JOURNAL OF INNOVATIVE ACADEMIC RESEARCH
ISSN : 3049-2122
VOLUME: 04 ISSUE: 02
RECEIVED: APRIL 25 REVISED: MAY 02 ACCEPTED: MAY 27 PUBLISHED: JUNE 13

Networked Intelligence for Mission-Critical Asset Maintenance

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Abstract

A Distributed Cognitive Maintenance Framework enables network-operated devices to create knowledge through data-informed reasoning and local actions. For mission-critical environments, Machine-to-Machine communication speed, reliability, availability, and consistency must be secured and continuously monitored. External interfaces and device behaviour must comply with security considerations and avoid congesting network bottlenecks during abnormal operation. Data traffic volume has to be proportional to the information gained. Moreover, independent device adaptation must not cause functional degradation of peer devices nor reduce overall network preparedness to handle deviations.

Existing devices operating at the edge of a Fog/Cloud environment are capable of supporting data collection and inference. They can reason locally, adapt operation to local context, and create knowledge that may benefit others. Reasoning capability, decision process transparency, and redundancy through cooperation may enable the application of cognitive maintenance, where local actions, knowledge-discovery processes, and information-sharing are applied to ensure availability. Cognitive maintenance should be considered an alternative, complementary, or add-on to preventive maintenance, condition-based maintenance, and predictive maintenance approaches.

Keywords: Cognitive maintenance, Resilience, Edge intelligence, Distributed reasoning, Manufacturing execution, Logistics, Control theory, Cyber–physical systems, Intrusion detection, Security management, Pollution management, Crisis management, Network management, Logistics management, Autonomous vehicles, Transport systems, Traffic control, Mission-critical networks, Condition-based maintenance, Predictive maintenance, Cloud computing, Fog computing, Edge computing .

1. Introduction

Mission-critical industrial networks must support real-time and non-real-time information flows for the accurate execution of Manufacturing Execution System (MES) and Logistic Execution System (LES) processes. Network maintenance relies on service-level agreements negotiated between stakeholders. Non-adherence to service-level guarantees causes severe operational disruptions and financial losses. The existing Confucius-said principle of preventive maintenance does not provide the desired operational reliability, especially in critical network deployments, raising the need for additional embedded cognitive intelligence. Distributed Cognitive Maintenance (DCM) that integrates intelligence into all devices located at the edge of the network enables continuous and automatic decision-making capabilities supporting transparent anomaly-detection routines and self-healing functionalities. DCM is realized through Distributed Cognitive–Reasoning Mechanisms (DCRM) based on individual maintenance capacities and collaborative redundancy. Enhancing network condition-awareness improves Distributed Cognitive Maintenance Reliability (DCMRR).

Table 1. Mission-Critical Network Performance Requirements

JOURNAL OF INNOVATIVE ACADEMIC RESEARCH
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VOLUME: 04 ISSUE: 02
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Parameter	Description	Importance in Cognitive Maintenance	Example Impact
Reliability	Ability of the network to operate continuously without failure	Ensures uninterrupted industrial operations	Prevents production downtime
Availability	Percentage of operational uptime	Maintains execution continuity of MES and LES systems	Reduces financial loss
Latency	Delay in data transmission and response	Enables real-time anomaly response	Faster fault mitigation
Security	Protection against malicious attacks and unauthorized access	Preserves integrity of autonomous systems	Prevents cyber intrusions
Scalability	Ability to support growing device populations	Supports expanding industrial infrastructures	Enables flexible deployment
Resilience	Capacity to recover from failures or attacks	Enhances operational continuity	Supports self-healing systems

1.1. Mission-Critical Network Requirements

Mission-critical networks must meet stringent requirements to enable the dependable operation of high-value automated systems. Reliability, latency, availability, security, scalability, and resilience are crucial attributes. Reliability implies that a mission-critical network operates correctly at least within acceptable bounds of frequency and duration. Low latency assures safe and timely operation in applications where the natural environmental processes involved unfold in the time scales of motion, manoeuvre, or control of movement.Sufficient availability ensures that business processes do not fail, skip steps, or achieve intermediates of insufficient quality for those latter steps not to require rework. Network security is paramount in mission-critical environments where the consequences of termination, or the alteration of behaviour, of the processes being supported are under consideration. Mission-critical machines or installations should operate correctly for billions of hours before a failure event occurs. A mission-critical network is capable of executing an arbitrarily chosen process, out of a given set of such processes, that fails with very low probability, and yet such a capability neither protects against security threats nor obviates the necessity of ensuring adequate availability. Resilient, responsive, fault-tolerant, flexible, and adaptive operation to attack, failure, or malfunction affects reliability, resilience, and security. It is commonplace to regard security and availability as being in conflict, but Distributed Cognitive Maintenance can enable harmony between these two attributes.

Relevant stakeholders encompass management, executives, engineers, development engineers, repairmen, field technicians, operators, and service customers. The environments considered include stock exchanges, embassies, prisons, hospitals, stock exchanges, automated teller machines, air traffic control, public state-services support, and metropolitan water management. Placing user-owned systems at the edge of serviceproviders’ systems is a natural solution to such availability.

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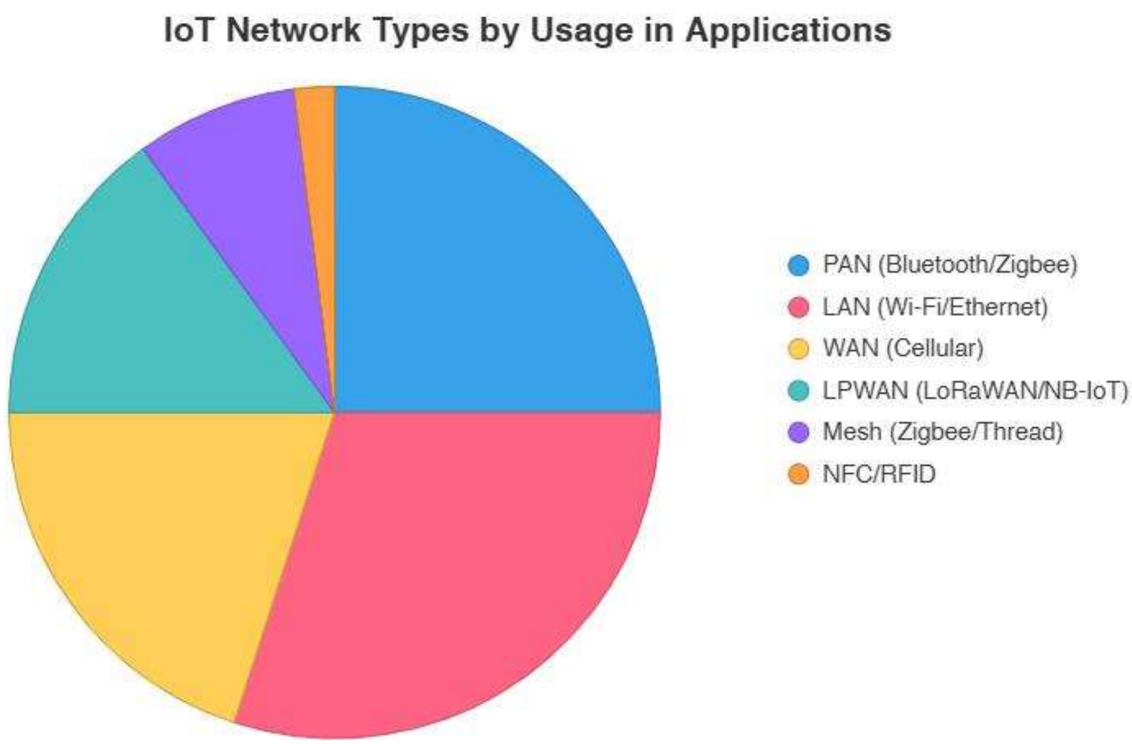

2. Background and Motivation

Research on maintenance aims to sustain the operational flow of devices, systems, physical spaces, and entire infrastructures. Distributed Cognition and Edge Computing are part of the wider domain of cognition. Cognition can also contribute to the proper operation of the associated services by hosting reasoning algorithms to support local decision-making, foster adaptation among autonomous nodes, and minimize the load and latency of interaction with the Cloud. Manufacturing Execution and Logistics orchestrate the actions of devices in the physical infrastructure. They need to be supported by information flows, control loops, and point-wise decisions. The respective data sources, timing requirements, and interdependencies must be identified.

Maintenance is a concern of nearly all industrial sectors due to the need to make production pipelines run as continuously, safely, and efficiently as possible. For manufacturing operators, such as power distributors, train service providers, and chemical plant owners, taking a reactive posture in maintenance is not an option anymore. Rather, the rapid development of Information and Communication Technologies (ICT) allows for the concept of Predictive Maintenance to quickly evolve into Condition-Based

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Maintenance and even Cognitive Maintenance. Nevertheless, these latter approaches have not yet been scaled down to the actual decision points within the industrial infrastructures nor have they been assigned to individual devices. By contrast, Device-Embedded Intelligence has been applying Distributed Cognition principles to non-mission-critical industrial networks. It has leveraged low-cost edge and Cloud systems using Distributed Cognition terminology to design a collaborative Machine Learning (ML) model among spatially proximate devices. Decision-making, reasoning, and Coordination among them can also be instrumented with such devices' native features.

Distributed Cognitive Maintenance Operational Stack

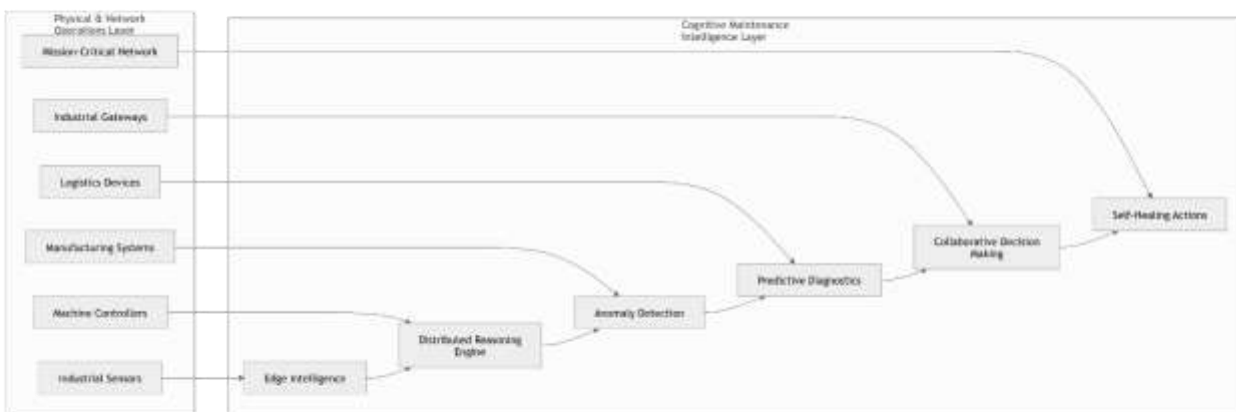

Table 2. Comparison of Maintenance Approaches

Maintenance Type	Decision Authority	Data Usage	Response Nature	Intelligence Level
Preventive Maintenance	External maintenance teams	Periodic inspection data	Scheduled	Low
Condition-Based Maintenance	Monitoring systems	Sensor condition data	Reactive/Threshold-based	Moderate
Predictive Maintenance	AI/Analytics platforms	Historical and real-time data	Predictive	High
Cognitive Maintenance	Distributed intelligent devices	Distributed contextual data	Autonomous and collaborative	Very High

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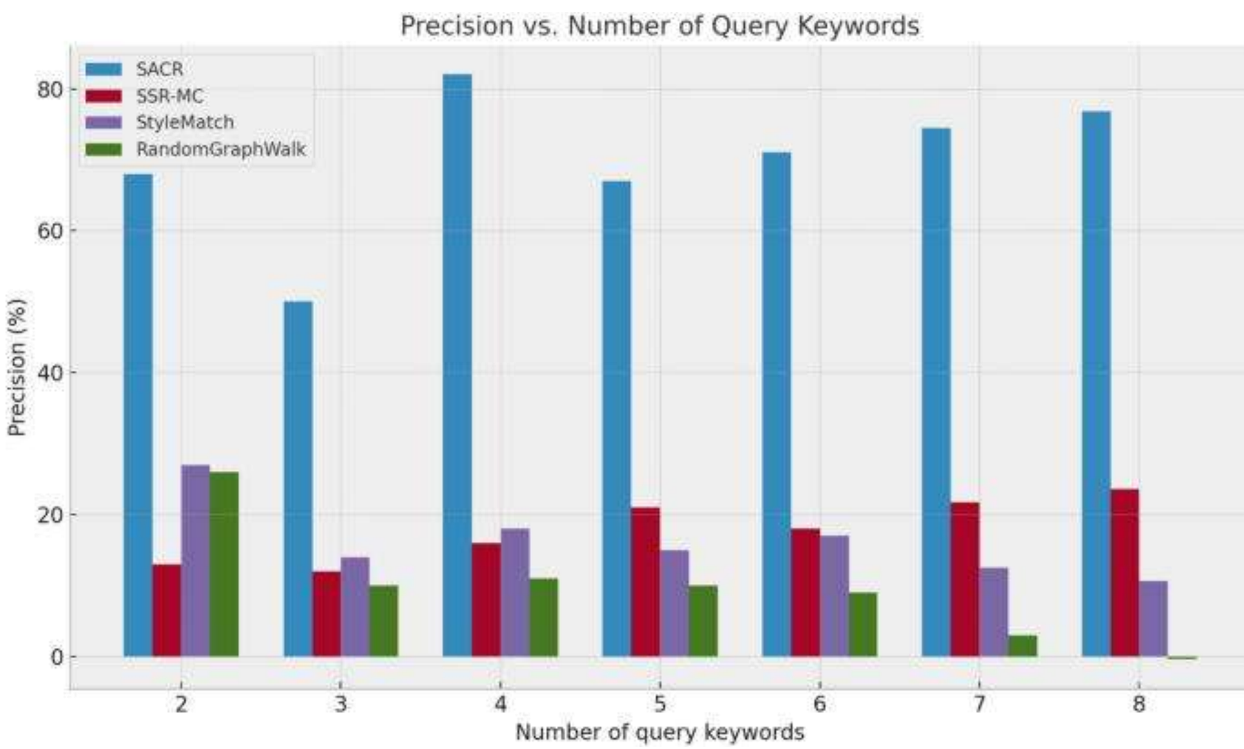
2.1. Manufacturing Execution and Logistics

Manufacturing execution and logistics are key domains of industrial information technology. A wide spectrum of information travels through these areas, including its geometry, quantity, frequency, timeliness, content, and recipient or source. A great deal of it is also shared between the production and logistics managements, although it ultimately has different meanings for each and must fulfil different delivery and detection constraints.

Production control can be modelled as a number of information-flow paths and closed control loops involving different types of controllers that act at various time scales. The information pathways are usually dictated by the actual manufacturing information, whereas the moment those data elements must be detected and/or delivered is determined by the operation of the relevant decision-making units. However, the fulfilment of the different timing constraints often relies on operations coordinated by the different control loops that control the sources of such data, giving rise to conflict situations. The fact that these operations require the cooperation of several production resources may also pose additional management and coordination problems, especially when routing and resource selection involve important costs or when the time allowed for such decisions becomes limited.



3. Conceptual Foundations

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Cognitive maintenance differs from traditional preventive maintenance, condition-based maintenance, and predictive maintenance in scope and intent. The core constructs of cognitive maintenance, the related terminology, and the theoretical framing are established. Cognitive maintenance refers to all activities associated with the information- and decision-centric maintenance of mission-critical industrial networks, performed by specialized actors using specialized sensor-to-action loops and decentralized reasoning capabilities.

Distributed Intelligence denotes the capability of using less consolidated intelligence through more frequent adaptations. Distributed Cognition describes a process in which information is used and transformed at multiple places and decision-making is enacted in many places by specialized (not necessarily human) agents acting jointly. Edge-Hosted Reasoning characterizes a situation where data-intensive intermediate-level analytics are hosted near the data source and context and temporal constraints are satisfied without overloading the network. Resilience is the capacity to absorb disturbances and still retain the same basic structure and ways of functioning. Redundancy is the presence of extra components that are not strictly necessary to the functioning of a system but that support the system when a part fails, and Collaboration is a process where two or more parties work together to realize outcomes that could not be realized independently. Together, these constructs set the stage for more detailed elaboration of Distributed Cognitive Maintenance.

Table 3. Distributed Cognitive Maintenance Framework Layers

Layer	Main Function	Components	Key Characteristics
Edge Layer	Real-time sensing and local reasoning	Sensors, controllers, actuators	Ultra-low latency
Fog Layer	Intermediate reasoning and coordination	Fog servers, edge intelligence modules	Distributed analytics
Cloud Layer	Model training and global optimization	Cloud AI platforms, data centers	Scalability and centralized learning

Mathematical Formulas:

1. Distributed Cognitive Maintenance Reliability Model (DCMRR)

The framework emphasizes reliability improvement through distributed cognition and collaborative redundancy.

$$DCMRR = \frac{\sum_{i=1}^{N} R_i \times C_i}{N}$$

Where:

- R_i= Reliability score of node i
- C_i= Cognitive adaptation coefficient

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- N= Total number of distributed nodes

2. Edge Intelligence Latency Optimization

Edge-hosted reasoning minimizes communication latency between industrial devices and decision systems.

$$L_{total} = L_{edge} + L_{fog} + L_{cloud}$$

Optimization objective:

$$\min(L_{total})$$

Where:

- L_{edge}= Edge processing latency
- L_{fog}= Fog layer latency
- L_{cloud}= Cloud communication latency

3. Predictive Maintenance Failure Probability

Used for predictive diagnostics and anomaly forecasting.

$$P_f(t) = 1 - e^{-\lambda t}$$

Where:

- $P_f(t)$= Probability of failure at time t
- λ= Failure rate
- t= Operational time

4. Sensor-to-Action Cognitive Feedback Loop

The paper repeatedly discusses sensor-to-action loops for autonomous maintenance.

$$A(t+1) = A(t) + \alpha(S(t) - D(t))$$

Where:

- $A(t)$= Action state

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- $S(t)$= Sensor observation
- $D(t)$= Desired operational state
- α= Learning/adaptation coefficient

5. Distributed Anomaly Detection Function

Relevant to intrusion detection and abnormal operation management.

$$AD(x) = \begin{cases} 1, & |x-\mu| > k\sigma \\ 0, & \text{otherwise} \end{cases}$$

Where:

- x= Current observation
- μ= Mean operational behavior
- σ= Standard deviation
- k= Threshold factor

6. Network Availability Equation

Mission-critical systems require extremely high availability.

$$Availability = \frac{MTBF}{MTBF + MTTR}$$

Where:

- $MTBF$= Mean Time Between Failures
- $MTTR$= Mean Time To Repair

7. Distributed Knowledge Sharing Efficiency

The framework discusses collaborative reasoning among nodes.

$$KSE = \frac{K_s}{B_w \times T_d}$$

Where:

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- KSE= Knowledge sharing efficiency
- K_s= Shared knowledge volume
- B_w= Bandwidth consumption
- T_d= Transmission delay

8. Edge Resource Utilization Model

Used for edge/fog computational balancing.

$$RU = \frac{CPU_u + MEM_u + NET_u}{3}$$

Where:

- CPU_u= CPU utilization
- MEM_u= Memory utilization
- NET_u= Network utilization

9. Predictive Health Monitoring Score

Supports health-state estimation before maintenance execution.

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

Where:

- H_s= Health score
- w_i= Feature importance weight
- x_i= Sensor feature input

10. Distributed Decision Confidence Model

Used for collaborative edge reasoning.

$$DC = \frac{\sum_{i=1}^{N} P_i \times W_i}{\sum_{i=1}^{N} W_i}$$

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Where:

- DC= Decision confidence
- P_i= Prediction from node i
- W_i= Trust weight of node i

11. Cognitive Maintenance Cost Optimization

$$C_{total} = C_m + C_f + C_d$$

Minimize:

$$\min(C_{total})$$

Where:

- C_m= Maintenance cost
- C_f= Failure recovery cost
- C_d= Downtime cost

12. Edge-Based Federated Learning Aggregation

Aligned with distributed industrial intelligence and collaborative model updates.

$$W_{global} = \sum_{i=1}^{N} \frac{n_i}{n} W_i$$

Where:

- W_i= Local model parameters
- n_i= Local dataset size
- n= Total data size
- W_{global}= Aggregated global model

13. Reliability–Security Tradeoff Function

The paper discusses balancing availability and security.

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$$RSI = \beta R + (1 - \beta)S$$

Where:

- RSI= Reliability-security index
- R= Reliability score
- S= Security score
- β= Balancing factor

14. Data Predictive Value Decay Across Layers

The paper states predictive value decreases with transmission delay across layers.

$$PV(t) = PV_0 e^{-kt}$$

Where:

- $PV(t)$= Predictive value after delay
- PV_0= Initial predictive value
- k= Decay constant
- t= Time delay

15. Maintenance Action Priority Function

$$MAP = \gamma_1 F_r + \gamma_2 C_r + \gamma_3 A_s$$

Where:

- F_r= Failure risk
- C_r= Criticality rating
- A_s= Asset severity
- $\gamma_1, \gamma_2, \gamma_3$= Priority weights

3.1. Cognitive Maintenance Principals

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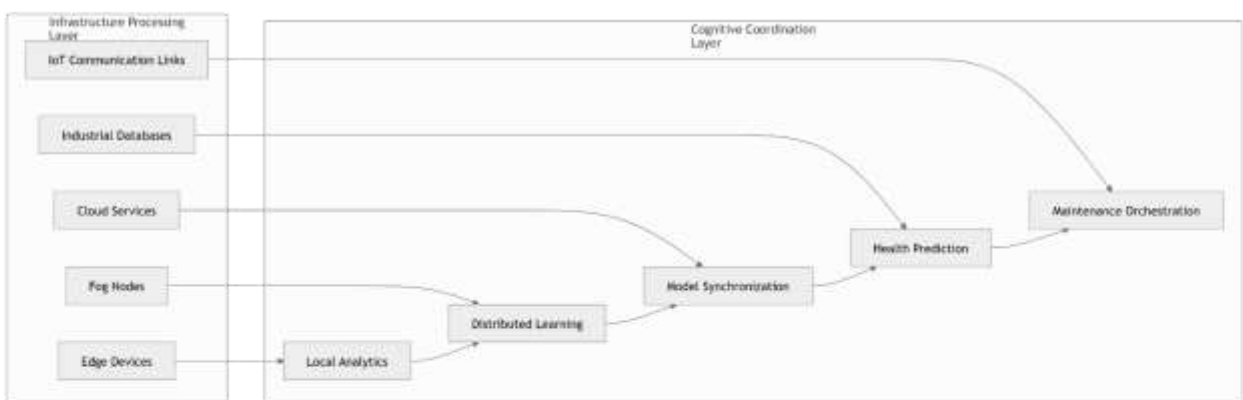
Distributed cognitive maintenance is distinct from preventive maintenance, condition-based maintenance, and predictive maintenance while encompassing attributes of these maintenance modalities. The identification of principle patterns provides a foundation for further decomposition into constructs that address the full range of maintenance activities. Temporal and resource scheduling, both for data collection and cognitive actions, is a necessary characteristic of a cognitive maintenance framework. Enabling near real-time information about health and performance and facilitating fault detection and diagnosis is an equally obvious requirement. Data-based machine-learning methods are crucial enablers of predictive diagnosis that shifts the focus of maintenance actions toward safety-critical events. Transitioning from implicit to explicit knowledge through a data-driven model that supports both fault condition and system health modelling is a hallmark of cognitive functions.

The deployment of machine-learning methods has surpassed the domain of technical data science specialists. Anomaly detection is the cognitive process most readily associated with sensing data. However, sensing data may also assist with the automation of action or restoration after action, while predictive health monitoring clarifies the health state of the system just before action is taken. The location of these data sources can vary geographically across the network or can occur within a single node, depending on the location of their physical components, physical control loops, and resource coordination needs. These factors influence the timing of synchronisation.

Edge–Fog–Cloud Cognitive Coordination



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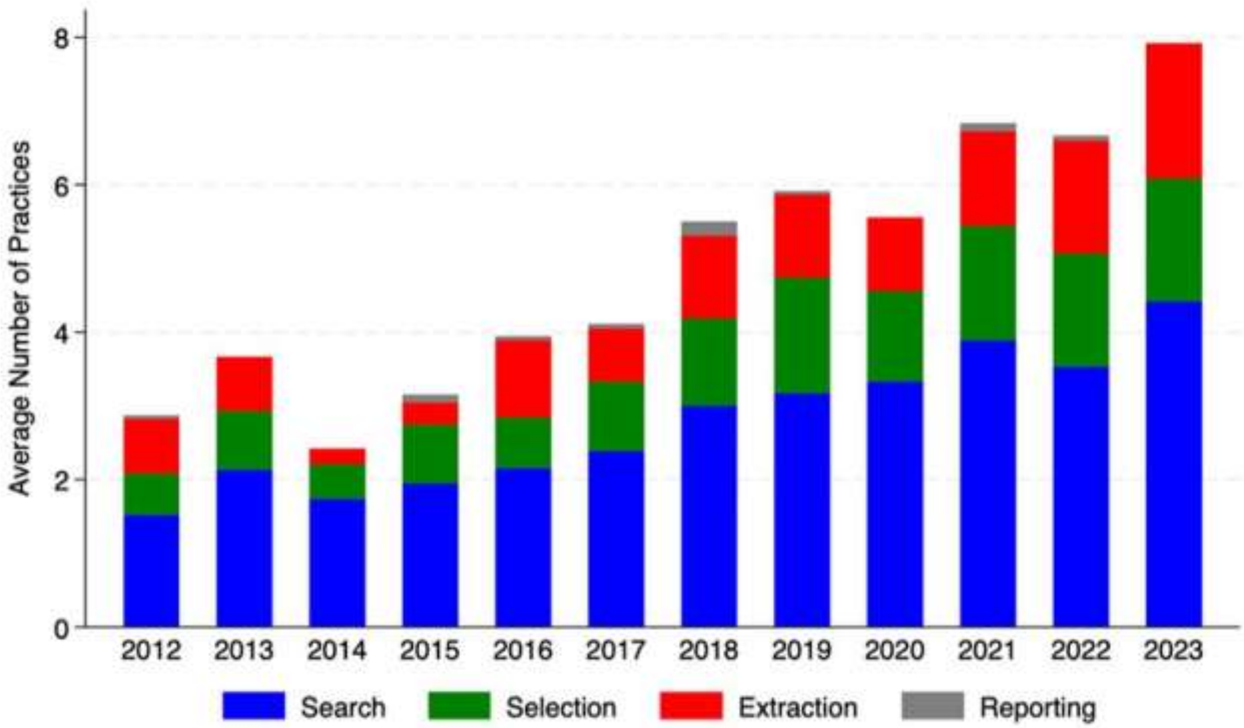

4. System Model and Assumptions

A formal model of the system facilitates thought process, reveals its strengths and weaknesses, and provides the basis for exploration. Formal assumptions are introduced to relate to previous cognitive maintenance models. The general system model expresses the concept with minimal detail, presenting actors, interfaces, and objectives. Evaluation criteria and metrics extend the structure for validation. The model focuses on distributed cognition and maintenance across an industrial network.

Industrial networks for the execution of manufacturing processes and logistics are composed of interconnected industrial equipment—machines, subsystems, tools, vehicles, and infrastructure—that autonomously or semi-autonomously perform actions. The equipment exchanges data, assumptions, conclusions, inferences, decisions, commands, corrections, and information necessary for monitoring, controlling, and managing its individual operation. Inherent properties that enhance cognition and reduce knowledge asymmetry of participating devices contribute to build a reliable, safe, and efficient production and logistic process.

Table 4. Distributed Cognitive Mechanism Components

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Component	Role	Techniques Used	Expected Outcome
Law-Makers	Define operational policies	Rule engines, policy management	Standardized maintenance actions
Local Reasoners	Perform local analytics and inference	Decision trees, Bayesian models, SVM	Autonomous diagnosis
Action Executors	Execute corrective operations	Sensor-to-action loops	Self-healing behavior
Collaborative Nodes	Share operational intelligence	Distributed communication protocols	Redundancy and resilience

4.1. Network Topology and Components

Distributed Cognitive Maintenance Framework for Mission-Critical Industrial Networks

A mission-critical network is depicted in Figure 1. Its topological structure and components conform to the definitions provided earlier. The network is organized in a three-layered arrangement, comprising edge, fog, and cloud segments. Information typically travels between nodes within the same layer or to the layer immediately above or below. The operation of a manufacturing execution network, including the controls, logic, and connectivity, inherently ensures a flow of information throughout the network.

Edges are directly connected to physical processes. They include the simplest edge-hosted controllers executing dedicated logic and the most advanced ones capable of local autonomy. The direct connection to the process allows the exchange of any volume of data collected by dedicated sensors. The real-time high rate of the data and time-critical latency should imply lossless capture. Consequently, the most time-sensitive information is retained inside the edge. When maintenance operations require data to be collected across layers, the additional end-to-end time brings a drop in data predictive value. The normal functioning of the edge ensures continuous information recycling, including model updates based on corrections as part of a sensor-to-action loop. If these models are up to date, an anomalous condition should anyway trigger data collection.

The fog is a distributed layer located in close proximity to the edge-hosted controllers, which should be technologically capable of hosting more complex reasoning systems, such as those enabling edge intelligence. Fog hosts condense and execute the reasoning process of a set of proximate edges. The consolidation of reasoning supports lower-end devices at the edges of the controlled process. These devices can be even simpler than the simplest edge-hosted controllers; their governance is completely delegated to the proximate fog hosts. The distributed cognitive maintenance process supporting all edges must guarantee proper coordination by addressing and solving conflictive situations among devices with no local reasoning capability.

Data that flow toward the cloud are not time critical. Time intervals between layers are thus much wider. The knowledge gained at the edges and fogs guides advanced offline maintenance actions, is validated, and exercises the training of machine-learning models. One dedicated cloud-hosting service supports the training and validation of all models throughout the industrial network.

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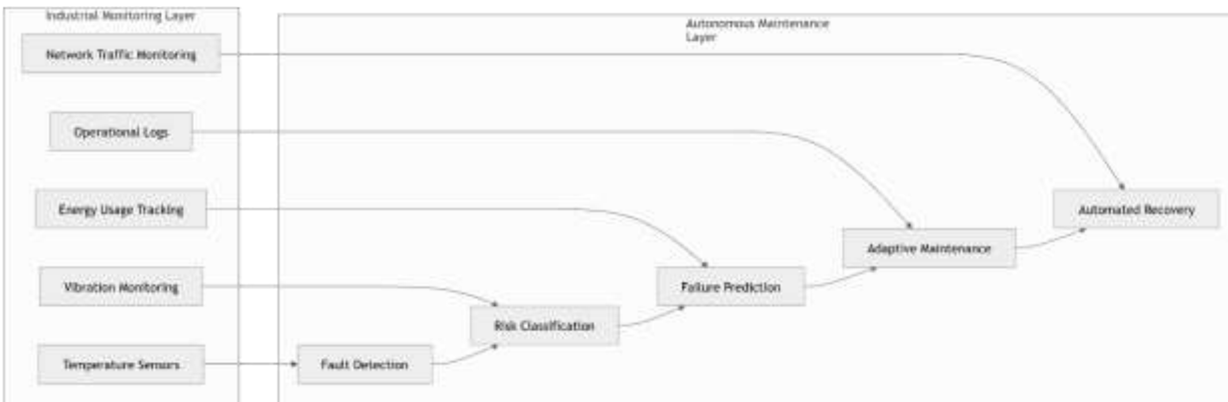
Any model updated or trained is injected into any other layer, be it edge, fog, or cloud. Hence, scalability is attained through the computational cloud, with demand dynamically distributed through the fog tiles keeping the latency at a bearable level.

Predictive Maintenance and Autonomous Response



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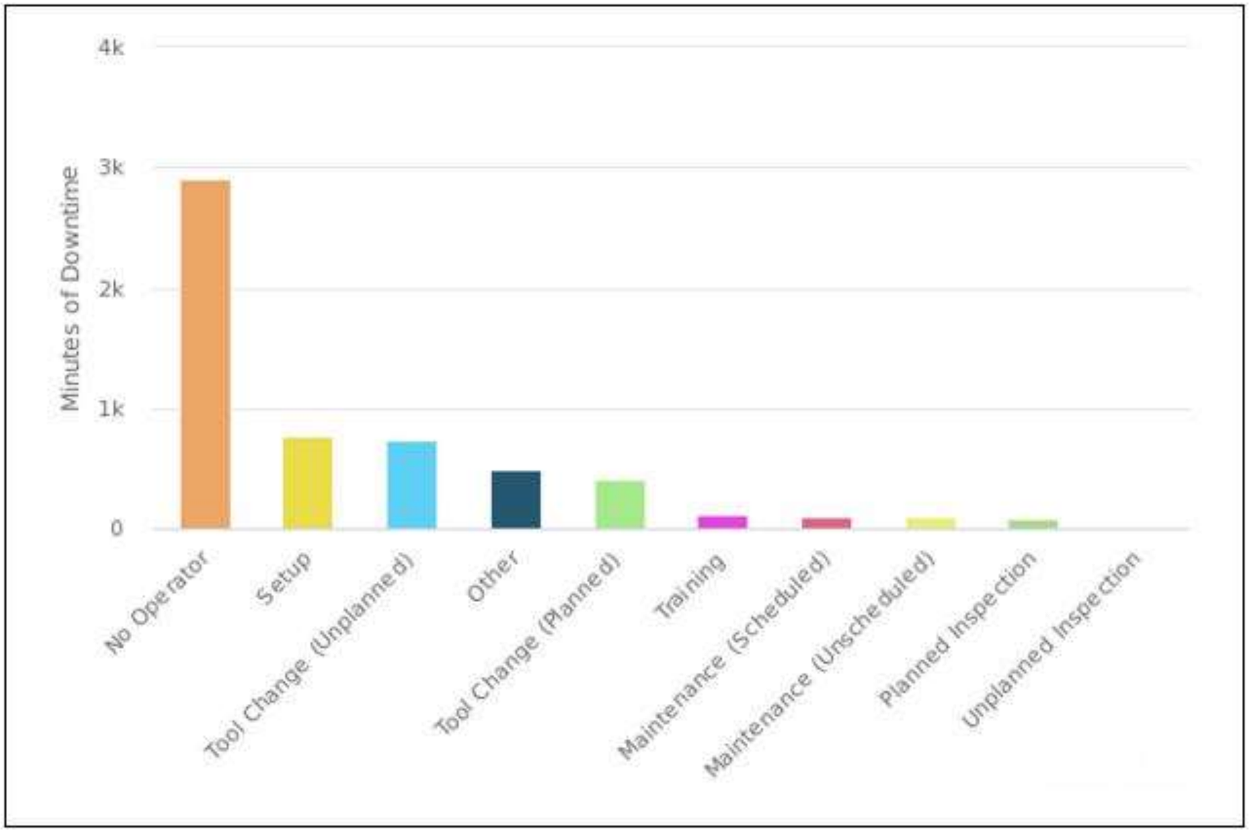

5. Distributed Cognitive Mechanisms

Local reasoning, edge intelligence, and collaborative adaptation empower network nodes to shape the decision space based on their specialized perception of the environment. The cognitive architecture at each node is composed of the following layers: law-makers, local reasoners, and action executors. Law-makers are responsible for establishing, enforcing, or suggesting action policies for the node or for other actors operating within the node's perception range. Local reasoners deploy basic information fusion methods, such as decision trees, Bayesian classifiers, support vector machines, and other supervised or non-supervised classifiers capable of handling the available resources.

Action executions are service-oriented modules that operate sensor-to-action loops to sustain localized functionalities. When armed with prediction models of the monitored objects, these actions can deploy automated measures, such as adaptive task allocation, corrective adjustments, and preventive actions. Their functioning introduces a proactive dimension in maintenance cognitive

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processes, as the information coming out of maintenance action performing units serves for updating data and predictive models across the network. Whenever actors running these types of functions can communicate, predict-model updates can exchange horizon, frequency of their referential data, and context of operation in order to ease local predictive modeling. Information about past operation states for which maintenance tasks triggered alarms, be it preventive through condition-based maintenance, corrective, or ideal (evidence of non-existent need for maintenance), can provide the needed data for the models at other nodes.

Table 5. Edge Intelligence Functionalities

Functionality	Description	Benefit
Local Data Processing	Processing data near the source	Reduced latency
Real-Time Analytics	Continuous anomaly evaluation	Faster detection
Distributed Learning	Sharing model updates across nodes	Adaptive intelligence
Data Fusion	Combining multiple sensor inputs	Improved prediction accuracy
Autonomous Adaptation	Self-adjusting operational behavior	Increased reliability

5.1. Local Reasoning and Edge Intelligence

Local reasoning mechanisms determine the maintenance actions of individual nodes, addressing the most pressing needs according to locally available information. All nodes possess basic reasoning capabilities realized by sensors, actuators, and a simple decision process enabling data-driven repetition of actions triggered by observed conditions. Such inherent reasoning capabilities can be further enhanced through the integration of local cognitive modules into spatially distributed edge servers. With access to real-time data streams from nearby nodes, edge-hosted reasoning can serve common distant sources of information and bypass the inherent limitations related to bandwidth, availability, and reliability of wide-area networks. Relying on data fusion techniques, edge-hosted reasoning can get a clearer picture of ongoing activities in the near neighborhood, enabling more reliable inference processes and more complex diagnostics, prognostics, and health management tasks.

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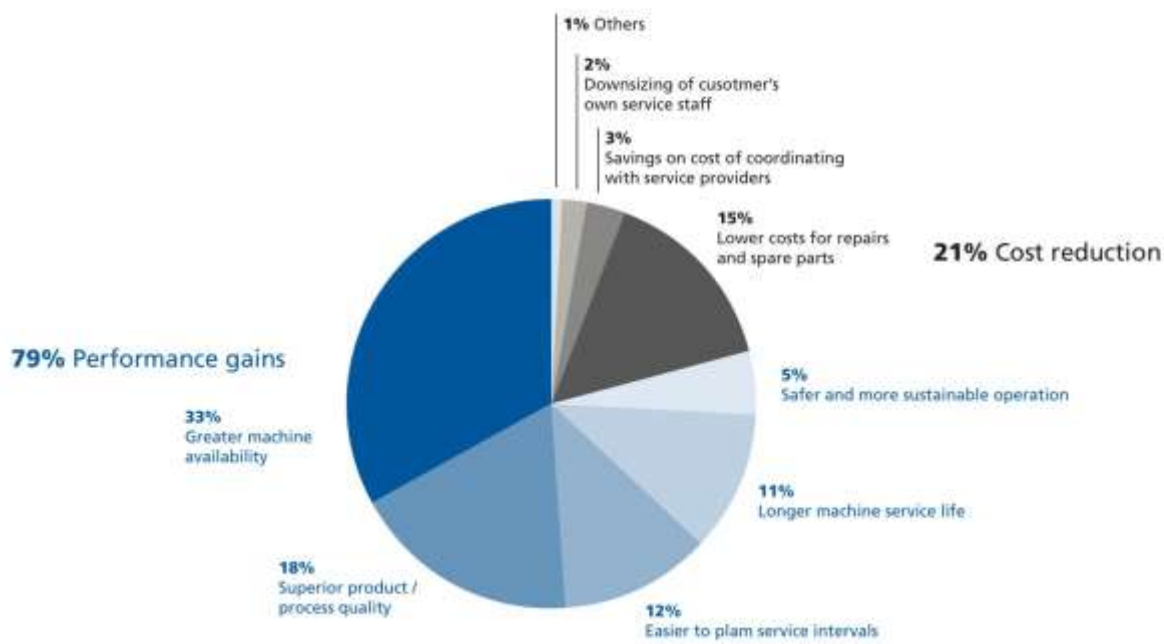

6. Maintenance Operations and Protocols

Maintenance operations, defined as activities executed on components to assure their healthy operation, in a cognizant context require the instantiation of protocols. These protocols govern the gathering of data, the inference and reasoning, the decision-making, and the accomplished action. Examples of maintenance operations include inspection, cleaning, adjusting, lubricating, repairing, updating, faulting, and replacing. In particular, operations performed on the physical components of the network potentially affect the physical condition of those components and probably add an extra risk. A prescription, limiting the occurrence of these operations to a specified subset of the network during a defined period, can lessen this risk. Hence, maintenance operations can belong to three categories: data collection, analysis and reasoning, and execution.

Maintenance activities are performed in tight relation with operation data and the autonomous nature of the process gives rise to the concept of predictive diagnostics. Indeed, the execution of predefined data collection routines enables the pre-emptive training of models, which is valuable in an unprepared scenario. Predictive diagnostics encompass anomaly detection, prognostics, health monitoring, and provide information essential to reasoning and decision-making. Such operations can be satisfied with a simple data pipeline, as the feature engineering is part of the pipeline in such a paradigm, and only the execution plan should preserve the model prediction.

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Table 6. Predictive Diagnostics Operations

Predictive Diagnostic Activity	Input Data	AI/ML Technique	Maintenance Outcome
Anomaly Detection	Sensor streams	Machine Learning classifiers	Early fault discovery
Prognostics	Historical degradation patterns	Deep learning models	Remaining useful life prediction
Health Monitoring	Operational telemetry	Statistical inference	Continuous condition awareness
Predictive Alerting	Environmental and operational data	Predictive analytics	Reduced unexpected failures

6.1. Predictive Diagnostics

Preventive maintenance (PM) actions, as the name implies, aim to prevent future failures. The expert responsible for maintenance runs tests, volunteers information, or executes maintenance-related tasks at pre-established times (scheduled PM). The machine may be out of operation during some of these different kinds of actions. Maintenance Operations will need to be further specified to determine what predictive diagnostics means in concrete operational terms. Potential examples lie at the intersection of Predictive Diagnostics and Maintenance Operations. The first example depicts a machine running at the operating point of high temperature. In general, high-temperature operation reduces air filter lifetime, oil deteriorates faster, and battery usage increases. Consequently, a temperature sensor FAC offers a predictive signal for these different components.

Predictive ranges based on domain knowledge can be developed for any Analytics with a clear effect on degradation rates. Predictive diagnostic capabilities steer maintenance-related diagnostics towards non-intended consumption patterns that impact component lifetime. Two examples follow. The first example shows a chiller operating with the water intake too low, where potential predictive range could stem from accumulative AI Modeling. The second example depicts a Controlled Temperature Area where too much power is used, opening the door for Actions to optimize operating levels.

Local-level reasoning mechanisms comprise the components of the local-loop architecture and enable sensor-to-action processes. Whenever a condition can be clearly associated with a triggered action that provides a beneficial effect, a simple pattern is established and constantly updated overtime by means of a simple rule-based learning process. Beyond data-driven repetitions, more elaborated reasoning approaches are suggested. Based on hidden Markov models, spatial–temporal patterns from diverse sources can be captured and used for requirements prediction. Partial coverage of the data-driven approach can also be relaxed through data imputation techniques, allowing updates and interdependence recognition despite the temporal absence of information.

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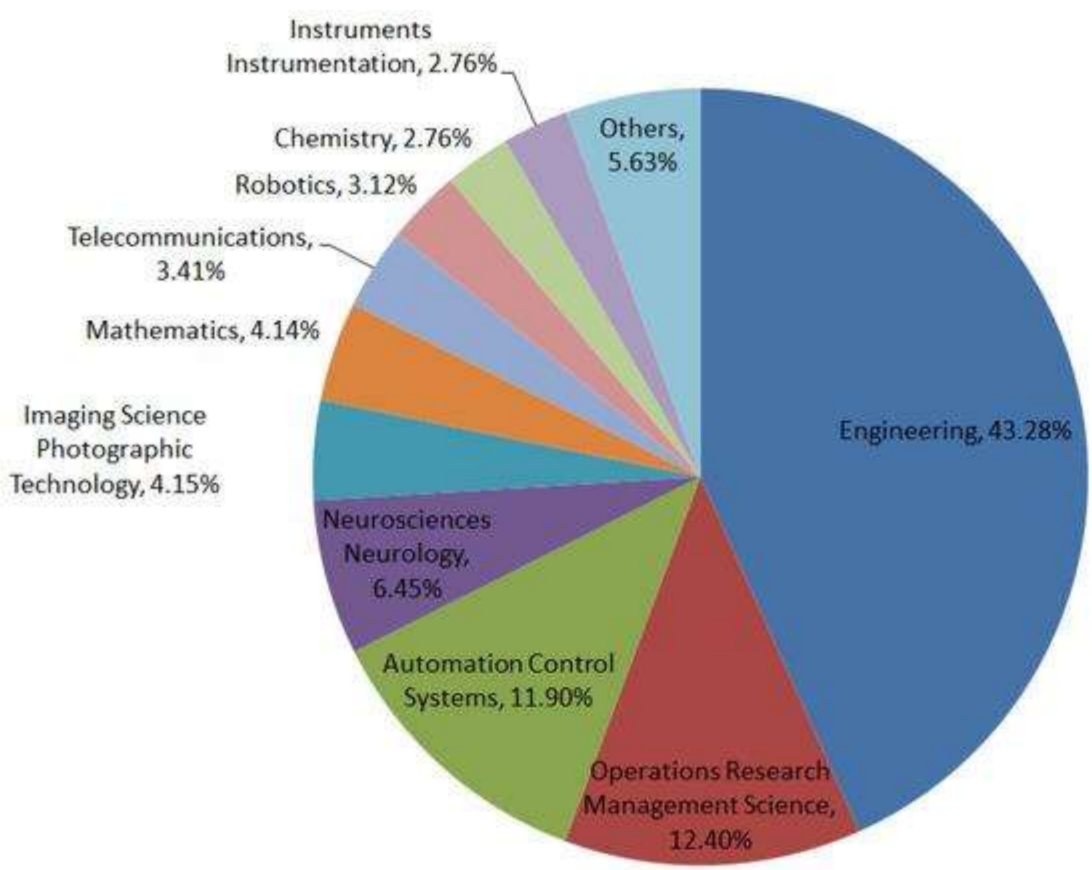
ISSN : 3049-2122
VOLUME: 04 ISSUE: 02
RECEIVED: APRIL 25 REVISED: MAY 02 ACCEPTED: MAY 27 PUBLISHED: JUNE 13

Local-level reasoning mechanisms form the core of the local-loop architecture by enabling direct sensor-to-action interactions within intelligent systems. These mechanisms operate by continuously monitoring environmental conditions and associating specific triggers with actions that yield beneficial outcomes. Through repeated observations and feedback, the system develops adaptive behavioral patterns using simple rule-based learning processes that evolve over time. In addition to these data-driven repetitions, more sophisticated reasoning techniques enhance the system's predictive and adaptive capabilities. Hidden Markov Models (HMMs), for instance, can capture complex spatial–temporal patterns from heterogeneous data sources, enabling accurate prediction of system requirements and contextual changes. Furthermore, the limitations caused by incomplete or missing data can be mitigated through data imputation methods, which infer absent information and maintain continuity in learning and decision-making. This combination of reactive rule-based adaptation, probabilistic modeling, and intelligent data completion allows local-loop architectures to achieve robust, context-aware, and resilient autonomous behavior.



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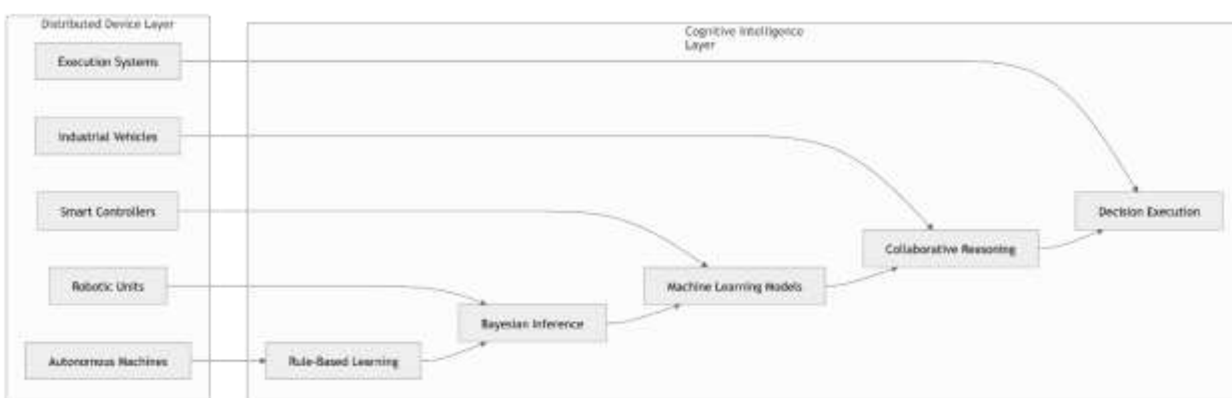
7. Conclusion

Developments across fields such as network technologies, machine learning, digital twins, operational autonomy, and cognitive solutions advance a new approach toward supporting maintenance operations across all industrial processes. Grounds for a distributed cognitive maintenance framework within mission-critical networks encompass the main drivers pushing modern initiates in related areas (e.g., manufacturing execution, logistics). Cognitive solutions operating along lower latency edges promise more efficient ways to support industrial autonomous processes. Centralized methods and reasoning may, however, compromise the reliability and availability of such solutions. The outlined foundation for distributed cognitive maintenance, focusing on elevated operational collaborative approaches and allowing efficient local data collection, health prediction diagnostics, and more, goes beyond existing literature on appliances.

Parts of maintenance operations are guided by the enabling properties of multiagent systems or under industrial application-driven processes. Key principles are, however, still only inductively introduced or articulated in a rudimentary way by surveyed approaches that are practically deployed in applied domains. Future updates formalizing other maintenance dimensions provide grounds to map aspects such as data connectivity, data flows, information relevance for predictive diagnostics, timing requirements, and operability as part of dynamic theory across the entire related technology stack. Furthermore, development is already in progress for the concept of predictive diagnostics, which inherently plays a foundational role against mission-critical network properties. Consideration of preventive maintenance operations rounds out the full maintenance cycle structure within a precursory localized system model.

Distributed Cognitive Reasoning Architecture



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