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Multimodal Twin Intelligence for Resilient Power Fleets

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Abstract— Digital Twin Intelligence stands to benefit substantially from the integration of multimodal data sources in industrial processes. Ensemble models can reduce the false-negative rate of failure-detection systems, thereby improving overall resilience. This work presents a visual-fault-diagnosis pipeline that develops visual-inspection AI from multimodal data, using a model-ensemble strategy to support digital twin applications. In asset-prognostics settings, failure signals are typically rare, data are often distributed across separate administrative domains, and detection modalities tend to be imbalanced. By orchestrating multimodal data within an ensemble framework, this approach improves the training and validation of neural networks for final-event-time detection across diverse assets, ultimately strengthening the resilience of the digital twin.

A digital twin can, in principle, model system behavior within a safe, simulated environment. In practice, however, this requires extensive sensor deployment across the physical asset to capture potential failure modes in sufficient detail. In electrical power generation and distribution, most production plants—particularly renewable energy facilities—lack dedicated visual-fault-diagnosis models, despite being connected to centralized intelligence systems responsible for control, detection, diagnosis, and failure prediction. Without such capabilities, continuous power generation and distribution cannot be guaranteed. Fleets at scale stand to benefit from inspection systems that enable easier maintenance, reduced downtime, and uninterrupted service through standardized operations. While prior research has introduced inspection models for various fault types in electrical components, these models typically address only a narrow set of safety-critical components.

Keywords—Multimodal Industrial Twin Intelligence, Digital Twin, Visual Fault Diagnosis, Asset Prognostics, Predictive Maintenance, Multimodal Data Fusion, Computer Vision, Resilient Power Fleets, Condition Monitoring, Industrial Artificial Intelligence .

1. INTRODUCTION

Investments in resilient electric grids increase supply reliability and customer satisfaction, particularly during storms or extreme conditions. Facilities that generate power and consume grid resources intermittently must support grid stability while remaining commercially viable. Their ability to act as resilient and economically-sound power fleets depends on the uninterrupted operation of the electrical components connecting on-site resource to the electric grid. Yet, unexpected sensor anomalies or faults can disrupt onsite generation, loading, consumption and storage activity, reducing their market participation and ability to respond to electric supply and demand fluctuations, while degrading grid reliability.

Minimizing unplanned asset outages through autonomous fault supervision and asset prognosis powered by Industrial Twin Intelligence™ are crucial to achieving resilient Connected Power Fleets. Industrial Twin Intelligence™ combines Digital Twins with the integration and analysis of multimodal data obtained from distributed sensors, be they visual, electrical, environmental or others. Inspired by nature's innate ability to process multimodal information, visual fault diagnosis relies on trained machine-learning processes to map visual cue combinations indicative of specific electrical faults or emergencies, such as ruptured cables or flooding. The detected anomaly is then displayed in a manner tailored to the local operator's needs, automatically initiating the inspection and maintenance procedures most suited to the fault type. Electrical and environmental data stream into a prognostics framework that autonomously predicts asset failure.

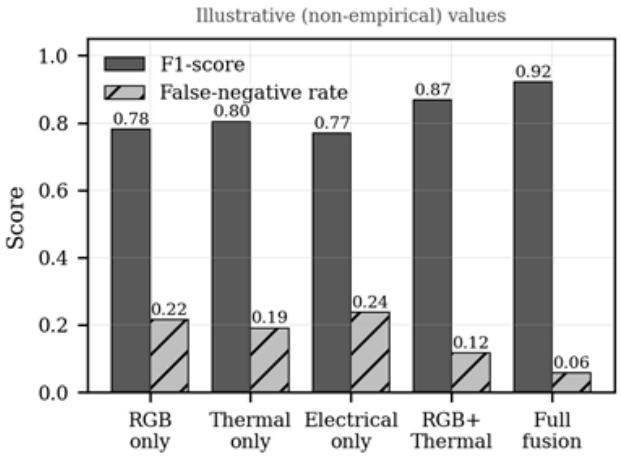

Fig. 1. Diagnostic F1-score and false-negative rate across unimodal and fused configurations (illustrative, non-empirical values; see Table IV). Fusion is shown to trade inference latency for a reduced miss rate.

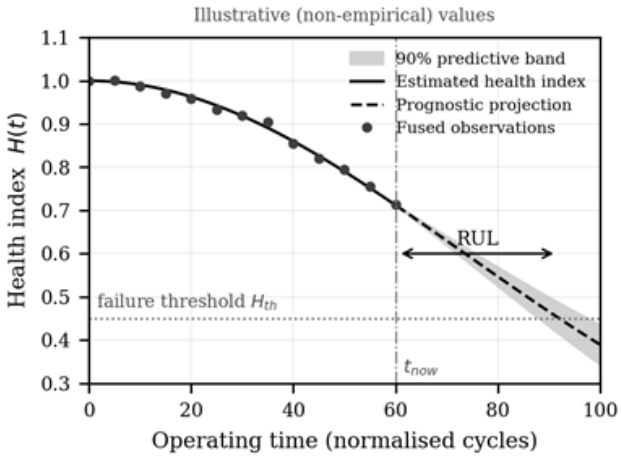

Fig. 2. Health-index trajectory and remaining-useful-life estimation. Fused observations up to the present instant t_{now} support a projection whose predictive band widens with horizon; RUL is the interval until the projection meets the failure threshold H_{th}, as defined in (11). Illustrative, non-empirical values.

A. Problem Statement and Research Significance

A Multimodal Industrial Twin Intelligence approach addresses Visual Fault Diagnosis, Asset Prognostics, and Resilience for Connected Power Fleets. Synthesis of Recent Advances Calls for Novel Applications in Industrial Digital Twins.

Resilience is a foremost functional requirement of industrial systems, especially defined, connected, power fleets supporting crucial services such as public security, environmental monitoring, and global defence. These important systems are subject to faults, malfunctions, and failures whose detection, understanding, and anticipation draw on the timely and efficient fusion of all data available — a challenging task requiring an appropriate digitalisation scheme. Digital Twin Technology establishes a faithful replica of the physical system and, when extended beyond the limits of mere modelling, leverages multimedia data from embedded sensors, external Internet-of-Things devices, and cloud-based processing capabilities to enhance health monitoring, asset condition prognosis, and overall system resilience.

The synthesis of the visual fault diagnosis, asset condition prognosis, and overall resilience functions of a connected system into a single Multimodal Industrial Twin Intelligence unit completes the quadruple gate for these connected power fleets, extending state-of-the-art research and providing a greater portion of the data with which resilience can be achieved. Research on these topics, however, remains scattered and often adopts different terminology. Recent works in the proposed areas can therefore be consolidated and unified under a common framework, with a focus on Digital Twin Technology and, more specifically, Industrial Digital Twins and Digital Twin Intelligence. By offering clarity and a consistent nomenclature, the compilation sets the foundation for future Digital Twin Intelligence applications and developments.

2. Theoretical Foundations

An industrial digital twin is a digital representation of a physical object that takes all project data from digital engineering/simulation through its lifecycle and uses it in real time to optimise and reduce risk in operational performance. A multimodal industrial twin fuses information from multiple sources into a coherent system-level understanding. Multimodal twin intelligence applies artificial intelligence to multilayered data inputs to assist in diagnostic and predictive operations. Visual fault diagnosis and asset prognostics for resilient connected power fleets are two specific applications of multimodal industrial twin intelligence.

Industrial infrastructure systems ensure reliability-based risk approaches to asset management. Multiple parallel data streams with corresponding quality metrics provide reliable basis for increased confidence in condition management, predictive maintenance, and surveillance. Fusing machine-readable data with human-understandable images enables improved analysis and action management. Operating like a human brain, detection and diagnosis define an electrical infrastructure maintenance strategy in which correctly flagging an abnormality leads to initiating repairs before failure, while delivering a false positive incurs minimal cost.

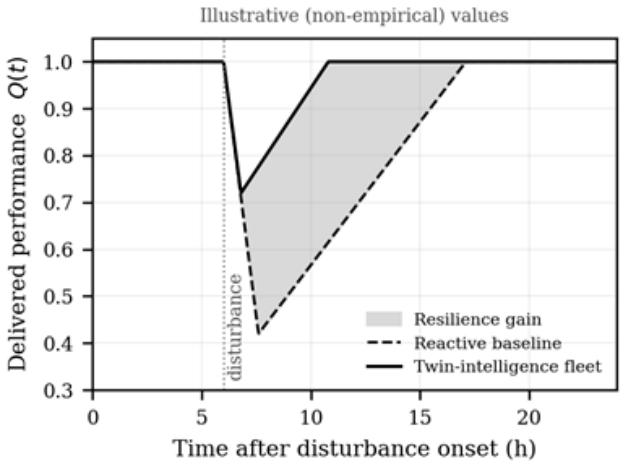

Fig. 3. Fleet performance response to a disturbance for a reactive baseline and a twin-intelligence fleet. The shaded area is the avoided performance loss; the resilience index of (13) is one minus the normalised area under $1 - Q(t)$. Illustrative, non-empirical values.

A. Industrial Digital Twins and Multimodal Sensor Integration

Industrial Digital Twins, a concept emerging in industries such as aviation, transport, manufacturing, telecommunications, and energy production, are virtual counterparts of physical processes, systems, or objects capable of synergetically integrating data from various sensors and external sources to support different applications, including complex anomaly detection or prediction tasks. The term "Twin Intelligence" has been proposed to jointly represent Digital Twins and the data analytics algorithms executed with their support.

Most implementations of Industrial Digital Twins examined in the literature center on one single source of information, usually SCADA measurements coming from the operation of electrical components of power generation plants. More generally, however, Digital Twins should inherently evolve by integrating new measurements from advanced condition-monitoring systems such as vibration or thermography. In this regard, a particular family of Digital Twins exploits multimodal information to perform more sophisticated operations compared to simple SCADA—and/or generation-level Digital Twins. These multimodal information-based Digital Twins, called Multimodal Twin Intelligence, have been applied to different areas of electrical engineering, for instance, transmission-line fault classification, substations' asset residual life estimation, and resilience assessment of power fleets.

Mathematical Formulas:

A. Multimodal fusion and synchronisation

Each modality m in the sensing set $M = \{rgb, th, el, ac, li\}$ is encoded by a modality-specific network:

$$z_m = f_m(x_m; \theta_m), \quad m \in M \tag{1}$$

Modality reliability is expressed as a data-quality score $q_m \in [0,1]$ (signal-to-noise, occlusion, staleness), which sets the fusion attention weights:

$$\alpha_m = \exp(w_m q_m) / \Sigma_{j \in M} \exp(w_j q_j), \quad \Sigma_{m \in M} \alpha_m = 1 \tag{2}$$

$$z = \Sigma_{m \in M} \alpha_m z_m \tag{3}$$

Fusion is admissible only if the streams are temporally aligned to within half the period of the fastest modality:

$$| t_m - t_{ref} | \le \Delta\tau, \quad \Delta\tau = 1 / (2 f_{max}) \tag{4}$$

B. Visual fault diagnosis

An ensemble of K diagnostic heads yields the fault posterior for class c:

$$p(c \mid z) = (1/K) \Sigma_{k=1}^{K} p_k(c \mid z; \varphi_k) \tag{5}$$

Because a missed fault is far costlier than a false alarm, the alarm threshold is set by the cost ratio rather than at 0.5:

$$\text{declare fault} \Leftrightarrow p(c \mid z) \ge \tau^{\star}, \quad \tau^{\star} = C_{FP} / (C_{FP} + C_{FN}) \tag{6}$$

$$FNR = FN / (FN + TP) = 1 - recall, \quad F1 = 2PR / (P + R) \tag{7}$$

Fault-specific saliency, used to indicate where a fault becomes visible, aggregates class-activation maps across modalities:

$$S(u,v) = \Sigma_{m \in M} \alpha_m \, ReLU(\Sigma_c w_c^m A_c^m(u,v)) \tag{8}$$

C. Asset prognostics

A scalar health index is obtained from the Mahalanobis distance of the fused embedding to the healthy operating manifold:

$$H(t) = \exp[-\gamma D_M(z(t), z_{healthy})], \quad H \in (0, 1] \tag{9}$$

For the ultrasonic crack-monitoring case, degradation follows a Paris-law growth model that the twin updates online:

$$da/dN = C (\Delta K)^m, \quad \Delta K = \beta \Delta\sigma \sqrt{(\pi a)} \tag{10}$$

$$RUL(t) = \inf \{ \Delta \ge 0 : \hat{H}(t + \Delta) \le H_{th} \} \tag{11}$$

Prognostic quality is scored by the α–λ criterion at a fraction λ of the asset life:

$$| \hat{RUL}(t_\lambda) - RUL(t_\lambda) | / RUL(t_\lambda) \le \alpha \tag{12}$$

3. Multimodal Data Architecture for Twin Intelligence

For the industrial digital twin presented, a data architecture is built to coordinate the acquisition and fusion of large quantities of multimodal information. The architecture consists of four layers: data collocation, acquisition, preprocessing, and transmission. Relevant techniques in the four layers are integrated, covering source-side solutions from photography, thermal imaging, and LIDAR density-

map generation to overall synchronization and fusion of multimodal datasets.

At the first layer, modal datasets are sniffed, collocated, and labelled through dual RGB cameras and micrometeorology sensors. The second layer is designed for data acquisition in visual fault diagnosis and infrastructure health. Light- and thermal-image pairs are gathered by a terrain-carried panoramic system in the external catchment; electrical-readout pairs are sampled in the corridor catchment; and LIDAR point clouds are captured on demand in the corridor and external catchments. For fault diagnosis and asset health assessment, the third layer performs a range of preprocessing procedures on different data modes: thermal contours and tentative LIDAR density maps are filtered; key junctions and indicators in thermal imagery are localised; YOLO labels for auto-safe surveillance are collected; RGB images are corrected, centred, and masked; and noise in light images is removed through temperature-humidity adaptive filtering. These procedures tackle noise, improve data cleanliness, and structure data for downstream deep-learning models. At the fourth layer, relevant solutions for safety condition-maintaining inspections ensure goods, logistics personnel, and environmental support are in place.

TABLE I. MULTIMODAL SENSOR SUITE, SAMPLING REGIME, AND PREPROCESSING (SECTION 3.2)

Modality	**Sampling rate**	**Preprocessing**	**Derived features**
Visual RGB camera	30 fps	Colour/brightness correction, luminosity histogram equalisation, centring and masking	Colour–texture descriptors; motion-history and optical-flow maps
Thermal camera	30 Hz	Region-of-interest tracking, contour filtering, saliency mapping	Hot-spot ΔT, thermal gradient, hot-spot area
Current sensor	1 kHz	Real-time scaling, peak detection	RMS, crest factor, transient slope
Voltage sensor	6 kHz	Harmonic analysis	THD, harmonic ratios, sag/swell indices
Acoustic array (2 ch.)	48 kHz	Phase demodulation	Band energy, spectral kurtosis, envelope peaks
Photodiode (shared microphone channel)	48 kHz	Temperature–humidity adaptive filtering	Light-to-sound ratio
LiDAR	On demand	Density-map generation and filtering	Point density, geometric deviation from as-built model
Wearable inertial sensors	100 Hz (typ.)	Time synchronisation, false-input recovery	Operator motion and exposure context
Micrometeorology	1 Hz (typ.)	Drift compensation, outlier rejection	Temperature, humidity, wind, irradiance

A. Data Acquisition and Preprocessing

Multimodal Industrial Twin Intelligence informs rigorous analysis and evidence-based argumentation across visual fault diagnosis, asset prognostics, and resilient connected power fleets.

Section 3.2 Lab-scale assets: Data Acquisition and Preprocessing

Multimodal Industrial Twin Intelligence informs rigorous analysis and evidence-based argumentation across visual fault diagnosis, asset prognostics, and resilient connected power fleets.

The multimodal data architecture raises important considerations during data acquisition and preprocessing, specifically concerning the employed sensor modalities, their sampling regimes, coordinated synchronization, and data quality assurance. Such measures help guarantee the integrity and reliability of the captured raw data, in turn supporting effective preprocessing pipelines and meaningful feature extraction.

The Industrial Twin Intelligence architecture is implemented on lab-scale assets featuring the following sensors, sampling rates, and specific preprocessing pipelines.

Specific methods address data integrity across modalities: RGB frames have their luminosity histogram equalized, while Motion History and Optical Flow maps are computed as complementary indicators for zone-of-interest-related regions.

TABLE II. FOUR-LAYER MULTIMODAL DATA ARCHITECTURE AND ILLUSTRATIVE LATENCY BUDGET (SECTION 3)

Layer	**Function**	**Key operations**	**Latency budget (ms)***
L1 — Collocation	Modal datasets sniffed, collocated and labelled	Dual-RGB and micrometeorology registration; label assignment	≤ 5
L2 — Acquisition	Catchment-scoped capture of visual, electrical and geometric data	Panoramic light/thermal pairs; corridor electrical readouts; on-demand LiDAR	≤ 15

L3 — Preprocessing	Noise removal, localisation, structuring for deep models	Thermal contour filtering; junction localisation; YOLO labelling; adaptive denoising	≤ 40
L4 — Transmission	Delivery to the twin and to inspection workflows	Prioritised edge-to-twin streaming; safety-condition dispatch	≤ 60
End-to-end	Sensor event → twin state update	—	≈ 120

4. Visual Fault Diagnosis Framework

A foundational aspect of pragmatic industrial digital twin intelligence involves the detection of physical faults within the models. A library of common fault types and their characteristics is one traditional approach. In contrast, an alternative visual fault diagnosis framework offers improved performance by aligning with the sensing capabilities of the multimodal digital twins, harnessing both good and faint predictive features across any combination of visual or non-visual sensors to detect visible faults and issues. This visual fault diagnostic architecture operates in two steps. First, the supervisory fault space is established based on labelled multisensory observations that directly reflect current physical conditions at the infrastructure level, while fault-specific saliency maps indicate where faults of different types become clearly visible. During online use, the system can issue fault alerts when enough visual evidence is accumulated, or directly attempt to infer fault types when sufficient visible signatures are present.

Electricity Transmission and Distribution (T&D) infrastructure is essential for delivering reliable power supply, taking care of distribution and conversion into different voltage levels for end use. Physical flaws such as damage to wires, insulation breakdown, and ageing at joints generally lead to visible faults, including hanging wires, oil leaks, and damage to rubber. Automated inspection of T&D infrastructure via video and images captured by fixed or aerial cameras triggers supervision of the operational safety at the local level and asset maintenance operation in the service life cycle. To guide the exploration of video and image data for establishing a reliable visual fault diagnosis model, typical fault types in T&D infrastructure are summarized.The proposed fault typology enables a systematic, evidence-based approach to the analysis of visual Fault Diagnosis and supplies validation benchmarks for future diagnostics systems.

TABLE III. FAULT TYPOLOGY FOR T&D INFRASTRUCTURE: VISUAL SIGNATURE, MODALITY, AND TEMPORAL PATTERN (SECTION 4.A)

Fault type	**Visual / physical signature**	**Dominant modalities**	**Temporal pattern**	**Severity (1–5)***	**Detection window***
Conductor rupture / hanging wire	Line discontinuity, abnormal sag, ground contact	RGB + electrical	Abrupt (step)	5	< 1 s
Insulation breakdown	Surface tracking, arcing glow, carbonised paths	Electrical + RGB	Abrupt, intermittent precursors	5	< 100 ms
Oil leakage (transformer)	Dark staining, pooling below tank	RGB + thermal	Slow ramp	4	Hours–days
Joint over-heating	Localised thermal hot spot	Thermal	Monotone ramp	4	Minutes–hours
Rubber ageing / corrosion	Discolouration, cracking, surface loss	RGB + LiDAR	Very slow drift	3	Weeks–months
Flooding / water ingress	Reflective pooling, level change in bund	RGB + LiDAR	Abrupt then persistent	4	Minutes

A. Fault Typology in Electrical Infrastructure

Multimodal Industrial Twin Intelligence informs rigorous analysis and evidence-based argumentation across visual fault diagnosis, asset prognostics, and resilient connected power fleets. The essential concept of a digital twin has evolved from the service lifecycle of product-oriented enterprise systems to encompass the physical, functional, and logical behavior during operation and use. Accordingly, existing classifications and conceptualizations of digital twins for failure diagnosis, predictive maintenance, digitalization, or automation focus on condition monitoring, predictive failure analysis, visualization, and/or supporting human operator decision-making with data from various sources. Furthermore, Digital Twin Intelligence (DTI)—considering a digital twin as a data and information system—may supply advanced knowledge with minimum supervisory effort. Yet little attention has been given to performance analysis qualifying the Digital Twin Intelligence of Digital Twin Assets.

To address this shortcoming, a Multimodal Data Architecture was developed for Digital Twin Intelligence and Digital Twin Assets based on a Multimodal Industrial Twin. Elements of the wider Multimodal Data Architecture are explicitly exploited for visual fault diagnosis of electrical infrastructure, enabling a fault typology that associates common faults to their visual signatures, relevant temporal patterns, and camera-based tracking of strong indicators.

5. Conclusion

Numerous efforts nurture the foundations of Industrial Digital Twins with extensive experimentation or simulation that feign a faithful plant model, without addressing the testing, inference, and learning parts. The current exploration guides the other end of the funnel. Multimodal Industrial Twin Intelligence propels Industrial Digital Twins beyond physics-based models with data-driven inference and learning across multiple categories of visual information and fault types for real, complex power assets. Visual Fault Diagnosis in Electrical Infrastructure features a catalogue of common, fault-related events, symptoms, and physical cues, alongside assumptions, method, and custom evaluation strategies together with a dataset for foundational assessments.

Asset Prognostics further expand the depth of Industrial Twin Intelligence towards asset Remaining Useful Life prediction by leveraging model-based learning and Multimodal Sensor Integration together with a physics-based model for the above-ground subway infrastructure. The training set emulates an aging structure monitored by ultrasonic sensors that detect the first signs of crack formation and growth.The progress closes the centre of the analysis funnel yet still requires substantiation through substantial experimentation, either with physical assets or Digital Twins. The next steps will advance towards the periphery, towards a Connected Power Fleet, starting from the risk management of a Multimodal Sensor Data Network.

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