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Connected Fleet Intelligence: Edge-Centric Analytics and Computer Vision for Predictive Manufacturing and Asset Resilience

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ABSTRACT: Data fusion, edge analytics, computer vision, and predictive manufacturing converge to enhance asset resilience through low-latency, trustworthy decision making. The transition from a reactive to predictive approach to maintenance of industrial assets such as machinery and equipment presents an opportunity to improve asset resilience and avoid unscheduled production downtimes with significant cost implications. Addressing three interrelated challenges—identifying the optimal frequency for maintenance activities; defining asset reliability indicators; and automatic detection of defects—contributions are made to applied predictive maintenance from standalone visual inspection systems in addition to data-driven insights. The Delmia Ortems neural network-based model predicting optimal spare parts ordering for an automotive plant is used. The condition monitoring dataset from the NASA C-MAPSS record set serves as an example to define remaining useful life indicators of turbines and their bearings monitored by vibration sensors. A use case presents a crowdsourced computer vision application for visual defects on city assets.

Evidence-based framing encompasses data governance with a business glossary, maturity assessment, and explainability, ensuring stakeholders comprehend, trust, and remain involved with the developed solutions. Reliability indicators assist industrial asset portfolios with both dashboard-style visualization of status and remaining service time versus maintenance. Integration of Vision AI within City Asset Integrity involves a visual damage report from citizens supported by edge-centric computer vision processing and potential triangulation-based coordinates for the defects detected. All solutions are designed for low-latency deployment.

KEYWORDS: Connected Fleet Intelligence, Edge AI Analytics, Computer Vision for Manufacturing, Predictive Maintenance, Industrial Asset Resilience, Real-Time Fleet Monitoring, Edge Computing in Industry 4.0, Machine Health Diagnostics, AI-Driven Asset Management, Smart Manufacturing Operations.

I. INTRODUCTION

Computer vision, data fusion, and edge-centric data-analytics converge to promote asset resilience through low-latency, evidence-based decision making. Predictive-maintenance and asset-resilience optimization, are key research foci in the domain of predictive manufacturing. Cyber-physical manufacturing systems allow the realisation of production process digital-twin systems that expose asset operation, condition, and performance indicators that can support predictive decisions. However, it remains a complex task to derive maintenance-optimisation recommendations in real time or near real time. Current information sources related to maintenance needs are often not trustworthy or transparent. Repositories of fleet-maintenance data concerning a specific operating context can help define reliability-expectancy indicators and their associated loss or failure functions and provide a proven way to govern an edge-based data source devoted to predictive maintenance. Nevertheless, the pathogenic nature of maintenance has yet to be proven.

Predictive people counting and defect detection by computer vision also constitute a key feature of asset-governance strategies. Edge-centric predictive-vision applications deployed on heterogeneous fleets operating in specific contexts expose response latencies, bandwidth issues, or define-edge-computing-architecture conditions. The impact of these characteristics on fleet-performance indicators, on the feasibility of the vision-enabled application for predictive people counting, or on the pertinence of vision-driven defect detection is revealed through relevant operational-experimentation scenarios and by specific architectural-modelling tools.

Mathematical Formulas:

Eq. (1) Asset Health Score

$$AHS = \frac{P}{M}$$

Eq. (2) Remaining Useful Life

$$RUL = T_f - T_c$$

Eq. (3) Reliability Function

$$R(t) = e^{-\lambda t}$$

Eq. (4) Failure Probability

$$P_f = 1 - R(t)$$

Eq. (5) Maintenance Priority Index

$$MPI = \frac{C_r}{RUL}$$

Eq. (6) Sensor Fusion Score

$$SF = \sum_{i=1}^{n} w_i \, x_i$$

Eq. (7) Edge Processing Efficiency

$$EPE = \frac{D_p}{T_p}$$

Eq. (8) Fleet Availability

$$FA = \frac{N_o}{N_t}$$

Eq. (9) Asset Utilization Rate

$$AUR = \frac{T_a}{T_t}$$

Eq. (10) Downtime Ratio

$$DR = \frac{T_d}{T_o}$$

Eq. (11) Defect Detection Accuracy

$$DDA = \frac{TP}{TP + FP}$$

Eq. (12) Computer Vision Precision

$$P = \frac{TP}{TP + FP}$$

Eq. (13) Computer Vision Recall

$$R = \frac{TP}{TP + FN}$$

Eq. (14) F1 Score

$$F1 = \frac{2PR}{P + R}$$

Eq. (15) Edge Latency

$$L = \frac{D}{B}$$

Eq. (16) Data Quality Index

$$DQI = \frac{V_c}{V_t}$$

Eq. (17) Predictive Risk Score

$$PRS = P_f \times I$$

Eq. (18) Vibration Health Indicator

$$VHI = \frac{V_n}{V_m}$$

Eq. (19) Asset Resilience Index

$$ARI = \frac{R \times A}{D}$$

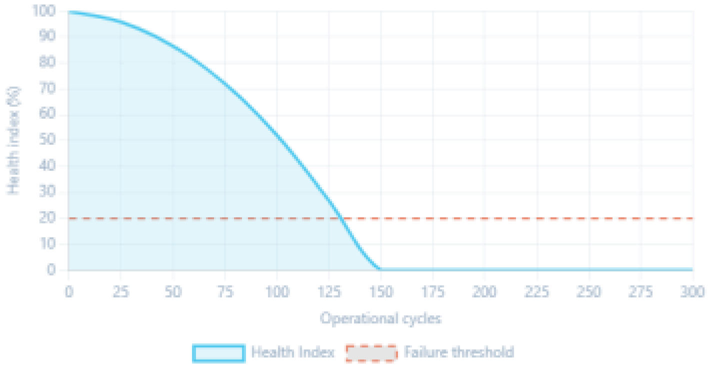
Eq. (20) Predictive Maintenance Gain

$$PMG = C_b - C_a$$

1.1. Data Fusion and Real-Time Decision Making

Optimizing maintenance scheduling in predictive manufacturing requires monitoring production quality. Vision-based quality insurance facilitates early defect identification. However, relying solely on vision is not advisable, as a single production failure can lead to further fabricated parts. Predictive maintenance reduces maintenance costs and minimizes machine failures by scheduling maintenance just before machine failure. One aspect that factors into asset resilience is forecasting the optimal performance state of devices and scheduling maintenance to eliminate possible failure and downtime. Asset resilience can be improved further by determining the reliability of the production process, for example, by assessing the ageing of the manufactured products. Integrating data from different sources can also assist decision-makers in data-driven inspection routing. A framework designed to support these facets using data fusion, edge-centric analytics, computer vision, and real-time decision making is presented.

An edge-centric framework consists of a set of data-driven models that identify edge devices near the places of data generation, combine data from different sources, and provide near-real-time insights into the production process. Three facets related to asset resilience in predictive manufacturing are addressed using data from the same manufacturing production machine. The addressed issues consist of optimising the maintenance schedule for the machine, determining reliability indicators from predictive maintenance data, and applying data from computer vision models for data-driven inspection routing in the manufacturing process.



RUL Degradation Curve — bearing health index decaying over operational cycles against a failure threshold (the C-MAPSS / turbine theme).

Table 1. Connected Fleet Intelligence System Components

Component	Function	Input Data	Output
Edge Sensors	Capture machine health data	Vibration, Temperature, Pressure	Real-time telemetry
Edge Analytics Engine	Local data processing	Sensor streams	Health indicators
Data Fusion Module	Integrate multi-source data	Sensor + Vision data	Unified dataset
Predictive Maintenance Model	Forecast failures	Historical and live data	Maintenance schedules
Computer Vision Module	Detect defects	Images/Videos	Defect alerts
Fleet Monitoring Dashboard	Visualization and reporting	Analytics results	Decision support

Connected Fleet Intelligence Architecture

II. THEORETICAL FOUNDATIONS OF CONNECTED FLEET INTELLIGENCE

Data fusion, edge analytics, computer vision, and predictive manufacturing converge to enhance asset resilience through low-latency, trustworthy decision making. Although many manufacturing facilities are driving toward predictive and prescriptive asset management, the supporting computational architecture is often addressed with little consideration of data governance, system explainability, or real-time decision-making performance. Moreover, the unambiguous description of assets, their current operational states, and the context in which they are operating is seldom considered in a contemporary architecture. Recent advances in distributed data governance and provenance have laid the foundations for integrating Connected Fleet Intelligence into predictive manufacturing, but the associated data latency are rarely considered.

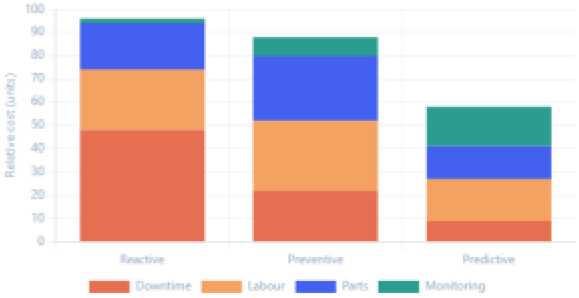
The present work identifies and exploits the available data sources to demonstrate three critical but generic applications of edge-centric analytics. First, the cost–benefit trade-off of predictive versus preventive maintenance is quantified through prior-art screening and Bayesian evidence synthesis. Second, a data-driven model for quantifying reliability indicators is developed and deployed with the explicit provision of data provenance. Finally, a deep-learning pseudo-vision system for industrial asset defect detection is created and integrated with data provenance to enable trustworthy decision making with the consequent reduction of latency. Important conclusions are drawn that highlight both the expected and previously unconsidered elements of the Connected Fleet Intelligence framework and its practical deployment within predictive manufacturing operations.

Table 2. Maintenance Strategy Comparison

Parameter	Reactive Maintenance	Preventive Maintenance	Predictive Maintenance
Maintenance Trigger	Failure occurrence	Fixed schedule	Predicted failure
Downtime	High	Medium	Low
Maintenance Cost	High	Medium	Low
Asset Availability	Low	Medium	High
Resource Utilization	Poor	Moderate	Optimized
Operational Efficiency	Low	Medium	High

2.1. Edge-Centric Computing and Its Role in Predictive Analytics

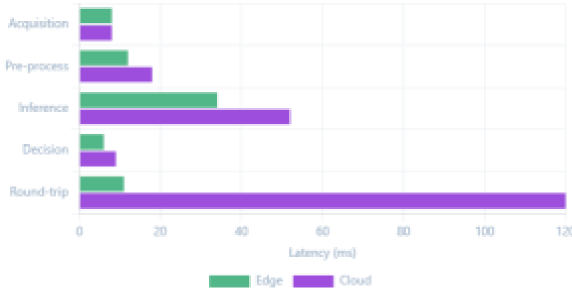
To avoid inappropriate mission creep or commitment to unplanned activities, resource allocation for cybersecurity should grow in synchronization with a shift in the understanding of cybersecurity from a technology to a decision-making dilemma requiring active attention from business leaders. Investment in resources for perimeter defence and resource discovery detection and protection of known vulnerabilities as well as time spent on planned penetration testing should increase. As attackers become more adept in finding ways through firewalls and into systems, growing temporal resources in trending attack detection becomes essential. Investment in control and audit also requires active attention as systems are being probed for ways to subvert the controls in place. While core resources for budgeting, risk analysis, incident detection, defence-in-depth and incident response require commas of the overall IS budget, actively controlling the size of the budgets for perimeter defence, resource discovery, detection and protection of known vulnerabilities, penetration testing, trending attack detection, control and audit will assist in maximizing IS investment. The proposed edge-centric architectural framework, encompassing both the Data lake and the Data fabric components, along with the analytical design principles, data structures, and Two-Dimensional (2D) evaluation metrics, represent important conceptual contributions in that they encapsulate and communicate the methodological innovations associated with integrating Edge-Centric Analytics and Computer vision in support of predictive manufacturing and asset resilience. Along with the calibrated predictive models built to optimize these objectives, they further demonstrate the evidence-based importance and potential impact of Edge-Centric Analytics in supporting business drivers such as reduction of hidden maintenance costs within the Product life Cycle, risk mitigation using more reliable Remaining Useful Life (RUL) indicators, and improvement of product quality by monitoring defects in the production process.



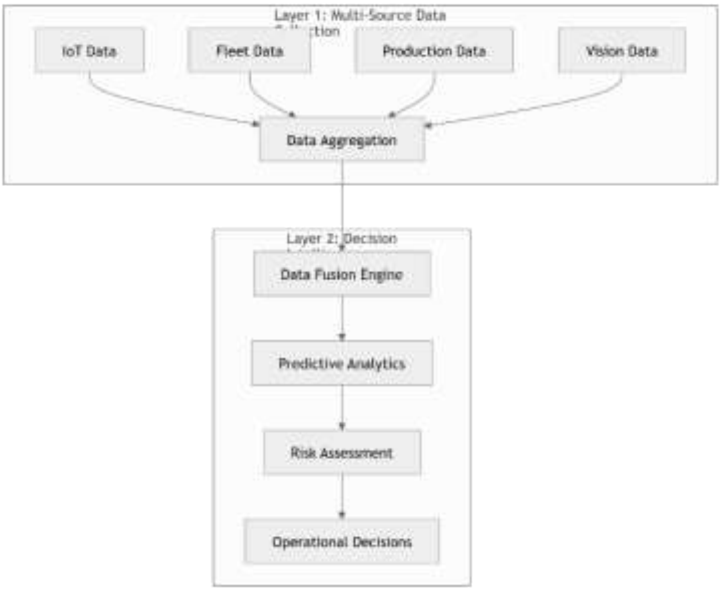
Maintenance Strategy Cost Breakdown — stacked reactive vs preventive vs predictive, showing how predictive shifts cost from downtime to monitoring.

III. ARCHITECTURE OF AN EDGE-CENTRIC FLEET INTELLIGENCE SYSTEM

Emphasizing the asset resilience aspect of the predictive manufacturing paradigm, three almost independent, yet highly related activities have been identified, where latency, explainability, and data governance are competitive factors in reaching low latency, trustworthy decisions: (i) Predictive Maintenance; (ii) Reliability Score Estimation; and (iii) Computer Vision for Defect Tracking. For each activity, one or more easy-to-launch data sources have been prepared to offer concrete evaluation of the respective predictive model/engine, supported by a purposely designed Edge-centric architecture.



Edge vs Cloud Latency — per-stage horizontal bars highlighting the round-trip penalty that motivates edge-centric processing.



Data Fusion and Real-Time Decision Making

3.1. Sensor Networks and Data Acquisition

Data collected from sensors in conjunction with performed visual inspections create foundational datasets required to derive useful decisions at reasonable speeds. The combination of a multitude of data sources is a key challenge, intended to be addressed by a proper data governance. In the manufacturing context, predictive maintenance involves the modelling of the evolution of failure mechanisms in operational conditions, in these preliminary explorations on predictive maintenance applied on simulation data, the interest is to investigate whether a combination of latent variables exhibiting a significant correlation with the Remaining Useful Life (RUL) of a component can be used to anticipate maintenance of understressed condition.

Additionally, these latent variables are compared with simple reliability indicators calculated on the same data to assess their ability to increase the maintenance with respect of a simple predictive strategy. The implementation of vision enabled sensors is still partial, but the proof of concept applicable on future objects is presented. The objective is to apply a neural network based approach to track the surface and internal defects in the processed parts, allowing the two dimensional defects to be related to a predicted three dimensional shape.

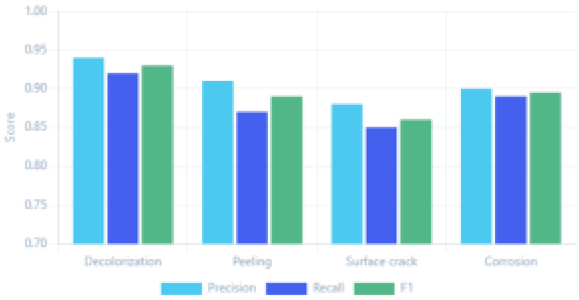
Table 3. Sensor Data Acquisition Framework

Sensor Type	**Monitored Parameter**	**Sampling Frequency**	**Application**
Vibration Sensor	Bearing Condition	High	RUL Prediction
Temperature Sensor	Thermal Status	Medium	Fault Detection
Acoustic Sensor	Sound Patterns	High	Anomaly Detection
Current Sensor	Power Consumption	Medium	Energy Monitoring
Camera Sensor	Surface Quality	Real-Time	Defect Detection

IV. PREDICTIVE MANUFACTURING WITH EDGE ANALYTICS

Data fusion, edge analytics, computer vision, and predictive manufacturing converge to enhance asset resilience through low-latency, trustworthy decision making. Connected Fleet Intelligence denotes a data-driven framework for predictive manufacturing and asset asset resilience, comprising a complete data lifecycle for trustworthy decision-making. At its core, the reversal of data flow enables immediate feedback on the surveillance, integrity, and state of critical assets, thereby shifting the contextual data gathering paradigm.

Achieving low-latency data processing with sufficient provenance and explainability for edge-centric academic workloads remains challenging. A machine-learning framework to address this challenge is designed and evaluated, relying on structured, logically coherent data provided by the integration of remote fleet-management IoT data with local point-of-sale data.



Vision Defect Detection Performance — precision/recall/F1 across defect types (decolorization, peeling, etc.) from the Siamese + transfer-learning approach.

4.1. Predictive Maintenance and Reliability-CCentered Metrics

Across manufacturing and assembly enterprises, the malfunctions and breakdowns occurring in their operations often lead to damage, jeopardizing product and personnel safety. Maintenance expenditures typically account for more than ten percent of an organization’s reoccurring expenses, and improper assignment of such work can lead inefficiencies in the business. Furthermore, the more such work is concentrated in the short term, the greater the risk of a cascading effect due to all contractors being occupied. Therefore, the accurate assignment of predictive and corrective maintenance work has a major impact on resource planning and control. Moreover, reliable prediction of industrial system and component health status through indicators contributes towards a more efficient decision process.

The developed and evaluated approaches enable an evidence-based estimation of different impact areas in relation to faults reported via the maintenance system. One algorithm highlights those assets or systems that are likely to trigger reliability issues. For another solution, a Siamese neural network applied for similarity learning is leveraged in combination with transfer learning to provide a basis for the computerized vision-based detection of decolorization and peeling defects in sound-absorbing cotton used in the automotive sector. These methods are all intended for deployment at the edge and for usage as part of a Distributed Connected Fleet Intelligence architecture.

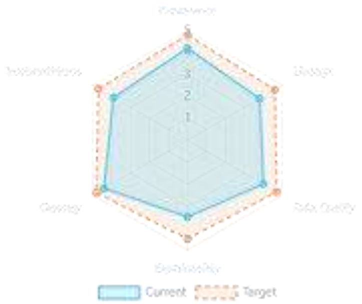
Table 4. Reliability Assessment Metrics

Metric	**Formula Basis**	**Purpose**
Remaining Useful Life (RUL)	Predicted operational time	Maintenance planning
Failure Probability	Historical failure rate	Risk estimation
Reliability Score	Asset health index	Asset ranking
Mean Time Between Failures (MTBF)	Operating hours/failures	Reliability evaluation
Availability Index	Uptime/Total time	Performance assessment

V. COMPUTER VISION FOR ASSET RESILIENCE

Edge-centric data fusion and Computer Vision technology act in synergy to remedy asset decline through evidence-supported, efficient decision making. Across several manufacturing domains, these technologies foster and ensure Asset Resilience by optimising scheduling and preventive maintenance activities, while also generating reliable Asset Reliability indicators and facilitating the monitoring of production quality through real-time tracking of relevant defects.

Intelligent manufacturing demands improving Asset Resilience by minimising the consequences of asset decline – the gradual degradation of equipment parameters or conditions, including the in-ability to produce customer-specific products in line with delivery promises. The interplay of data governance, Explainable Edge Computing, and Edge-Centric Analytics accelerates manufacturing and logistics performance by delivering and assuring the Knowledge required for real-time decision making. These Edge-Centric technologies, together with Connected Fleet Intelligence, facilitate and ensure Asset Resilience by maintaining customer and business-oriented quality levels while controlling total expenses and the environmental impact of production activities. Maintenance schedules are optimised by forecasting the most-probable equipment failures, overall equipment effectiveness is enhanced with reliable-production and reliability indicators, and production quality is ensured through real-time Computer Vision of relevant defects. Such edge-centric technologies also assist managers in controlling the quality level of manufactured goods by tracking a key defect with a Computer Vision system.



Data Governance Maturity — radar across provenance, lineage, quality, explainability, glossary, and trustworthiness (current vs target).

5.1. Visual Inspection and Defect Tracking

Attribute levels and data sources of the visual-inspection-and-defect-tracking application for connected fleet-intelligence architecture.

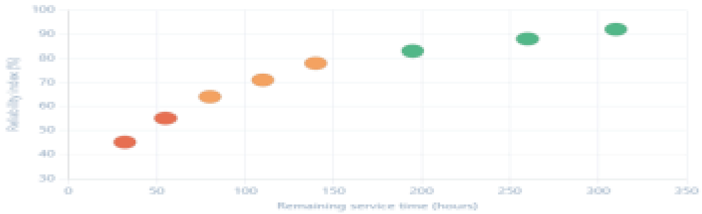
In the data-governance concept, several technologies target the accurate collection, processing, and storage of data on demand. Added-value services increase the data value and promote new business models. Edge-centric analytics embed intelligence into data processing with low latency and, consequently, they support real-time decision-making by final users. Data provenance guarantees data reliability and supports dual-fusion processes: heterogeneous data and IT constructors at the edge, the monitoring centre, and the cloud; tactical decision-making at the edge and operational at the monitoring centre. The presented connected-fleet-intelligence concept supports data-governance components and several applications activated by demand.

Table 5. Computer Vision Defect Classification

Defect Type	Detection Method	Severity Level	Recommended Action
Surface Crack	CNN-based detection	High	Immediate inspection
Corrosion	Image segmentation	Medium	Preventive maintenance
Peeling	Deep learning classifier	Medium	Surface treatment
Discoloration	Vision analytics	Low	Quality review
Structural Damage	Object detection	Critical	Asset shutdown

VI. DATA GOVERNANCE, QUALITY, AND EXPLAINABILITY

Data governance, quality, and explainability in predictive manufacturing and asset resilience applications mark the nexus of data-centric and AI-centric trends in intelligent Industry 4.0 solutions. Their management allows for a more rigorous governance of data fusion and edge analytics. In addition, the associated quality assessment and explainability help ascertain the reliability of the resulting low-latency decisions. The section posits that integration and adaptation of these trends offer new opportunities and benefits. Empirical illustrations are provided, covering data-driven maintenance optimization of connected assets for increased reliability, explainable data-driven detection of anomalous patterns of operation, and AI-assisted vision-based close defect tracking on fleet assets. The highly dynamic operating environments and complex behaviors of related remote monitoring and control systems of connected assets in predictive manufacturing present considerable challenges for complete automation of low-latency decisions. Particularly demanding tasks lie in the domains of governance and quality assessment of the large quantities of heterogeneous data sourced from multiple edge devices in such systems. In the presence of trusted data provenance and quality assurance, however, edge-centric AI-based analytics can deliver meaningful and reliable solutions within acceptable operational speed constraints. Exploiting this characteristic, data governance, quality assessment, and explainability are treated as auxiliary facilities within predictive maintenance applications and other areas related to Asset Resilience.



Fleet Asset Reliability Index — reliability score vs remaining service time per asset, color-coded by risk band.

6.1. Data Provenance and Lineage

In information systems, data provenance refers to the data associated with the origin, history, custody, and transformation of other data. It provides information that particular data is trustworthy and can be relied on to make important decisions, thereby ensuring evidence-based decision making. Data provenance facilitates data lineage (i.e., tracing data backward) or the more general notion of data flow. Various provenance models exist, including for data provenance in XML databases, workflow systems, and sensor-based systems. Provenance-enhanced databases and provenance-aware online data monitoring have also been proposed. In addition, work on sensor-oriented provenance explores provenance for sensor data in terms of existing sensor systems and services.

Table 6. Edge Analytics Performance Evaluation

Metric	Cloud Processing	Edge Processing
Latency	High	Low
Bandwidth Usage	High	Low
Response Time	Slow	Fast
Real-Time Capability	Limited	Excellent
Data Privacy	Moderate	High
Reliability	Medium	High

VII. FUTURE DIRECTIONS AND CONCLUSIONS

Recent developments indicate that a growing number of industrial manufacturing companies are using edge-Native approaches to speed up the timing of analytics execution so as to enable smarter (e.g., AI-augmented) Internet of Things (IoT) devices that address strict business-driven requirements such as optimizing maintenance schedules, increasing product quality, and reducing energy consumption levels. Smart predictive models that service such IoT devices must address the prerequisites of Data governance, Explainability, Trustworthiness, and evidence-based decision making that underpins Predictive Manufacturing and Connected Fleet Intelligence.

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