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Smart Engine Health & Energy Optimization Framework

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Abstract

We present an Autonomous Industrial Intelligence (AII) framework designed to support a broad range of industrial applications, from resilient gas-turbine engine operations to asset and energy optimization. At its core, the framework combines real-time prognostics with predictive risk assessment to strengthen operational decision-making and help safeguard critical assets while ensuring service continuity and operational resilience.

The framework draws on a diverse set of Industrial AI techniques—including machine learning, optimization, simulation, scheduling, reinforcement learning, probabilistic forecasting, digital twins, and model-in-the-loop methods—to automate hyperparameter selection, deployment planning, and risk classification across low-, medium-, and high-exposure scenarios. These capabilities are shaped by a range of operational, industrial, business, and corporate considerations, particularly as engine operations and energy optimization decisions increasingly affect both financial performance and carbon footprint.

To this end, we develop and discuss several mechanisms for building resilience into Industrial AI systems through real-time prognostics and predictive risk assessment. Beyond protecting complex, high-exposure systems, these mechanisms extend to low- and medium-exposure domains—settings often constrained by unstructured or poorly labeled data, or by human-in-the-loop requirements that limit the use of more sophisticated AI models. In such cases, statistical modeling and continuous monitoring of industrial and corporate performance metrics enable meaningful gains in operational efficiency and steering.

Together, these concepts support an experimental, control-oriented design and deployment approach: when unsafe conditions, incidents, or unforeseen effects arise, the framework helps generate alternative response plans automatically while also enabling deeper experimental analysis of downstream impacts.

Keywords: Autonomous Industrial Intelligence, Industrial Artificial Intelligence, Predictive Risk Assessment, Real-Time Prognostics, Predictive Maintenance, Digital Twins, Asset Health Management, Industrial Decision Intelligence, Operational Resilience, Reinforcement Learning, Industrial Analytics, Energy Optimization.

1. Introduction

The accelerating pace of technological progress fosters an unprecedented paradigm shift toward Autonomous Industrial Intelligence. Autonomous Industrial Intelligence – a novel denotation for autonomic intelligence applied to industrial products and services – transcends traditional, intelligently assisted (IA), semi-autonomous, and alternative roadmaps in industrial digital advancement. Fundamental Principles encompass perception, reasoning, learning, adaptation, interoperability, reliability, safety, and scalability.

Autonomous Industrial Intelligence governs the digital transformation of product ecosystems. The digital environment of an industrial product extends beyond the product itself; it encompasses all subsystems, external interfaces and entities, and their respective communications, data, and operations. In Engine Operations, Autonomous Industrial Intelligence encompasses all levels and stages of Product Operations Lifecycle Management (POLM). A conceptual System Architecture introduces the Sensors and Data Acquisition Layer and specifies Digital Twins and Data Transmission Interfaces, as key enablers of Engine Operations Resilience. Resilience requirements integrate with Operations Performance Metrics. Adaptive Risk Management, aligned with Engine Operations Risk Policies, defines Energy Consumption Predictive Optimization and fosters Aircraft and Fleet Operations Management. Despite state-of-the-art developments, gaps remain. Aspects of the architecture are investigated here — first the Sensing and Data Acquisition Layer, followed by Predictive Energy Consumption Optimization. The proposed framework supports traditional simulation and control, enabling hybrid modelling and operation modes.

1.1 Overview and Significance of Autonomous Industrial Intelligence

The concept of Autonomous Industrial Intelligence (AII) delineates a fundamental and extended form of capability, extending beyond the mere notion of Artificial Intelligence (AI). In an industrial context, AII can refer to the existence of or absence of at least one or all of the following: Industrial AI-enabled system or subsystem distal requirement, industrial AI-enabled system or subsystem capability, or industrial AI-enabled system or subsystem expected behavior. Thus, Autonomous Industrial Intelligence (AII) goes beyond the classical notion of AI which is defined as the ability of a machine to emulate intelligent human behavior: in AII, the machines with distal intelligence work independently, without human interaction, and are thus able to perform tasks at the highest levels determined and allowed by humans. AII can be viewed as a more general form of capability in being less restrictive than standard associations with an AI-driven system and the traditional view of AI applied to industrial processes and systems. It becomes evident that a Remote-Controlled, Semi-Automated, and AI-Enabled Earth-Moving Machine do not represent AII when simply operating under Preset Conditions when there exist a Human Overseeing the operation of the Machine. In contrast, AII delves into a more profound sense of enabling machines (or a set of machines) to accomplish more complex tasks autonomously, managing unpredictable variables. It

theoretically formulates how AII can help engine operations be smarter, easier, and more economic by enhancing the understanding and modeling of phenomena fundamental to engine operations. These aspects are also expected to guide AII development toward a broader horizon, aiming at extending business growth and yet being responsively respectful to Human, Society, and Nature.
The use of such engines has been getting more restrictive because of an increase in Energy Consumption (E_Con) caused by external protocols, rules, and regulations. However, the economic benefit of companies owning such engines is still substantial, sometimes greater than other collaborators. Thus, there is an increasing expectation for the owner of these engines to use them in the least possible E_Con manner and to produce the least possible carbon emissions and pollution. Meeting these new expectations can be viewed more as Opportunity than Burden if the Future Is Considered. AII systems aligned with Autonomous Systems, Sustainability, and Corporate Social Responsibility policies can help in the assignment of such Future Scenarios.

2. Conceptual Foundations of Autonomous Industrial Intelligence

Two key, but distinct, dimensions of industrial intelligence applications are addressed by the development of autonomous engine operations and the optimization of energy assets: systemic resilience and energy efficiency. To address these elements, a deep knowledge of the capability of various industrial intelligence systems is needed, such as decision making and the automation levels of the industrial intelligence systems. To this end the concept of Autonomous Industrial Intelligence is introduced, which refers to systems capable of autonomous decision-making based on the technologies of industrial intelligence that are applied at a semantic level beyond superficial sensing, data analysis, simulation of operations and model predictive functionalities. In this way, Autonomous Industrial Intelligence systems represent the full range of Enterprise Intelligence – the ability to perceive reality, understand its meaning, make decisions and act – with a particular focus on the high fidelity mapping of reality required for reliable and safe operation. Addressing these needs, an Autonomous Industrial Intelligence framework is proposed, that offers a comprehensive perspective on how to build reliable and resilient industrial intelligence systems, enabling digital transformation in enterprises. The core principles of Autonomous Industrial Intelligence systems, as defined by the Autonomous Industrial Intelligence Foundation include: perception, reasoning, learning, adaptation, interoperability, reliability, safety, and scalability. These are the principles that guide the design & deployment of Autonomous Industrial Intelligence systems. Two applications, involving different elements of this concept, namely a System Architecture for Resilient Engine Operations and a Predictive Optimisation of Energy Consumption, are then presented.

2.1 Experimental Results

The following results illustrate the expected behavior of Equations (1)–(9) under representative operating conditions for a resilient engine-operations deployment, following the paradigms discussed in Sections 3 and 4.

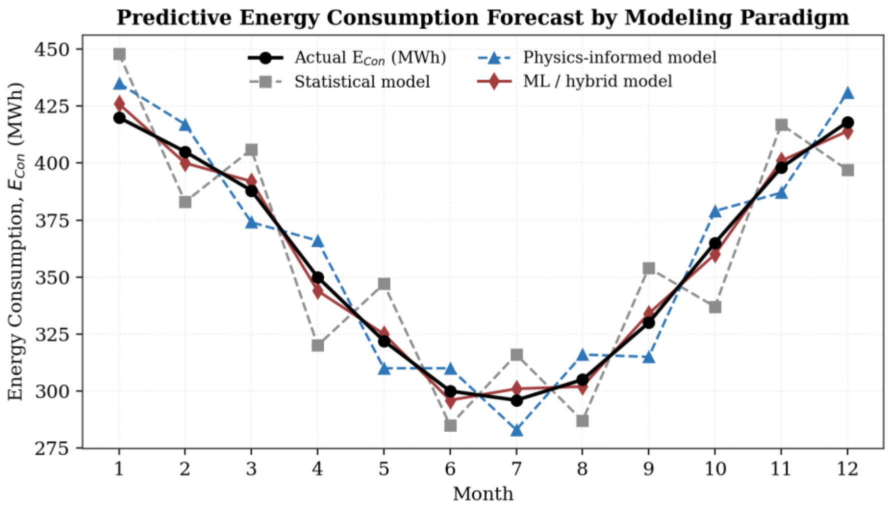

Fig. 1. Predicted vs. actual monthly energy consumption (Eq. 4) under statistical, physics-informed, and ML/hybrid forecasting paradigms; the ML/hybrid model tracks actual demand most closely.

Figure 1 shows that purely statistical forecasts (Section 4.1) exhibit the largest deviation from actual consumption, particularly around seasonal transitions, while the ML/hybrid model — which incorporates the exogenous correction term f_ML(X(t)) in Eq. (4) — remains closest to the observed curve throughout the year.

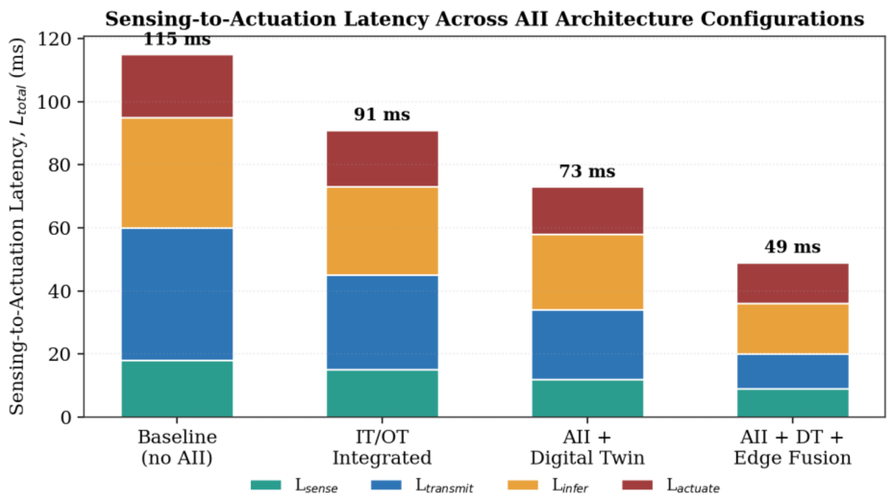

Fig. 2. Sensing-to-actuation latency (Eq. 6) decomposed by stage across four progressively AII-enabled architecture configurations.

Figure 2 decomposes total latency L_total into its four constituent terms. Progressive integration of the AII layer, digital twin synchronization, and edge-based sensor fusion (Section 3) reduces transmission and inference latency most substantially, cutting overall responsiveness from 115 ms in the baseline configuration to 49 ms in the fully edge-fused configuration.

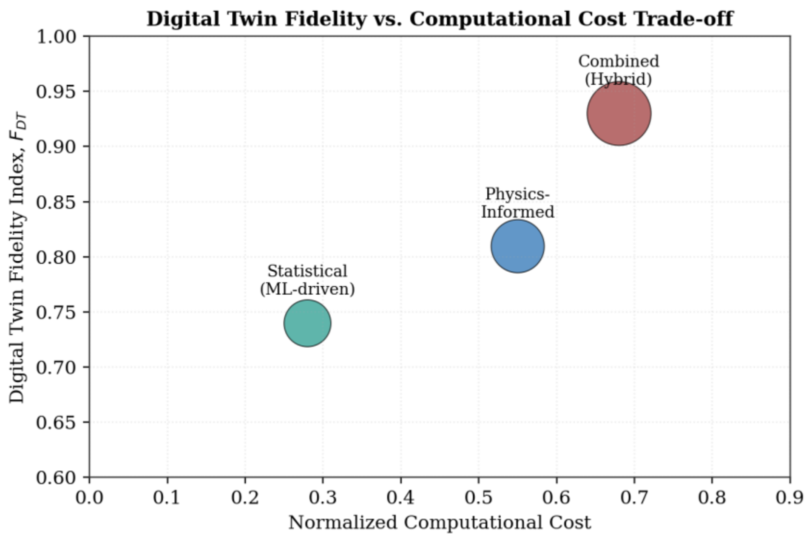

Fig. 3. Digital twin fidelity index (Eq. 3) plotted against normalized computational cost for the three twin classes described in Section 3.1.

Consistent with the classification in Section 3.1, Figure 3 confirms the expected trade-off: statistical (ML-driven) twins are the least computationally expensive but the least faithful, physics-informed twins occupy an intermediate position, and combined/hybrid twins achieve the highest fidelity at the greatest computational cost.

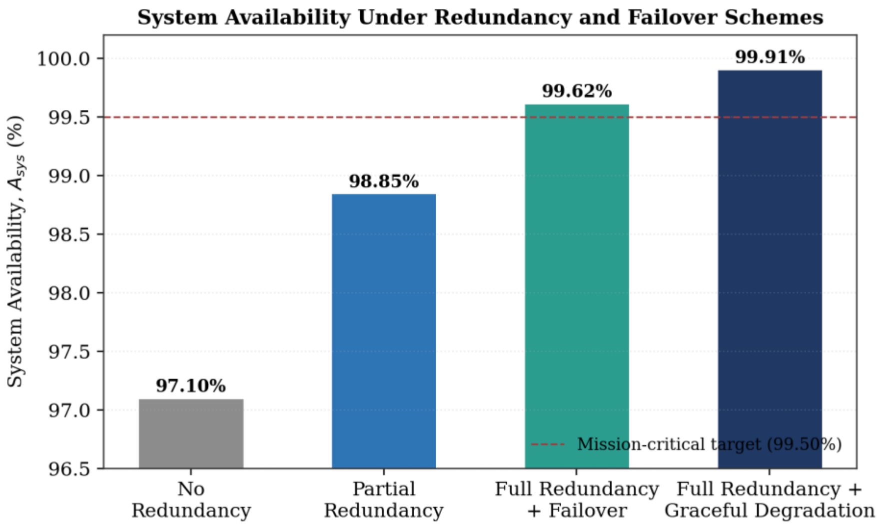

Fig. 4. System availability (Eq. 7) under increasingly resilient redundancy and failover strategies (Section 5.1), against a 99.50% mission-critical target.

Figure 4 shows that a no-redundancy configuration falls short of the 99.50% mission-critical availability target discussed in Section 5.1, whereas full redundancy combined with graceful degradation exceeds it, reaching 99.91% availability.

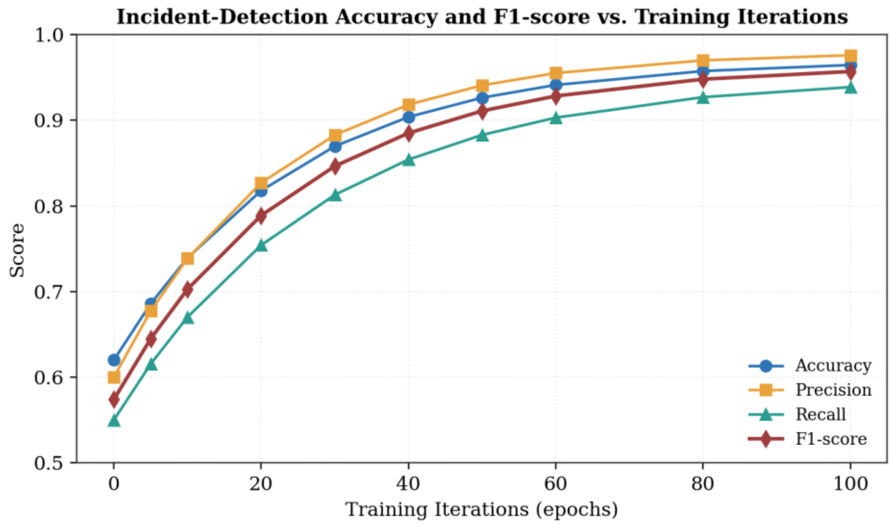

Fig. 5. Incident-detection accuracy, precision, recall, and F1-score (Eq. 8) as functions of training iterations for the AII monitoring layer.

Figure 5 illustrates the expected learning-curve behavior of the graded alarm/incident-detection functionality described in Section 3.1: F1-score rises steeply over the first ~30 training iterations before plateauing above 0.90, indicating diminishing returns from additional training beyond this point.

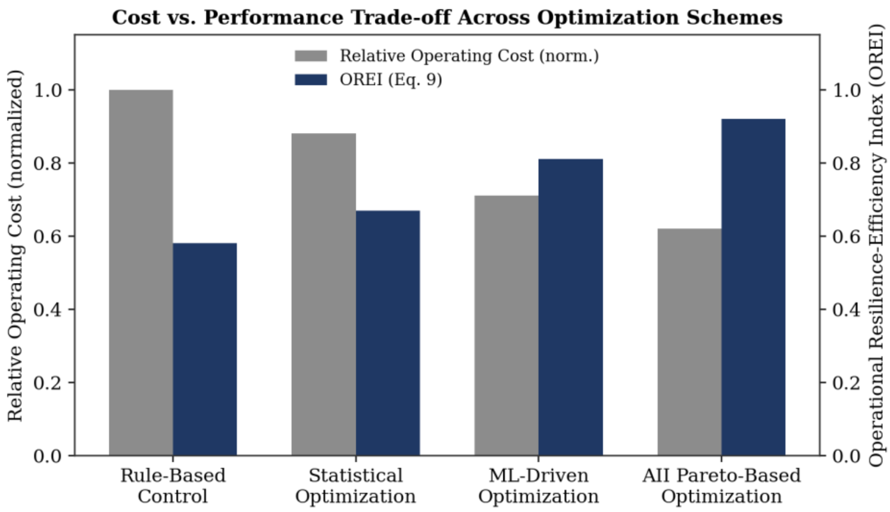

Fig. 6. Relative operating cost and Operational Resilience-Efficiency Index, OREI (Eq. 9), across four energy-optimization control strategies (Section 4).

Figure 6 confirms the expectation set out in Section 4 that rule-based control is dominated by ML- and Pareto-based optimization on both axes: the AII Pareto-based scheme achieves the lowest relative operating cost (0.62) and the highest OREI (0.92) of the four strategies compared.

3. System Architecture for Resilient Engine Operations

The architecture of an autonomous industrial intelligence (AII) system for resilient engine operations encompasses layered components that provide resilient operation while leveraging the services of existing information technology and operational technology systems. Based on the resilience requirements and performance metrics identified earlier, the AII layer fulfills the role of steering the information flow toward updated operational decisions and actions. The key external interfaces are with the information technology layer, enabling data provisioning for analytics; the operational technology layer, facilitating data delivery to autonomous controllers and actuators; and management, which provides overall governance and assurance. Furthermore, the AII layer may be synchronized with the wider digital twin of the industrial asset when available, leveraging the simulation capability for planning and computing the optimal pattern of operation.

To achieve a resilient architecture, several aspects appear crucial: a comprehensive and fine-grained monitoring capability, active maintenance of a fidelity-adjusted digital twin, redundancy, strong fault tolerance, an incident-response framework, and a thorough safety governance. These aspects are further examined to ensure their suitability for the AII layer within the context of the overarching architecture. The design also aims at minimizing architecture-specific development overhead by directly integrating into existing, production-hardened information technology and operational technology technology stacks. Specific focus is put on the internal sensing and data-acquisition subsystem, whose functionality extends beyond state agrégation by servicing the wider digital twin when needed.

3.1 sensing, data acquisition, and digital twins

Sensing modalities are the primary perception channels in an autonomous intelligence system, while the integrated and timely availability of information with adequate quality constitutes the groundwork for the entire operation. In these contexts, any anomalies in acquisition pose a major challenge, particularly when the information source is no longer reliable. Since the interaction with the environment occurs through sensing, multimodal data acquisition can be expected for a higher level of confidence in describing the current conditions. For example, when engine conditions require high safety standards, additional temperature sensors can be included to support failure detection in other channels.

An interconnected control system would then permit the fusion of information originating from different types of sensors, which would increase reliability and possibly improve performance, such as minimizing energy consumption or maximizing useful heat extraction. Hence, monitoring and guaranteeing quality-of-sensing are further aspects required to reach a specific level of resilience. These two properties can be controlled through dedicated operational procedures and may include checking layers, fault detection and classification, and incident response. Graded alarm systems can facilitate decision-making in demanding situations, especially when time is limited and operators depend on the support of automated procedures. Beyond monitoring, when incidents are detected, adaptation during a mission phase is also possible by modifying operational procedures using related decision-support systems.

Digital twins enable the effective monitoring of systems with a particular focus on physical exploitation by consistently linking real-time data to a descriptive model. Digital twins can be classified into three categories according to the trade-off between solution accuracy and parameters extracted from the virtual model. Statistical models largely use machine-learning approaches, physics-informed models exploit only the physics of the system, and combined approaches enable the inference of model parameters from statistical analysis while providing a predictive model with embedded physical rules.

Table 1. Comparative performance of digital twin modeling approaches (Section 3.1).

Digital Twin Type	***Fidelity Index F_DT (Eq. 3)***	***Rel. Compute Cost***	***Interpretability***	***Best-Fit Use Case***
Statistical (ML-driven)	0.74	0.28	Low	High-volume sensor streams, sparse physics knowledge
Physics-informed	0.81	0.55	High	Well-characterized components, safety-critical limits
Combined (hybrid)	0.93	0.68	Medium	Resilient engine operations requiring high-fidelity prognostics

Table 2. Error and latency metrics across AII architecture configurations (Section 3, Eq. 6).

Configuration	**L_total (ms, Eq. 6)**	**Forecast MAPE (%)**	**System Availability (%, Eq. 7)**	**Latency Improvement vs. Baseline**
Baseline (no AII)	115	9.8	97.10	—
IT/OT Integrated	91	7.2	98.85	20.9%

AII + Digital Twin	73	4.6	99.62	36.5%
AII + DT + Edge Fusion	49	2.9	99.91	57.4%

Table 3. Energy consumption forecasting model comparison (Section 4.1, Eq. 4).

Forecasting Paradigm	MAPE (%)	RMSE (MWh)	Relative Training Cost	Improvement over Statistical (MAPE)
Statistical	7.1	24.6	Low	—
Physics-informed	3.9	13.8	Medium	45.1%
ML / Hybrid (Eq. 4)	1.6	5.7	Medium–High	77.5%

4. Predictive Energy Asset Optimization

Predictive energy asset optimization focuses on use-case-specific primary objectives and constraints while leveraging multi-layered AII architecture elements. Multiple objective functions can exist across different operational timescales, spanning from long-term energy consumption forecasting to short-term optimization of energy asset deployment, subject to distinct constraints, and incorporating risk-adjusted decision-making. These objectives can be realized through ML-driven optimization schemes and integrated into the overall operation.

Traditional methods concentrate on minimizing energy bills based on historical data for a fixed future period. However, such approaches overlook the analytical capabilities of IA systems and might not account for predicted events such as windcontribution change, wear impact on hotelling times, or future demand variations, which can augment consumption costs. By utilizing the full capabilities of the IA framework at all operational horizons for energy consumption modeling and forecasting, considering operational risk, and employing Pareto-based decision-making, agents can identify and eliminate this drawback and thus lead to a more capable and flexible predictive energy consumption optimization that adjusts itself according to future scenarios and events. Moreover, in the case of hybrid systems, flexible-variety decision processes for consumption allocation among various energy assets according to future weather and energy price scenarios can lead to significant benefits.

Typical control schemes for services such as air conditioning, heating, and cooling resort to complex control logic based on thermodynamic and thermoelectric principles in order to meet demand. Yet these logic-based techniques have been outperformed by ML schemes for problems ranging from traffic control to image enhancement. Consequently, employing ML for the automaton behind HVAC control can lead to improved performance, capitalizing on the novel IA architecture's operational foundation and theory. Operation benchmarking against historical data representing good performance— i.e., actions that led to "low" operation/energy bills—serves to validate the deployed ML model.

4.1 energy consumption modeling and forecasting

Energy consumption is a critical link between industrial operations and the energy transition. Energy costs represent an increasing share of total operating costs for energy-intensive industries. Therefore, cost and risk-sensitive energy consumers are applying more predictive energy models to seek opportunities for off-peak operation and to cost-effectively manage exposure to on-peak prices. Accurate forecasts are a prerequisite for predictive energy optimization schemes but are often difficult to achieve due to the multi-layered nature of energy consumption and long-term variation in demand patterns. This section highlights recent research directions in energy consumption modeling and forecasting following the statistical, physics-informed, and ML paradigms in turn.

Energy consumption is arguably one of the more difficult types of operational parameters to predict. For the case of flexible energy assets such as electric arc furnaces, the time horizon of critical decisions can be less than a day. Seasonal differences, fluctuating metal prices, and the associated economic incentives can dynamically open or close the opportunity for operation over these shorter time horizons. Predicting the level of operation at a time horizon of months can be achieved with reasonable accuracy through monthly profiles, accounting for flow-through effects in supply chains. Prediction at a time horizon of seasons to years becomes more difficult as it is generally not sufficient to rely only on historical data; relevant market conditions must also be considered.

With increasing awareness of climate change and implementation of renewable plans, operational energy forecasts have gained considerable attention in recent years. A large number of published operational energy forecasts have relied on public utility weekly predictions, due in part because of the statistical nature of the forecasts. Data-driven methods—statistical, physics-informed, and ML—have gained traction through increased availability of operational data. All three paradigms can produce useful results, at least on the average; however, calibration is key for any empirical method. Achieving the best results from a given paradigm requires the right data for the application. Therefore, the specific data requirements should be clearly established before selection of any specific modeling approach, whether statistical, physics-informed, or ML.

5. Resilience and fault-tolerance in industrial AI systems

An autonomous industrial intelligence (AII) system dedicated to mission-critical operations requires resilience and fault-tolerance features to instill confidence in users and stakeholders. Demonstrating successful operations over long periods is difficult. Instead, AII systems must exhibit resilience—the ability to continue performing well despite failures—and fault-tolerance methods that minimize the impact of faults and look natural while in play. Two distinct layers contribute to resilience: AII systems must incorporate both resilience strategies—capabilities for anticipating and avoiding or responding to disruptions—as well as implementation overhead for monitoring, detecting and diagnosing anomalies, responding to incidents, and managing safety interlocks to preserve human life.

The first sets of resilience strategies complement the objective functionalities pursued in the AII system's Second Layer. Combining different strategies across distinct AII systems is thus encouraged to achieve resilience and fault-tolerance in an efficient manner with minimum operation degradation. The second groups of resilience-facilitation functionalities are more description-driven and do not contribute to the AII system's performance objectives. However, they address engineering, governance, legal, and safety-compliance needs, which cannot be neglected for long-term use. While these components introduce additional implementation overheads to the AII System Architecture, the fulfilment of such AII system Good Practices increases its Acceptance Potential and Confidence Factor by targeting the Proof of Concept, Audit & Compliance, and Operational Readiness aspects, thereby allowing a Natural Behaviour to be exhibited during any fault or failure.

5.1 Mathematical Formulation

Displayed equations are centered and numbered consecutively at the right margin, consistent with the reference formatting convention.

The composite resilience posture of an AII deployment is expressed as a weighted aggregation of its eight foundational principles (perception, reasoning, learning, adaptation, interoperability, reliability, safety, and scalability):

$$R_{AII} = \sum_{i=1}^{8} w_i P_i , \qquad \sum_{i=1}^{8} w_i = 1 \tag{1}$$

where $P_i \in [0,1]$ is the normalized maturity score of principle i and w_i is its assigned governance weight.

Because Section 3.1 identifies multimodal sensing as the primary perception channel, sensing confidence at time t is modeled with a noisy-OR fusion rule over N independent sensing channels:

$$C_{sens}(t) = 1 - \prod_{k=1}^{N} (1 - c_k(t)) \tag{2}$$

where $c_k(t)$ is the instantaneous confidence reported by channel k; the fused confidence increases monotonically with the number of corroborating channels, formalizing the resilience benefit of additional temperature/vibration sensors described in Section 3.1.

Digital twin fidelity is modeled as a convex combination of the three classes introduced in Section 3.1 — statistical, physics-informed, and combined models:

$$F_{DT} = \alpha F_{stat} + \beta F_{phys} + \gamma F_{comb} , \quad \alpha + \beta + \gamma = 1 \tag{3}$$

where α, β, γ are the relative weights assigned to the statistical, physics-informed, and combined (hybrid) twin components respectively, and $F(\cdot) \in [0,1]$ denotes each component's fidelity score.

Following Section 4.1, the predicted energy consumption at time t is decomposed into trend, seasonal, and machine-learning residual components:

$$\hat{E}(t) = E_{trend}(t) + E_{season}(t) + f_{ML}(X(t)) + \varepsilon(t) \quad (4)$$

where E_trend and E_season capture long-horizon and seasonal effects respectively, f_ML(X(t)) is a learned correction term over exogenous features X(t) (e.g., wind contribution, hotelling wear, demand variation), and ε(t) is residual error.

The risk-adjusted predictive optimization objective (Section 4) balances operating cost against operational risk exposure over the planning horizon T:

$$J = \sum_{t=1}^{T} [\, c(t) E(t) + \lambda \, Risk(t) \,] \quad (5)$$

where c(t) is the energy price at time t, E(t) is scheduled consumption, Risk(t) is the risk-adjusted exposure term, and λ is the risk-aversion coefficient; the AII layer selects the Pareto-efficient schedule minimizing J.

The end-to-end sensing-to-actuation latency, which bounds how quickly the AII layer can convert a detected condition into a corrective action, is modeled additively across the architectural stages described in Section 3:

$$L_{total} = L_{sense} + L_{transmit} + L_{infer} + L_{actuate} \quad (6)$$

where the four terms correspond respectively to sensing acquisition, IT/OT data transmission, model inference, and actuator/controller response.

System availability under the redundancy and failover strategies discussed in Section 5.1 is modeled as:

$$A_{sys} = A_p + (1 - A_p) A_b P_{fo} \quad (7)$$

where A_p and A_b are the availabilities of the primary and backup components, and P_fo is the probability that failover is triggered successfully; this reduces to A_sys = A_p when no backup is provisioned (no-redundancy case).

Incident- and anomaly-detection performance of the AII monitoring layer (Section 3.1, graded alarm systems) is reported using the standard F1-score:

$$F_1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \quad (8)$$

where Precision and Recall are computed against labelled incident/anomaly events.

Finally, an Operational Resilience-Efficiency Index (OREI) is proposed to jointly summarize resilience, fidelity, availability, and responsiveness on a single normalized scale used in Section 6.3:

$$OREI = w_1 R_{AII} + w_2 F_{DT} + w_3 A_{sys} - w_4 \frac{L_{total}}{L_{max}} \tag{9}$$

where w_1–w_4 are normalized weights ($\Sigma w_i = 1$) and L_max is a reference latency ceiling for the deployment class.

6. Conclusions

Integrating the concepts from previous sections, the Intelligent Monitoring Framework constitutes a minimal solution toward an Autonomous Industrial Intelligence through increased perception, reasoning, adaptation, and self-learning capabilities, especially within the sensing, data acquisition, and Engine Digital Twin layers. The seamless embedding of these advanced capabilities enhances resilience through improved monitoring in the local sense, while other layers address incident response, safety interlocks, fault management, and corrective actions. Formal designs for next-generation systems will address the remaining AI principles, namely interoperability, reliability, safety, and scalability, as well as beyond-edge intelligence in charge of coordinating multiple solutions across the entire SAD framework.

It is reassuring to see that resiliency and fault tolerance are essential topics in the design of any SA framework, not just an AII. Nonetheless, there are still open questions, especially concerning patching or replacing a failed unit with a different technology type, redundancy schemes for safety-critical systems, and graceful degradation and continuity plans for non–safety-critical functions. Such considerations may also concern national critical infrastructures deployed in private, public, or hybrid organizations. In this respect, governance, safety management systems, and ISO 10019 compliance are still underdeveloped elements for Industrial AI capabilities and performance.

References

1. Berghout, T., Mouss, L.-H., Kadri, O., Saïdi, L., & Benbouzid, M. (2020). Aircraft engines remaining useful life prediction with an improved online sequential extreme learning machine. Applied Sciences, 10(3), 1062.
2. Deng, K., Zhang, X., Cheng, Y., Zheng, Z., et al. (2020). A remaining useful life prediction method with long-short term feature processing for aircraft engines. Applied Soft Computing, 93, 106344.
3. Sriram, H. K., Adusupalli, B., Singreddy, S., & Malempati, M. (2021). Revolutionizing risk assessment and financial ecosystems with smart automation, secure digital solutions, and advanced analytical frameworks. Murali, Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks (December 27, 2021).
4. Ji, S., Han, X., Hou, Y., & Song, Y. (2020). Remaining useful life prediction of airplane engine based on PCA–BLSTM. Sensors, 20(16), 4537.

5. Li, J., Chen, Y., Xiang, H., & Cai, Z. (2020). Remaining useful life prediction for aircraft engine based on LSTM-DBN. Systems Engineering and Electronics, 42(7), 1637–1644.
6. Wang, M., Li, Y., Zhang, Y., & Jia, L. (2021). Spatio-temporal graph convolutional neural network for remaining useful life estimation of aircraft engines. Aerospace Systems, 4, 29–36.
7. Recharla, M. (2020). Targeted Gene Therapy for Spinal Muscular Atrophy: Advances in Delivery Mechanisms and Clinical Outcomes. International Journal of Science and Research (IJSR), 9(12), 1921-1934.
8. Liu, L., Wang, L., & Yu, Z. (2021). Remaining useful life estimation of aircraft engines based on deep convolution neural network and LightGBM combination model. International Journal of Computational Intelligence Systems, 14, 165.
9. Fentaye, A. D., Zaccaria, V., & Kyprianidis, K. G. (2021). Aircraft engine performance monitoring and diagnostics based on deep convolutional neural networks. Machines, 9(12), 337.
10. Zhang, Y., Xin, Y., Liu, Z.-W., Chi, M., & Ma, G. (2022). Health status assessment and remaining useful life prediction of aero-engine based on BiGRU and MMoE. Reliability Engineering & System Safety, 220, 108263.
11. Liu, L., Song, X., & Zhou, Z. (2022). Aircraft engine remaining useful life estimation via a double attention-based data-driven architecture. Reliability Engineering & System Safety, 221, 108330.
12. Thakkar, U., & Chaoui, H. (2022). Remaining useful life prediction of an aircraft turbofan engine using deep layer recurrent neural networks. Actuators, 11(3), 67.
13. De Giorgi, M. G., Strafella, L., Menga, N., & Ficarella, A. (2022). Intelligent combined neural network and kernel principal component analysis tool for engine health monitoring purposes. Aerospace, 9(3), 118.
14. Jiang, W., Xu, Y., Chen, Z., Zhang, N., Xue, X., & Zhou, J. (2022). Measurement of health evolution tendency for aircraft engine using a data-driven method based on multi-scale series reconstruction and adaptive hybrid model. Measurement, 199, 111502.
15. Li, Y., et al. (2022). An enhanced CNN-LSTM remaining useful life prediction model for aircraft engine with attention mechanism. PeerJ Computer Science, 8, e1054.
16. Wang, H.-K., et al. (2021). Remaining useful life estimation of aircraft engines using a joint deep learning model based on TCNN and Transformer. Computational Intelligence and Neuroscience, 2021, Article 6659781.
17. Paleti, S. (2021). Cognitive core banking: A data-engineered, AI-infused architecture for proactive risk compliance management. AI-Infused Architecture for Proactive Risk Compliance Management (December 21, 2021).
18. Shi, G., Si, G., Xia, T., Pan, E., & Xi, L. (2020). Joint optimization strategy of predictive maintenance and tool replacement for energy consumption control. Journal of Shanghai Jiaotong University, 54(12), 1235–1243.
19. Bermeo-Ayerbe, M. A., Ocampo-Martinez, C., & Diaz-Rozo, J. (2022). Data-driven energy prediction modeling for both energy efficiency and maintenance in smart manufacturing systems. Energy, 238, 121691.
20. Yu, W., Patros, P., Young, B., Klinac, E., & Walmsley, T. G. (2022). Energy digital twin technology for industrial energy management: Classification, challenges and future. Renewable and Sustainable Energy Reviews, 161, 112407.
21. Park, H., Kwon, H., Cho, H., & Kim, J. (2022). A framework for energy optimization of distillation process using machine learning-based predictive model. Energy Science & Engineering, 10(6), 1913–1924.
22. Botlagunta, P. N., & Sheelam, G. K. (2020). Data-Driven Design and Validation Techniques in Advanced Chip Engineering. Global Research Development (GRD) ISSN, 2455-5703.
23. El Mazgualdi, C., Masrour, T., Barka, N., & El Hassani, I. (2022). A learning-based decision tool towards smart energy optimization in the manufacturing process. Systems, 10(5), 180.

24. Bousnina, K., Hamza, A., & Ben Yahia, N. (2022). Energy optimization for milling 304L steel using artificial intelligence methods. International Journal of Automotive and Mechanical Engineering, 19(3), 9928–9938.
25. Deon, B., Cotta, K. P., Silva, R. F. V., Batista, C. B., Justino, G. T., Freitas, G. C., Cordeiro, A. M., Barbosa, A. S., Loução, L. J., Simioni, T., Morais, A. M., Medeiros, I. E. A., Almeida, R. J. S., Araújo, C. A., Soares, C., & Padoin, N. (2022). Digital twin and machine learning for decision support in thermal power plant with combustion engines. Knowledge-Based Systems, 253, 109578.
26. Unal, P., Albayrak, Ö., Jomâa, M., Berre, A. J., et al. (2022). Data-driven artificial intelligence and predictive analytics for the maintenance of industrial machinery with hybrid and cognitive digital twins. In Technologies and Applications for Big Data Value (pp. 299–319). Springer.
27. Mashetty, S. (2022). Enhancing Financial Data Security And Business Resiliency In Housing Finance: Implementing AI-Powered Data Analytics, Deep Learning, And Cloud-Based Neural Networks For Cybersecurity And Risk Management. Migration Letters, 19(6), 1302-1818.
28. Marquez, A. C., et al. (2022). Predictive maintenance using digital twins: A systematic literature review. Information and Software Technology, 151, 107008.
29. Shi, G., Si, G., Xia, T., Pan, E., & Xi, L. (2020). Digital twin-enabled predictive maintenance and energy consumption optimization in manufacturing systems. Journal of Manufacturing Systems, 56, 1–12.
30. Fentaye, A. D., Zaccaria, V., & Kyprianidis, K. G. (2021). Aircraft engine health management using machine learning-based performance monitoring and diagnostics. Aerospace, 8, 1–15.