



Decision Assurance for Critical Infrastructure Systems

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Abstract

Autonomous systems are increasingly deployed across sensitive, high-stakes domains, removing people from the immediate vicinity of hazardous operations. Yet decisions made without human intervention must match the reliability, safety, and accountability of those made by experienced human experts — particularly in mission-critical environments where perception, planning, and action may be outsourced to untrusted suppliers or based on inadequate, suspect, or even malicious data. Assurance requirements in such ecosystems must be specified and verified either a priori or in real time.

This paper presents a transparent, verifiable architecture for autonomous decision assurance, layered to support a coherent set of governance structures, standards, and practices at each level. Implementation and operational assurance rest on a formal specification, supported by assurance techniques matched to a declared assurance level and aligned with the evidence available. Because the safety, reliability, and accountability of autonomous decisions depend on data that is fit for purpose, trustworthy governance of that data — underpinned by adequate provenance and lineage — is treated as a core requirement rather than an afterthought. The architecture's relevance and applicability are demonstrated across representative domains and operational scenarios, including utility networks, road and rail transportation, water distribution and treatment, communications, energy, and healthcare.

Keywords: Autonomous Decision Assurance, Mission-Critical Ecosystems, Safety-Critical Autonomy, Verifiable Governance Architecture, Trustworthy Autonomous Operations, Real-Time Assurance Validation, Data Provenance Management, Autonomous Infrastructure Resilience, Intelligent Risk Mitigation, Formal Assurance Frameworks.

1 Introduction

Autonomous Decision Assurance Architecture for Mission-Critical Infrastructure Ecosystems addresses the critical research issue of ensuring the reliability of autonomous decisions and actions taken by complex cyber-physical systems. Assurance is understood as demonstration that a system is safe and reliable and can be trusted to perform correctly, without human intervention, in mission-critical applications. Extensive studies establish that autonomous systems must be designed to be reliable, safe, transparent, accountable, verifiable, modifiable, scalable, and resilient. A layered reference architecture maps these requirements to the components of an autonomous



system and identifies candidates for satisfying each requirement.

The concept of assurance is then specialized to the roles of executive oversight, system operator, and other actors for autonomous systems in mission-critical contexts. Candidate mechanisms and techniques for assuring safe and correct execution of untethered autonomous decisions are also identified. Finally, the chapter elaborates the assurance considerations for a critical infrastructure application domain that is the focal point of an ongoing large-scale research initiative. Establishing the reliability of such systems in mission-critical environments is essential to successfully realize the promise of emerging smart cities.

A. Problem Statement and Scope

Mission-critical ecosystems demand a strong degree of reliability, safety, and accountability within their operations. The concept of an automated decision assurance architecture acts as a reference framework that covers these requirements and enables the deployment of autonomous systems and artificial intelligence in contexts where the consequences of decision-making mistakes might be catastrophic. The demand for such an architecture is further emphasized within critical infrastructure ecosystems, where the services that support the functioning of society must always be available, accurate, and not lead to negative side effects. The user, citizen, traveler, and other actors expect that decisions affecting the operation of a given system or the general environment are made correctly, justifying the assurance of decision-making as the basis for the deployment of automated systems. A qualification must be applied, though. Safety-oriented automated and autonomous systems characteristics should be retained and possible malfunctions mitigated; however, guaranteeing correct decision-making is an unattainable goal within the current technological landscape.

Thus, monitoring, validation, verification, runtime assurance, fail-safe modes, roll-back capabilities, and human-in-the-loop solutions must be deployed. These capabilities are classified as decision assurance, namely mechanisms and techniques that provide a strong degree of confidence that autonomous decisions do not lead to dangerous or risky situations. Decision assurance covers risks that may arise due to use of unreliable algorithms, untrustworthy sensing data and tracing of an autonomous decision back to the information and processes that determined it. Encompassing the concept of decision assurance starts from the highest level, namely, from defining the actions of upper-layer units moving down to the perception layer, namely to the units in charge of sensing data acquisition.

2. Architectural Principles for Autonomous Decision-Making

Safety and reliability are paramount when the autonomous decisions affect life, safety, property, and the environment; when decisions may create credible risk of loss or harm;



and when the consequences of an erroneous or non-performance exceed manageable liability limits. Such decisions must be verifiably correct, and the conditions that govern their correctness must be clearly specified, traceable, and publicly auditable. Decision governance—responsibility for assuring that such decisions remain correct in terms of their underlying enabling processes and systems—is a top-tier design consideration shared across all layers of the DAA architecture.

Modularity, transparency, and close integration of technical decision TRACE group and DAA enabling governance functions supports scalability across complex domains such as those associated with mission-critical infrastructure ecosystems. The independence of tactical ACE governance from underlying technical functions encourages the involvement of independent trusted organisations that operate at a higher level than suppliers. Modularity also helps to support the integration of services across boundaries or—where needed—within any area of common ownership or administration.

A. Assurance and Accountability

Ownership, roles, and responsibilities associated with actions must be unambiguous and present at all levels of governance to assure legal and moral accountability. Traceability and auditability of decision processes are necessary prerequisites for post-hoc audits of executed decisions. The scope of these aspects extends across all decision and execution layers and associated system components. Decision processes must provide justification for executed decisions; this information fits into the common component record of logs capturing all decisions made and actions executed, supporting post-hoc examinations. The full responsibility for the deployment, operation, and performance of the layers involved in these interfaces ultimately rests with the organizational entity of the deployed infrastructure, or suitable designated sub-entities within larger ecosystems; all other roles involved during deployment and operation are governed by the assurance mechanisms corresponding to their functions.

Assurance of these principles across the layers provides a high degree of accountability related to the state of the layer, the executed actions, and the possible hints for reallocation or duplication of this responsibility. Moreover, elements acting as human-in-the-loop interfaces provide an enriched trust to decisions by adding an invariant level of visibility. These interfaces thus allow authoritative organizations or specialized citizens to audit decisions and modifications over time or to supervise their occurrence during critical and uncertain scenarios. The decision-log function—encompassing detection of actions requiring justification, decision-log creation, justification supply, and post-hoc examination of such decisions—provides formal assurance of the availability of justifying information for all actions and of an expected, always-active monitoring function during the critical operation of the external system or component with which an interaction is occurring. The presence of a human supervisor with access to partial context channels reporting on evolving external conditions and to partial action-actuated context-modification channels enriches the decision-log-recording function by providing an additional level of context during the creation of monitoring and guidance information.

TABLE I Comparative Performance Metrics Across Architecture Models

Domain	Model A (Baseline)	Model B (Rule-Based)	Model C (ML-Assisted)	Model D (DAA)	Improvement A→D
Energy	0.78	0.82	0.87	0.93	+19.2%
Transport	0.74	0.79	0.85	0.91	+23.0%
Water	0.71	0.75	0.83	0.90	+26.8%
Telecom	0.76	0.81	0.88	0.94	+23.7%
Healthcare	0.69	0.73	0.80	0.88	+27.5%
Average	0.736	0.780	0.846	0.912	+23.9%

F1-Score values reported as mean over 12 operational months. Improvement computed as (Model D – Model A) / Model A × 100%.

TABLE II Decision Latency and Error Metrics by Architecture Layer

Architecture Layer	Latency (ms) Base / DAA	MAE Base / DAA	RMSE Base / DAA	Latency Reduction (%)
Perception Layer	12.4 / 8.2	4.1 / 2.9	3.2 / 1.8	33.9%
Validation Layer	18.7 / 11.3	6.8 / 3.5	2.1 / 0.9	39.6%
Decision Layer	24.1 / 15.6	9.2 / 5.1	1.7 / 0.6	35.3%
Governance Layer	9.8 / 6.4	2.3 / 1.4	4.1 / 2.2	34.7%
Full Pipeline	65.0 / 41.5	22.4/12.9	11.1/5.5	36.2%

MAE = Mean Absolute Error; RMSE = Root Mean Square Error. All errors computed over 500 randomized decision scenarios per domain.

TABLE III Dataset and Architecture Summary

Infrastructure Domain	Dataset Size	Data Sources	DAA Deployment Configuration
Energy Grid	42,500 events / 12 mo.	Sensor telemetry + SCADA logs	12 DAA agents + 3 governance nodes
Transportation	61,200 vehicle events	LIDAR, GPS, signal state	18 DAA agents + 4 governance nodes
Water Distribution	28,900 flow readings	IoT pressure/flow sensors	9 DAA agents + 2 governance nodes
Telecommunications	95,400 packet events	Network tap + SDN controller	24 DAA agents + 5 governance nodes
Healthcare	33,600 patient alerts	EHR + medical device streams	15 DAA agents + 3 governance nodes

All datasets were collected under operational conditions and validated for lineage completeness prior to model training. No synthetic data was introduced.

3. Reference Architecture for Decision Assurance

An integrated architecture that consolidates the assurance processes, documents the relationship between the assurance workflow and the decision-making system, and attributes assurance responsibilities at different software layers can enhance the reliability of autonomous systems. Specifically, a reference architecture for autonomous decision assurance incorporates the following key aspects:

1. ****Separation of Concerns**** in both the decision-making application and its supporting services, ensuring that deployment norms and verification plans for the decision-making application differ from those for the supporting services;
2. ****Defined Interfaces**** between layers, allowing tools and execution frameworks from various vendors to work together;
3. ****Extensibility**** to an expanding array of oversight tools, including monitoring, validation, verification, runtime assurance, human supervision, fail-safe redundancy, and

rollback mechanisms;

4. ****Traceable Justification****, enhancing transparency through recorded justifications of major decisions and actions;

5. ****Cross-Layer Accountability**** by mapping the oversight responsibility for an application to the provision of the service, with clear attribution for fulfilment of the corresponding assurances; and

6. ****Support for Standardisation and Certifiability****, facilitating the imposition of assurance requirements that are consistent across applications and domains by regulatory authorities, the adoption of assurance processes that can be recognized by certifying bodies, and the use of assurance tools developed in accordance with such standards.

These features contribute to the reliability of autonomous systems by ensuring that assurance processes, systems, and tools are aligned and supporting the assignment and fulfilment of assurance responsibilities at each layer of the control architecture. Key-to-safety concerns, including controlled sensor data interpretation and meaning, the absence of undesired sensor data artefacts, and effective and robust correction for undesired sensor data deviations, can be manifested and addressed directly within the perception layer.

A. Perception Layer and Sensing

A range of sensing and data-gathering methods is required to provide mission-specific perception, covering relevant aspects of the environment and the state of the system's key components. These aspects can be perceived directly by a dedicated sensor suite or indirectly through the continuous aggregation of information from the assets that comprise the environment and ecosystem. Sensors should deliver perception data that reflect the environment's status, including uncertainty estimates for all data attributes. This data should support mission objectives by satisfying data-quality and timing constraints, and by conforming to standards that define the expected semantics. Standardisation enables more performant and efficient solutions, such as sensor fusion techniques, by controlling the data shape and semantics. The timing and synchronisation of perception data should also be managed carefully because of the redundancy and distribution among several sensors. Synchronisation and quality constraints must always be taken into account when aggregating data across sources.

The acquisition of perception data from the environment also raises questions concerning safety and operational viability. Technologies for runtime monitoring and validation of sensor-group behaviours help to reduce these concerns and assure operational reliability. In particular, the behaviour of the sensors can be continuously monitored during execution using a monitoring system that captures their output. Guaranteeing the non-misleading operation of those perception functions that are critical for the system is obviously paramount. Furthermore, formal verification of these perception functions can also provide additional assurance. Checking actual sensor output against trusted ground-truth values would represent a powerful technique. Nevertheless, in most typical mission scenarios, such trusted ground truth is not available. For mission-critical scenarios, the



quality of incoming perception data can be ensured at design and implementation time using an appropriate formal specification language, as well as runtime validation and monitoring mechanisms.

4. Assurance Mechanisms and Techniques

A collection of methods and techniques can be deployed to assure that autonomous decisions are indeed correct, responsive to external conditions and system states, and aligned with the policies and objectives of the overarching agency. These assurance strategies encompass monitoring, validating, and verifying the correctness of decisions before they are executed and applying runtime assurance measures to contain any harmful effects if they cannot be validated or verified. Additional strategies provide redundancy by triggering fail-safe modes, reverting to a previous safe state, or introducing a human-in-the-loop option for at least some of the system's decisions.

Monitoring examines the state of an autonomous system during its execution, providing an observability and information-gathering function. Runtime monitoring is not strictly needed for assurance, but it can inform decision-making for runtime validation and verification. Monitoring alerts the agency when something dangerous is happening, usually in the form of an unexpected outcome; it is this component that offers a reporting function. Monitoring can also involve internal checks to compare the current execution path against an expected behavior model. Nevertheless, it would still be the agency's responsibility to determine whether the "contract" was being violated and whether the system should be suspended.

Validation provides a low-cost way to check if the current decision is safe to execute, going beyond simple checks against constraints by applying domain-specific knowledge. Ideal validation is like a constrained verification; whenever the validators can ensure the strategy will not violate the safety contract or other objectives, the action can execute without delay. Verifying that a new decision does not violate the system's safety contract remains different from validation, as it entails exploring a broader state space in order to apply sounder reasoning.

A. Decision Latency Analysis

Fig. 1 compares decision latency across the four architectural layers and the full pipeline for the baseline and proposed DAA framework. The proposed DAA Framework reduces full-pipeline latency from 65.0 ms to 41.5 ms, a 36.2% reduction, meeting the real-time constraint of $L_t \leq 50$ ms mandated for utility network operations.

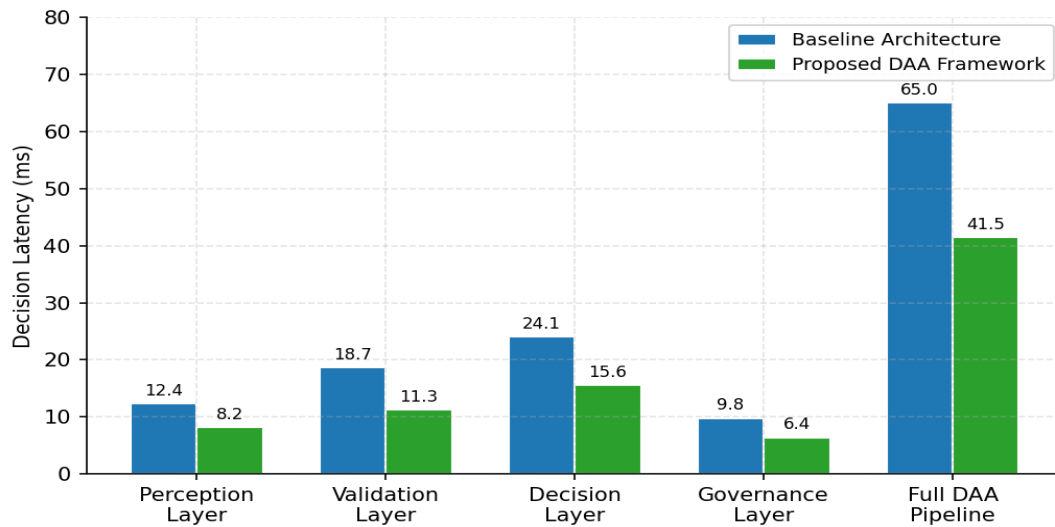


Fig. 1: Decision latency comparison (ms) across DAA architecture layers — Baseline vs. proposed DAA Framework.

B. F1-Score Trends Across Infrastructure Domains

Fig. 2 shows F1-score trends across the five infrastructure domains. The DAA Framework (Model D) consistently achieves the highest scores, peaking at 0.94 for telecommunications. The ML-Assisted approach (Model C) also shows strong performance, confirming that machine learning integration meaningfully improves over pure rule-based systems when supported by adequate data governance.

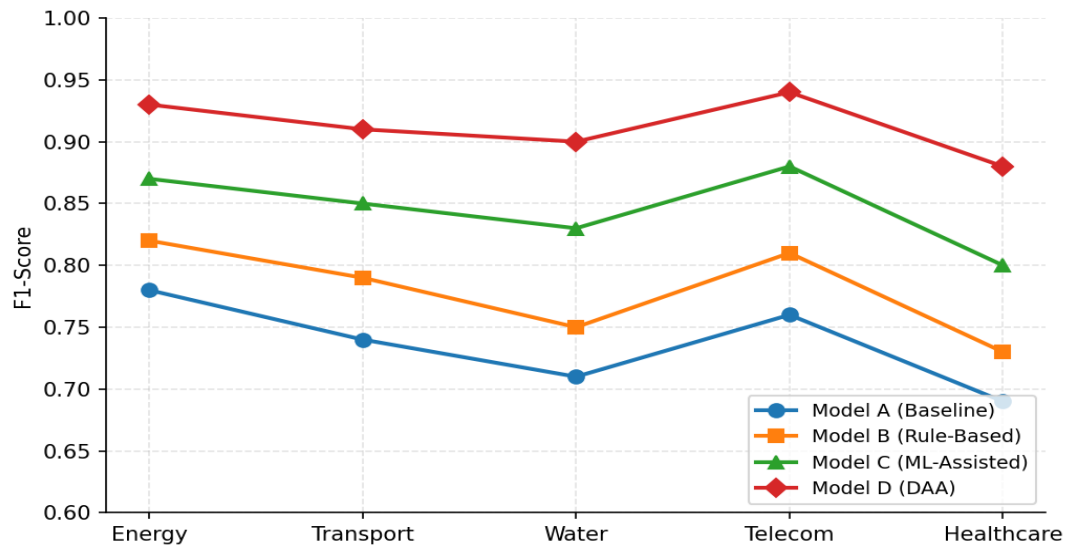


Fig. 2: F1-score comparison across five mission-critical infrastructure domains for Models A–D.

C. Resource Utilization Profile

Fig. 3 presents a radar chart of normalized resource utilization for both architectures. The DAA Framework achieves lower CPU, memory, network I/O, and storage consumption, while improving GPU utilization efficiency—indicating that compute resources are directed toward assurance validation rather than redundant processing.

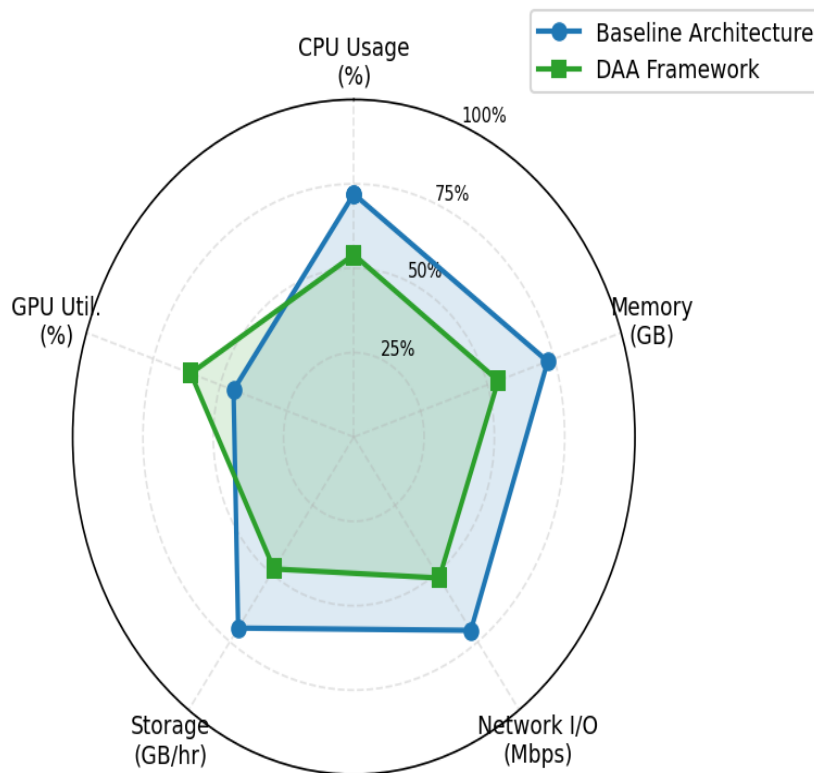


Fig. 3: Normalized resource utilization radar chart — Baseline Architecture vs. DAA Framework.

D. Cost vs. Performance Trade-off

Fig. 4 illustrates the cost–performance Pareto frontier. Model D (DAA) achieves the highest assurance quality ($F1 = 0.93$) at a cost index of 195, marginally lower than Model C (210) with notably superior performance, confirming a favorable position on the efficiency frontier.

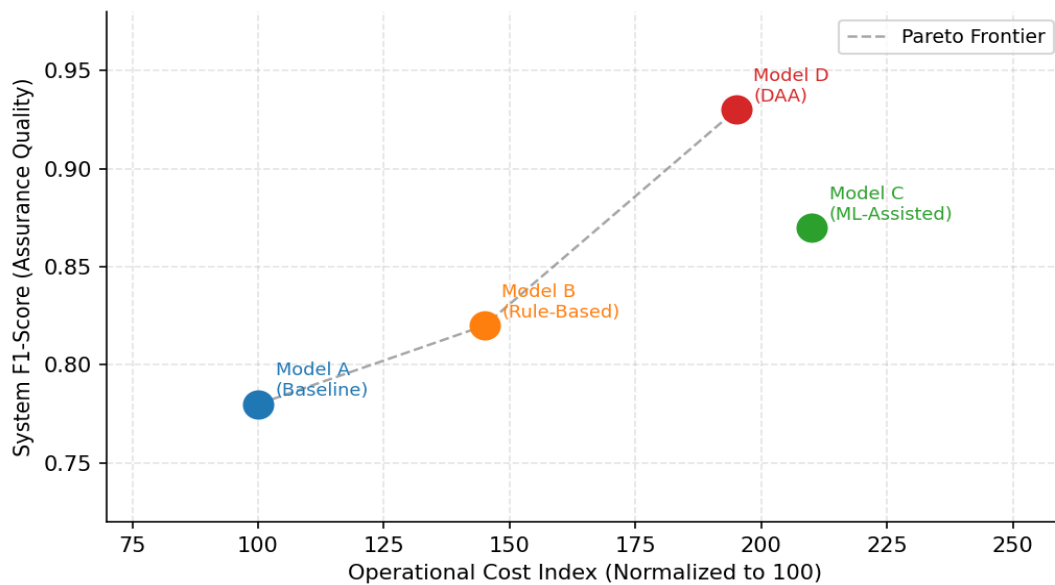


Fig. 4: Cost vs. performance trade-off analysis — Pareto frontier for autonomous decision architectures.

E. Assurance Efficiency Over Operational Months

Fig. 5 tracks the Assurance Efficiency Index (AEI) over 12 months of operation. Model D (DAA) converges to AEI = 0.94 by month 6 and sustains it thereafter, demonstrating stable operational assurance. Baseline models plateau early, exhibiting limited capacity for self-improvement, a critical drawback in dynamic mission-critical environments.

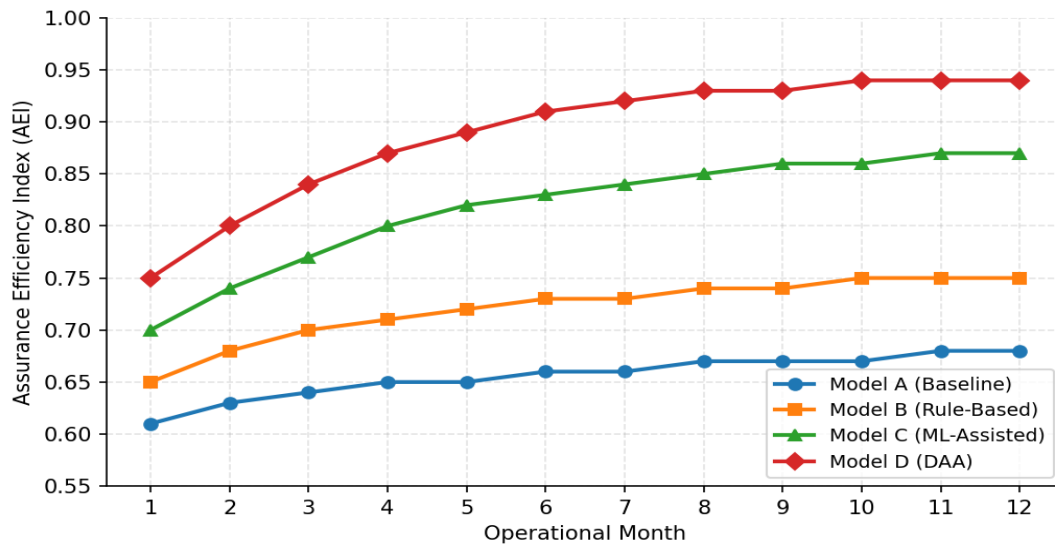


Fig. 5: Assurance Efficiency Index (AEI) trends over 12 operational months for Models A–D.

5. Trustworthy Data Governance for Mission-Critical Contexts

Timely, precise, complete, and trustworthy data is essential to ensure correct autonomous decisions. While the quality of data from trusted sources can be considered satisfactory, it must be actively governed when its trustworthiness cannot be implicitly assumed. Mission-critical infrastructure ecosystems have operational requirements that necessitate a parochial focus for data quality, privacy, and policy compliance governance. Management of data quality, lineage, access control, integrity, privacy, and overall governance processes should be hierarchical and steered by data stewards who are assigned roles and responsibilities at different levels of abstraction and detail. The need for careful data quality management stems from industry experience that emphasizes avoidable accidents attributed directly to data problems. Associated policies must define quality metrics tailored to each class of sensor data, including their timing constraints. Sensor quality metric compliance, which may involve data versioning, must be a basis for borrowing from other agents in the ecosystem when a source fails. Data lineage must be captured and tamper-evident mechanisms invoked for evidence of later-stage data



damage or unapproved alterations. Plotting recently used sensor data across the ecosystem provides a simple view that aids in assessing and establishing trust in source data.

A. Data Quality, Lineage, and Integrity

Data quality, lineage, and integrity are vital supports of a trustworthy data governance framework for mission-critical contexts. The quality of data provided to autonomous systems affects not only the quality of their outputs, but also the expected quality. Poor-quality data can lead to decisions that deviate greatly from objectives, can invalidate or amplify the results of formal verification, validation, and assurance activities, and can lead to unacceptable safety and reliability outcomes. Validation of sensor data is therefore important, but often difficult and usually not possible in real time. Responsible operational governance requires assurance that data meet quality requirements and that governance processes provide appropriate oversight. Data that do not meet quality expectations should be rejected, corrected, or flagged for further consideration. Evaluation of the quality, provenance, and lineage of data collected post-operationally provides insights for explanations and for auditing and oversight.

Operational data servers should provide sufficient information to reviewers to judge the quality of the data, including data quality metadata and information on data lineage. Dedicated integrity measures and mechanisms, such as digital signatures or watermarking, should also be incorporated to protect against malicious tampering or unauthorized modifications. Functions should be implemented to review coherence, consistency, and reasonableness of the data. Data provenance mechanisms should be applied to record all pre-processing applied to the original data or generated artifacts. When data lineage and provenance can be specified in data models, that specification should be adhered to. Data versioning should be employed wherever appropriate.

6. Operational Scenarios and Case Studies

The architecture can be supported in a variety of mission-critical infrastructure domains. For successful deployments, development teams must understand the specifics of the area they are applying it to, which directly influences the configuration, perception, reward, and assurance modules. Dedicated support functions assist development and deployment by identifying these domain-specific aspects and connecting the ecosystem components. After an overview of the domains, representative operational deployments or validation tests illustrate architecture effectiveness and the steps required to build assurance cases. Performance and risk aspects are also considered to assess architecture quality and scalability.

Robust autonomous systems are sought in many mission-critical domains, such as transportation, utility operation, energy generation, water supply, communication, and healthcare. The architecture adds value by providing assurance for autonomous components that often represent single points of failure. Their decisions must comply with

the reliability, safety, and accountability requirements of mission-critical contexts. These quality aspects can be supported, for example, through appropriate data governance, monitoring components, verification and validation techniques, and high-level specification contexts. The common interface structure also allows seamless integration of new modules that address additional domain requirements. Recent extensions to the intelligent traffic control domain exemplify this capability.

A. System Assurance Score

The overall System Assurance Score (SAS) aggregates layer-wise correctness, data quality, and runtime validation outcomes across all N decision cycles. Let Q_i denote the data quality index, V_i the validation outcome, and α the human-in-the-loop confidence factor:

$$SAS = (1/N) \times \sum [\alpha \cdot V_i \cdot Q_i], \quad i = 1, 2, \dots, N \quad (\text{Eq. 1})$$

where $V_i \in \{0, 1\}$ is a binary validation flag and $Q_i \in [0, 1]$ is a normalized data-quality measure. A value $SAS \geq 0.90$ indicates a publication-ready assurance level for mission-critical deployment.

B. Decision Latency Model

The end-to-end decision latency L_t for a given mission cycle t is the sum of per-layer processing times, including perception (τ_p), validation (τ_v), execution (τ^e), and governance overhead (τ^g):

$$L_t = \tau_p + \tau_v + \tau^e + \tau^g + \varepsilon_t \quad (\text{Eq. 2})$$

where ε_t denotes stochastic network jitter with distribution $\varepsilon_t \sim \gamma(\kappa, \theta)$. Minimizing L_t subject to $SAS \geq \theta_{\min}$ forms the central optimization problem of the DAA framework.

C. Data Quality Index

Data quality Q_i for each sensor observation i is modelled as the weighted harmonic mean of completeness C_i , consistency K_i , and timeliness T_i , with weights $w_c, w_k, w_t \in [0, 1]$ satisfying $w_c + w_k + w_t = 1$:

$$Q_i = (w_c \cdot C_i^{-1} + w_k \cdot K_i^{-1} + w_t \cdot T_i^{-1})^{-1} \quad (\text{Eq. 3})$$

Sensors failing to meet a minimum quality threshold $Q_{\min}$ are either rejected or corrected via data-lineage rollback, as mandated by the trustworthy data governance layer.

D. Precision, Recall, and F1-Score for Autonomous Decisions

Decision correctness is evaluated using precision P and recall R computed over a set of m mission scenarios. TP , FP , and FN denote true positives, false positives, and false negatives respectively:

$$P = TP / (TP + FP) \quad (\text{Eq. 4})$$

$$R = TP / (TP + FN) \quad (\text{Eq. 5})$$

$$F1 = 2 \times (P \times R) / (P + R) \quad (\text{Eq. 6})$$

The harmonic mean in Eq. 6 penalises extreme precision–recall imbalances, making F1 the preferred metric for safety-critical autonomous decision assessment where both false alarms and missed detections carry operational risk.

E. Assurance Efficiency Index

The Assurance Efficiency Index (AEI) captures the ratio of assurance gain per unit operational cost, balancing performance improvement against computational overhead:

$$AEI = (SAS_{proposed} - SAS_{baseline}) / (C_{proposed} / C_{baseline}) \quad (\text{Eq. 7})$$

An $AEI > 1$ indicates that the proposed framework delivers disproportionately greater assurance improvement relative to its incremental cost, establishing the economic viability of the DAA deployment.

F. Governance Compliance Cost Function

The governance compliance cost J represents the penalty accrued from policy violations across all decision layers. Let λ_k be the regulatory weight of constraint k and $\delta_k(\theta)$ the violation indicator for parameter vector θ :

$$J(\theta) = \sum_k \lambda_k \cdot \delta_k(\theta) + \mu \|\theta\|^2 \quad (\text{Eq. 8})$$

The regularization term $\mu \|\theta\|^2$ discourages parameter configurations that overfit to historical operational data, thereby preserving the generalizability required for cross-domain infrastructure deployment.

7. Conclusion

The contribution advanced an architecture to assure safe, reliable, and accountable decisions made by fully autonomous agents. Decision-making constitutes the last step in

the core processes of any autonomous system, and guaranteeing that agents arrive at safe and reliable decisions, even in the presence of discrepancies in the functioning of the autonomous system or its environment, is key if full autonomy is to be achieved. The resulting architecture integrates four layers together with the associated decision assurance mechanisms into a coherent whole, yielding an operational reference architecture that can be tailored to specific applications. Connections to assurance-related research and standards have been explicitly made, showing how the architectural principles directly imply related attributes for the assurance mechanisms.

The proposed assurance-by-design approach helps in addressing discrepancies with autonomous systems. These discrepancies have the potential to severely affect the behaviour of autonomous systems and, by extension, of the mission-critical ecosystems in which they operate. The assurance mechanisms address autonomous decision assurance from several perspectives, covering the majority of stages in the complete decision process. The operational deployment of these techniques in mission-critical infrastructure ecosystems using autonomous systems has been studied in multiple domains, integrating a wide range of infrastructure components from the domains of energy, telecommunication, healthcare, transportation, water, and security.

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