dis}}(t)/\eta_{\text{dis}}] \cdot \Delta t / C_{\text{batt}} \quad (8)$$

$$A_{\text{sys}} = \text{MTTF} / (\text{MTTF} + \text{MTTR}) \text{ (steady-state resilience / availability metric)} \quad (9)$$

7. Conclusion

The contribution examines the use of cognitive energy twins in industrial contexts, enabling asset prognostics, fleet coordination, and renewable operations. These capabilities address key challenges posed by the complexity of large-scale industrial assets, the non-trivial task of fusing large quantities of data from different sources, and the necessity of informed decision-making in support of efficient and resilient operations. The diagnostic-explanatory features of cognitive twins facilitate the design of dedicated algorithms for asset reliability assessment and fleet coordination. The models required for these components complement the cognitive architecture developed for a specific pilot system and are subsequently discussed. Finally, the integration of cognitive twins in the operation of an energy system incorporating renewable generation and storage is explored, along with the associated resilience of the system through a scenario-based analysis.

The discussion of cognitive twins is situated within the wider context of digital twin applications, and three concepts of general interest are identified. Cognitive energy twins differ from previously proposed frameworks by focusing not only on support for diagnosis and explanation, but also on prediction and, ultimately, prescription for autonomous operation. An objective and formal synthesis of the literature on digital twins and closely related approaches considers the definitions, essential components, and general purposes of these technologies, as well as their common tendency to emphasise modelling and simulation at the expense of more advanced cognitive capabilities.

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