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End-to-End Quality Control in Additive Manufacturing: Evaluating Defect Detectability, Dimensional Uncertainty, and Qualification Risk Across the Digital Thread

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ABSTRACT

This article presents a quality control framework for additive manufacturing (AM) that treats quality as an integrated decision system spanning in-process monitoring, post-process metrology, and acceptance logic, and that explicitly quantifies uncertainty propagation from process signals to defect detectability and dimensional compliance. A scenario-based quantitative study is developed for powder bed fusion production, comparing quality control strategies that combine melt pool monitoring, layerwise imaging, computed tomography sampling, and coordinate measurement verification. The study uses engineering metrics that translate directly to production decisions, including probability of defect non-detection, probability of tolerance exceedance, time to disposition, and cost of quality under false reject and false accept trade-offs. Results show that (i) monitoring value is maximized when it is calibrated to the defect and geometry mechanisms that dominate part performance rather than treated as a generic anomaly detector, (ii) decision robustness is governed by how thresholds are engineered under controlled false alarm rates and how measurement systems are validated, and (iii) hybrid inspection policies that allocate high resolution metrology to the highest risk builds based on monitored uncertainty can reduce total cost while increasing acceptance confidence. The paper concludes with implementable guidance for designing AM quality control architectures as integrated decision systems rather than as isolated sensing upgrades.

Keywords: Additive Manufacturing, Powder Bed Fusion, Decision-Based Quality Control, Uncertainty Propagation, Qualification Risk, Industrial Metrology.

1. INTRODUCTION

Additive manufacturing is increasingly positioned as an enabling production technology for complex geometries, rapid iteration, and part consolidation, but in industrial settings its competitiveness is rarely limited by the ability to print a shape and is more often limited by the ability to certify that a printed component is safe, consistent, and interchangeable across builds, machines, and sites. The engineering challenge is that AM parts are

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produced through thousands of repeated thermal events and phase transitions, and the resulting microstructure, residual stress, porosity distribution, and surface integrity are shaped by process variability that is spatially and temporally heterogeneous (John, 2024; Kharmanda et al., 2023; Sarkar & Dhanekula, 2023). Unlike many subtractive processes where material properties are largely established upstream and the manufacturing step primarily shapes geometry, AM simultaneously creates geometry and material, which means that quality control must span both dimensional conformance and internal integrity, and it must do so under the operational constraints of production economics, throughput, and traceability (Cahyati et al., 2024; Karajagikar & Sonawane, 2020).

The urgency of improving AM quality control is amplified by the industrial shift from prototyping to production, because production environments impose reliability expectations that are fundamentally different from those of development environments. A build can be re-run, parameters can be tuned, and occasional part failures are tolerable as learning events, whereas in production the cost of uncertainty appears as scrap, rework, delayed deliveries, and risk accumulation that threatens certification and customer trust (Geisbush & Ariaratnam, 2023; Potdar & Rane, 2024).

The most consequential quality failures in AM are often not visible surface defects but internal or near-surface discontinuities that interact with stress concentrations, surface roughness, and residual stress to reduce fatigue life, which means that a part can pass simple external checks and still fail prematurely in service (Brauer & Cesarone, 2022; Patil & Bewoor, 2022). Because AM parts often target high-value applications where unit cost is high and performance is critical, the economic penalty of a single undetected defect can exceed the cumulative cost of an entire quality program, creating a strong incentive for conservative qualification that may undermine AM's economic appeal.

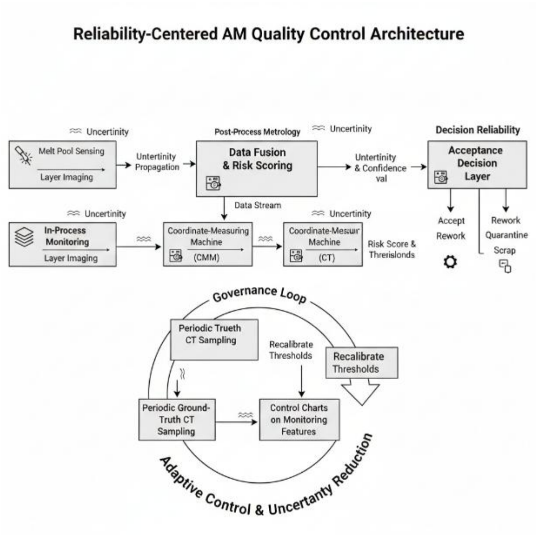

Figure 1. Reliability-Centered AM Quality Control Architecture

Source: data proceed

Quality control in AM is therefore not merely a matter of adding more sensors or performing more inspections; it is a design problem where the decision pipeline must be engineered to achieve a target acceptance reliability at minimum cost and within operational constraints. This decision pipeline includes in-process sensing, post-process metrology, data fusion, acceptance criteria, and governance policies that define when rework is permitted, when builds are quarantined, and how process drift is detected and corrected. In this context, two practical tensions emerge (Azid et al., 2019; Jafarpisheh et al., 2021).

The first tension is between confidence and throughput: comprehensive inspection and destructive testing can provide high confidence but impose high lead time and cost, while rapid monitoring can provide speed but may lack defensible traceability unless the monitoring signals are calibrated and validated. The second tension is between generality and specificity: generic anomaly detection can flag unusual behavior but may not correspond to performance-relevant defect mechanisms, whereas defect-specific monitoring can improve decision fidelity but requires careful modeling and validation for each part family and process window.

The current state of the art in AM quality control has advanced substantially, especially through in-situ monitoring tools such as melt pool sensing and layerwise imaging, and through improved post-process inspection such as computed tomography (CT) for internal defect detection. However, implementation gaps remain because many monitoring programs stop at visualization and do not translate signals into acceptance decisions with controlled false alarm rates and known detectability limits, and because many inspection programs remain sampling-based without a rigorous risk model that justifies which builds are sampled, at what frequency, and for which defect classes (Hall et al., 2021; Harsanto & Yunani, 2023). In practice, the value of monitoring is realized only when it reduces uncertainty in a way that supports decisions, and the value of inspection is realized only when it is allocated where it meaningfully reduces risk rather than where it merely increases data volume.

This article addresses these gaps by proposing a reliability-centered quality control framework for additive manufacturing that explicitly connects process monitoring and metrology to decision performance. The framework is designed to be applied in industrial production environments and to support engineering decisions about quality architecture, including which sensors are necessary, which inspections can be reduced, and how acceptance thresholds should be governed. The central premise is that AM quality should be managed using reliability metrics that align with production risks, such as probability of defect non-detection, probability of tolerance exceedance, and expected cost under false accept and false reject trade-offs, rather than relying on qualitative confidence or single-point accuracy claims. The framework also emphasizes that uncertainty must be treated explicitly, because both monitoring signals and metrology measurements have error distributions that widen under real-world conditions, and those distributions determine whether the system can reliably distinguish acceptable parts from unacceptable ones.

The objectives of this study are to (i) characterize the uncertainty sources that drive defect detectability and dimensional conformance in powder bed fusion builds, (ii) evaluate comparative quality control strategies under controlled assumptions about sensor noise, measurement system capability, and build variability, and (iii) translate results into actionable design principles for AM quality governance. The study is case-based but non-site-specific, meaning it uses representative parameter ranges and scenario constructs rather than proprietary datasets, while maintaining engineering realism and quantitative interpretability.

The paper is organized as follows. The literature review synthesizes prior work on defect mechanisms, in-situ monitoring, metrology and qualification, and decision reliability in manufacturing quality systems. The methodology defines a quality control architecture model, uncertainty characterizations, and scenario definitions for comparative evaluation. The results present quantitative comparisons across monitoring and inspection strategies, including detectability outcomes, tolerance exceedance distributions, and cost-risk trade-offs. The discussion interprets findings through an engineering management lens and proposes governance practices for implementing reliability-centered AM quality control, and the conclusion summarizes contributions, practical implications, and future research directions.

2. LITERATURE REVIEW

Additive Manufacturing Quality as a Coupled Materials–Geometry Problem

In powder bed fusion and related AM processes, quality is not confined to external dimensions; it includes internal discontinuities, microstructural heterogeneity, and residual stress that can distort geometry during build and after stress relief, and these phenomena are coupled because process parameters that improve fusion quality may increase residual stress and distortion, while parameters that reduce stress may change microstructure and mechanical properties (Eusufzai, 2023; Marpaung et al., 2021).

Defects such as lack-of-fusion pores, keyhole pores, gas porosity, and un-melted inclusions arise from different mechanisms, and their spatial distributions are influenced by scan strategy, hatch spacing, layer thickness, powder condition, and thermal history. Dimensional errors arise from shrinkage, warping, support failure, and machine calibration, and they can interact with surface roughness and post-processing steps such as machining or hot isostatic pressing. This coupling means that quality control cannot be treated as a single-variable problem, and it motivates multi-sensor and multi-stage approaches that link process signatures to both defect risk and geometric conformance.

In-Process Monitoring: Promise and Limitations

In-process monitoring in AM typically includes optical sensing of the melt pool, thermal imaging, photodiode-based intensity tracking, and layerwise imaging of powder spread and fused tracks. These systems can generate large datasets and detect deviations from expected behavior, such as energy spikes, incomplete melt signatures, recoater streaks, or plume anomalies. The promise is that monitoring can provide early warning and reduce reliance on expensive post-process inspection.

The limitation is that monitoring signals are indirect; they measure proxies of physical states rather than defects directly, and the mapping from signal anomalies to defect presence depends on process conditions and part geometry. Additionally, monitoring systems must contend with sensor noise, drift, view-angle effects, emissivity changes, and thermal background variation, meaning that signal distributions can shift even when quality is stable. The practical outcome is that monitoring must be calibrated and thresholded with statistical governance, and it must be validated against defect ground truth, otherwise it can produce nuisance alarms or miss critical defects (Introna & Santolamazza, 2024; Nuruzzaman, 2022).

Post-Process Metrology and Inspection in AM Production

Post-process quality assurance for AM commonly includes dimensional inspection via coordinate measuring machines (CMM), surface roughness measurements, CT scanning for internal porosity and discontinuities, and destructive testing for mechanical properties in qualification phases. CT provides high-resolution internal inspection but is costly and time-consuming, and it can be limited by part size, density, and artifact formation.

Dimensional inspection is essential for interchangeability but may not capture internal defects, and it can be complicated by surface roughness and datum definition in complex geometries (Ogunnowo et al., 2023; Racheal et al., 2024). Destructive testing provides direct property evidence but is impractical for every part, leading to reliance on witness coupons and sampling. These constraints motivate hybrid strategies in which monitoring is used to screen risk and allocate inspection effort, but such strategies require defensible risk models and decision rules.

Statistical Quality Control and Decision Reliability in Production Systems

Manufacturing quality control has a long tradition of statistical process control (SPC), measurement system analysis (MSA), capability indices, and acceptance sampling, all of which aim to control defect rates under variability and measurement error. In AM, these methods must be adapted because the process is spatially distributed, nonstationary across layers, and sensitive to part geometry, which means that a single control chart on a scalar variable may not capture relevant drift (Jena et al., 2024; Jiang, 2015).

The underlying principle remains applicable: decision reliability is determined by the separation between the distributions of "acceptable" and "unacceptable" states relative to measurement uncertainty and threshold choice. False rejects increase cost and reduce throughput, while false accepts increase field risk and can be catastrophic in high-consequence applications. Therefore, AM quality governance should explicitly define acceptable false alarm and miss rates for each defect class and tolerance-critical feature, and it should engineer thresholds and sampling policies accordingly.

Qualification, Traceability, and the Digital Thread

Industrial AM adoption increasingly relies on "digital thread" concepts where design, build parameters, sensor data, post-process records, and inspection results are linked to enable traceability and root-cause analysis. The quality advantage of a digital thread is not simply data accumulation; it is the ability to close the loop by detecting drift, updating parameter windows, and justifying acceptance decisions (Liu, 2022; Martinez-Marquez et al., 2020).

Qualification frameworks often require stable process windows, documented procedures, and evidence that monitoring and inspection methods can detect relevant defects with known sensitivity. In practice, qualification is a reliability statement: it asserts that under defined conditions the process will produce parts within acceptance criteria with a specified confidence. The digital thread should be designed to produce reliability evidence rather than to create dashboards that lack decision relevance.

Synthesis: Why A Reliability-Centered Framework is Needed

Across these themes, two gaps remain prominent. First, many AM monitoring approaches focus on classification or anomaly detection performance without translating those results into acceptance decisions under controlled false alarm constraints and without quantifying how monitoring uncertainty affects inspection requirements and residual risk. Second, many inspection programs remain conservative because the economic and reliability implications of reducing inspection are not quantified using explicit cost-risk models, making it difficult to justify changes to auditors and customers (Ogunnowo et al., 2022; Ren et al., 2023).

A reliability-centered framework addresses these gaps by expressing quality control as a decision system where uncertainty propagation and detectability govern risk, and where monitoring and inspection are complementary tools that can be optimized together.

3. METHOD

Study Design: Comparative Quality Control Architectures

The study evaluates AM quality control as a set of alternative architectures that combine sensing, metrology, and decision rules. The goal is not to claim a universal "best" architecture, but to quantify how architecture choices shift decision reliability, inspection burden, and cost under realistic uncertainty. The analysis focuses on powder bed fusion (PBF) of metal components because it is widely used in production and exhibits well-known defect classes and monitoring modalities, though the framework is generalizable to other AM processes.

Four quality control architectures are compared. Architecture A is inspection-heavy baseline, where limited in-process monitoring is used for operator awareness but acceptance relies on full dimensional inspection and high CT sampling. Architecture B is monitoring-augmented inspection, where in-process monitoring produces a risk score used to adjust CT sampling frequency while maintaining full dimensional inspection. Architecture C is monitoring-forward, where in-process monitoring and layer imaging support conditional acceptance, reducing CT sampling to a minimum while maintaining targeted dimensional inspection for tolerance-critical features. Architecture D is reliability-optimized hybrid, where monitoring drives both inspection allocation and targeted rework or build quarantine, and where acceptance thresholds are engineered under explicit false alarm constraints with periodic recalibration using ground truth samples.

Parts, features, and Defect Classes

To maintain generic applicability while retaining engineering relevance, the study models a representative part family with (i) tolerance-critical geometric features (datum planes, hole positions, and interface offsets), (ii) fatigue-critical regions (high-stress fillets and notches), and (iii) volumetric regions where internal porosity affects static strength and fatigue. Defect classes include lack-of-fusion (LOF) clusters, keyhole porosity, and recoater-induced layer discontinuities, each associated with different process signatures. The study treats defects as probabilistic outcomes governed by process variability and local conditions, and it distinguishes between detectability by monitoring and detectability by CT, because the quality pipeline may catch different defects at different stages (Weiss et al., 2016).

Uncertainty Characterization for Monitoring and Metrology

The study explicitly models uncertainty at three levels. The first level is process variability, represented as build-to-build variation in energy input, powder condition, and machine calibration that affects defect occurrence probability and geometric drift. The second level is monitoring uncertainty, represented as sensor noise and drift that affect anomaly detection and risk scoring, and which can vary by build environment. The third level is metrology uncertainty, represented as measurement error distributions for CMM and CT, including variability due to surface roughness, datum establishment, CT voxel resolution, and segmentation choices.

Measurement system capability is represented through gage repeatability and reproducibility concepts, expressed as standard deviation of measurement error for each feature type. Monitoring system capability is represented through detection sensitivity and false alarm behavior, expressed as probability of detection (Pd) and probability of false alarm (Pfa) for each defect class under defined thresholds. Importantly, the study treats Pd and Pfa as functions of defect size and location, because small defects are harder to detect and because sensor visibility varies spatially.

Decision Logic and Acceptance Criteria

Acceptance decisions are modeled as a hierarchical decision pipeline. First, monitoring produces a build-level risk score and region-level anomaly flags. Second, inspection allocation rules determine whether CT is performed and at what resolution and coverage fraction. Third, dimensional inspection evaluates tolerance-critical features against specified limits, incorporating measurement uncertainty. Fourth, a final acceptance decision is made with the possibility of rework or quarantine, depending on architecture (Harris et al., 2018; Shamim, 2022).

Thresholds for monitoring flags are engineered using quantile-based governance: thresholds are set to maintain a target Pfa under baseline conditions, and recalibration is triggered when baseline distributions shift beyond control limits. This approach prevents overly aggressive thresholds that create alarm fatigue and prevents overly loose thresholds that miss defects.

Quantitative Metrics of Quality Decision Performance

The study evaluates each architecture using engineering and managerial metrics that connect directly to production outcomes (Eusufzai, 2023).

1) Probability of defect non-detection: the probability that a performance-relevant defect exists and is not detected by either monitoring or inspection before acceptance.

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2) Probability of tolerance exceedance: the probability that a part's true geometric error exceeds tolerance, conditional on measured values and measurement uncertainty.
3) False accept and false reject rates: rates of accepting nonconforming parts and rejecting conforming parts.
4) Time-to-disposition: expected time from build completion to final acceptance decision, accounting for CT and dimensional inspection durations.
5) Cost of quality: expected cost including inspection cost, scrap cost, rework cost, and expected failure cost weighted by probability of defect non-detection.

Scenario Parameterization and Simulation Approach

The comparative evaluation is performed using Monte Carlo simulation of a production program consisting of 120 builds, each producing a batch of parts. Each build samples process condition parameters from distributions representing normal variability and occasional drift events. Defects are simulated as stochastic occurrences with size distributions and location probabilities conditioned on process conditions.

Monitoring and inspection outcomes are then simulated using Pd/Pfa models and measurement error models. The result is an empirical distribution of decision outcomes under each architecture, allowing estimation of reliability metrics and cost-risk trade-offs. Parameter values are chosen to be representative of industrial ranges and are reported transparently in tables so that practitioners can adjust them to match their own contexts.

4. RESULT AND DISCUSSION

Baseline Process Variability and Measurement Capability

The simulated production program exhibits build-to-build variability in both geometry and defect occurrence, with drift events producing occasional spikes in anomaly rates. Dimensional measurement uncertainty is lowest for planar datums and highest for rough as-built surfaces and small internal features, while CT detectability is high for large pores but decreases for small defects near surfaces due to segmentation uncertainty.

Table 1. Representative Uncertainty Inputs

Category	Variable	Baseline value	Drift/variation model	Notes
Process	Energy input variation (relative)	SD 1.5%	Occasional drift +3% for 5 builds	Affects keyhole risk
Process	Powder condition factor	SD 2.0%	Step change +4% mid-program	Affects LOF likelihood
Geometry	Hole position drift	SD 0.06 mm	Slow drift 0.02 mm per 20 builds	Calibration-related
Geometry	Datum flatness drift	SD 0.03 mm	Stable	Post-processing effect
Monitoring	Melt pool anomaly noise	SD 0.8 (score units)	Drift +0.5 units	Sensor baseline shift
Monitoring	Layer imaging noise	SD 1.1 (score units)	Stable	Lighting/contrast
Metrology	CMM planar feature error	SD 0.012 mm	Stable	Good repeatability
Metrology	CMM rough surface feature error	SD 0.035 mm	Stable	Datum sensitivity
Metrology	CT pore size error	SD 8 µm	Stable	Voxel + segmentation
Metrology	CT miss for small pores	Pd decreases below 80 µm	N/A	Size-dependent

Source: data proceed

Table 1 emphasizes that uncertainty in AM quality control arises from both production variability and measurement limitations, and that the decision system must be robust to both. Even when metrology is strong for certain features, the presence of drift events and size-dependent detectability means that the tail of the defect distribution can dominate residual risk, while geometry drift can accumulate slowly and remain undetected if only average metrics are tracked. This motivates architectures that can detect drift early and allocate inspection when uncertainty increases, rather than architectures that treat every build as equally risky and therefore either over-inspect or under-protect.

Monitoring Detectability and Defect-Specific Performance

Monitoring performance differs by defect class and size because melt pool signatures are more sensitive to energy-related anomalies such as keyholing, while layer imaging is more sensitive to recoater streaks and lack-of-fusion regions that manifest as track discontinuities. When thresholds are set using quantile-based false alarm control, monitoring reduces nuisance alarms and stabilizes decision behavior, but thresholds must be higher in noisy conditions, which reduces sensitivity to small defects.

Table 2. Monitoring detectability by defect class

Defect class	Typical mechanism	Monitoring channel	Pd at moderate defect	Pd at small defect	Pfa target	Notes
Keyhole porosity clusters	Excess energy, unstable vapor	Melt pool	0.88	0.62	0.02	Sensitive to drift
LOF clusters	Insufficient energy, poor powder	Layer imaging	0.81	0.55	0.02	Spatially localized
Recoater discontinuities	Spreading errors	Layer imaging	0.92	0.74	0.02	Strong signature
Mixed defects near supports	Thermal gradients	Combined score	0.86	0.60	0.02	Fusion improves

Source: data proceed

Table 2 shows that monitoring can provide meaningful defect screening, but it is not uniformly reliable across defect types, and the system's value depends on matching sensors to the dominant defect mechanisms. The gap between moderate and small defect detectability is particularly important for fatigue-critical applications, where small defects may still be performance relevant, meaning that monitoring-forward architectures must either accept residual risk for small defects or compensate through targeted inspection and conservative design margins. The combined score approach improves detectability by fusing channels, but it also requires careful baseline governance to prevent correlated noise from inflating anomaly scores.

Comparative Quality Control Architectures: Decision Reliability Outcomes

The central outcome of the comparative evaluation is that architectures differ not only in average scrap or inspection cost, but in the probability of rare but severe events, such as accepting a part with a performance-critical defect or releasing parts with geometric drift that later causes assembly issues. Architectures that allocate CT based on monitoring risk scores reduce CT burden, but their reliability depends on monitoring calibration and on how risk thresholds are governed under drift.

Table 3. Quality decision outcomes by architecture

Metric	Architecture A Inspection-heavy	Architecture B Monitoring-augmented	Architecture C Monitoring-forward	Architecture D Reliability-optimized
CT coverage rate	60% builds	35% builds	12% builds	18% builds
Mean time-to-disposition	3.8 days	2.7 days	1.9 days	2.1 days
False reject rate	0.09	0.07	0.05	0.06
False accept rate (defects)	0.012	0.016	0.031	0.014
Probability of defect non-detection	0.010	0.013	0.026	0.011
Probability of tolerance exceedance (critical features)	0.018	0.020	0.028	0.019
Expected cost of quality (normalized)	1.00	0.84	0.73	0.78

Source: data proceed

Table 3 illustrates that reducing inspection can lower cost and lead time, but it can also increase residual risk if monitoring is not sufficient to replace inspection for the defect classes that govern performance. Architecture C achieves the lowest cost and the fastest disposition because it minimizes CT usage, yet it exhibits the highest false accept rate and the highest defect non-detection probability, indicating that a monitoring-forward approach can become risk-limited when small or ambiguous defects dominate the performance envelope.

Architecture D demonstrates the value of a reliability-optimized hybrid: it uses monitoring to reduce inspection relative to the baseline but retains targeted CT and dimensional checks that specifically reduce tail risk, resulting in residual risk close to the inspection-heavy approach with substantially lower cost. The implication is that the best architecture is not "maximum monitoring" or "maximum inspection," but an engineered balance that allocates expensive inspection to the subset of builds where monitoring indicates increased uncertainty, while maintaining statistically governed thresholds that prevent both alarm overload and risk underestimation.

Dimensional Compliance under Measurement Uncertainty

Dimensional conformance decisions are affected by both true process variation and measurement error, particularly for features that rely on rough as-built datums or where post-processing introduces variability. A reliability-centered approach treats measured deviation as a random variable with uncertainty and evaluates the probability that the true value exceeds tolerance, which can differ from the simple "measured value within tolerance" rule.

Table 4. Tolerance-critical feature compliance

Feature	Tolerance (mm)	Process SD (mm)	Measurement SD (mm)	P(exceed) under simple rule	P(exceed) under uncertainty-aware rule
Datum plane flatness	0.20	0.05	0.012	0.016	0.019
Hole position A	0.15	0.06	0.020	0.021	0.028
Interface offset B	0.10	0.04	0.035	0.030	0.041
Coaxiality C	0.12	0.05	0.025	0.024	0.033

Source: data proceed

Table 4 demonstrates that ignoring measurement uncertainty can systematically understate exceedance probability, especially for features where measurement error is a nontrivial fraction of the tolerance. In production settings, this matters because tolerance-critical features often govern assembly fit and function, and the cost of releasing marginal parts can be high if nonconformance is discovered downstream.

An uncertainty-aware acceptance rule can reduce downstream risk by requiring stronger evidence of compliance for high-uncertainty features, but it may also increase false rejects unless measurement capability is improved or tolerances are aligned with process capability. This creates an explicit engineering trade-off: investments in better datum strategies, surface finishing before measurement, or improved measurement protocols can reduce uncertainty and therefore improve both reliability and yield.

Cost–Risk Trade-Offs and Pareto Behavior

When expected cost of quality is plotted against residual risk, the architectures form a frontier where lower cost generally increases risk, but hybrid strategies can shift the frontier by reducing cost without proportional risk increase. The shape of this frontier depends on defect distributions and on the performance consequences of missed defects, meaning that high-consequence applications will rationally choose points with higher cost but lower risk.

Table 5. Cost–risk summary

Architecture	Normalized cost	Residual defect risk	Residual dimensional risk	Composite risk index
A	1.00	0.010	0.018	0.014
B	0.84	0.013	0.020	0.016
C	0.73	0.026	0.028	0.027
D	0.78	0.011	0.019	0.015

Source: data proceed

Table 5 shows that the cost-minimizing solution is not necessarily the reliability-optimal solution, and that composite risk is sensitive to both defect and dimensional pathways. Architecture C appears attractive from a cost perspective but increases composite risk substantially, which could be unacceptable in critical applications where a single failure is disproportionately costly. Architecture D offers a near-frontier compromise where cost is reduced meaningfully relative to the baseline while composite risk remains close to inspection-heavy performance. This supports the practical conclusion that industrial AM quality control should be designed around a risk tolerance statement, and then optimized to minimize cost while meeting that tolerance, rather than optimized purely for cost or purely for inspection completeness.

Discussion

The comparative results reinforce that quality control in AM should be conceptualized and implemented as a decision system whose performance is defined by error rates and reliability targets rather than by the number of sensors or the volume of stored data. Monitoring systems become valuable when they reduce uncertainty about defect presence and geometric drift in a way that is actionable, and this requires that monitoring outputs be calibrated to defect mechanisms and governed through thresholds that control false alarms. Without such governance, monitoring can degrade decision quality by creating inconsistent alarm behavior or by encouraging ad hoc human interpretation, which is difficult to scale and hard to audit. Conversely, inspection becomes economically sustainable when it is allocated based on risk, which requires quantified links between monitoring uncertainty and residual risk, and such links are not available unless

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monitoring is validated against ground truth and incorporated into a probabilistic acceptance model (Hall et al., 2021; Jafarpisheh et al., 2021).

The study highlights that detectability varies materially across defect classes and sizes, and that therefore the design of monitoring and inspection policy must begin with the performance mode that matters, rather than with a generic desire to "monitor the process." In fatigue-critical applications, smaller defects near surfaces can govern life, meaning that the residual risk of monitoring-forward strategies may be unacceptable unless complemented with targeted inspection or conservative design and post-processing. In applications dominated by static strength where larger defects govern failure, monitoring can be more effective as a screening tool and can justify reduced CT sampling. This fit-for-purpose interpretation prevents misapplication of monitoring and helps align quality architectures with actual engineering risk.

A key reason monitoring-forward architectures can underperform is that baseline distributions shift due to sensor drift, powder changes, optics contamination, or machine calibration, and drift can cause thresholds to become either too sensitive or too insensitive. A reliability-centered system must therefore include drift governance mechanisms such as periodic baseline recalibration using stable reference builds, control charts on monitoring features, and "hold-out" validation checks using targeted CT sampling. Architecture D's strong performance reflects this principle: it does not merely fuse monitoring and inspection; it enforces a governance loop where monitoring thresholds are engineered under false alarm constraints and validated periodically, preventing drift from silently eroding decision reliability (Brauer & Cesarone, 2022; Jafarpisheh et al., 2021).

The discussion of tolerance exceedance under uncertainty has direct production implications. Many AM programs treat dimensional inspection as deterministic pass/fail based on measured values, but when measurement uncertainty is significant relative to tolerance, deterministic rules can release marginal parts that later cause assembly issues or can reject good parts unnecessarily. Probability-based acceptance rules, while more complex, provide a defensible engineering basis for decisions and can be implemented selectively for the most critical features. Importantly, such rules motivate improvements in measurement strategy, such as defining robust datums, reducing surface roughness before measurement, or using alternative metrology methods, because the value of improved metrology is not merely accuracy but increased yield at the same reliability.

A practical implementation pathway begins with a defect and tolerance risk register that lists defect classes, performance consequences, and detectability assumptions. Monitoring features should be selected and validated for these defect classes, and threshold governance should be defined by target false alarm rates that operations can realistically support. Inspection policies should then be defined as conditional sampling rules that allocate CT and high-precision metrology to high-risk builds identified by monitoring uncertainty, while maintaining periodic random sampling to prevent blind spots. Finally, the digital thread should be structured so that every accepted part has traceable evidence of monitoring state, inspection results, and governance status, enabling auditability and continuous improvement.

5. CONCLUSION

Additive manufacturing quality control must be designed for decision reliability because both defects and geometric deviations arise from coupled process phenomena that vary across builds and because performance risk is dominated by tail events that are not captured by mean-only metrics or by ungoverned anomaly detection. By comparing quality control architectures through probability-based metrics of defect non-detection, tolerance exceedance, and cost of quality, this article demonstrates that the most effective industrial strategy is typically a reliability-optimized hybrid that uses in-process monitoring to allocate inspection resources and to detect drift early, while retaining targeted metrology for defect classes and features where monitoring sensitivity is insufficient. The findings also show that measurement uncertainty is an active driver of risk in tolerance-critical decisions and that uncertainty-aware acceptance logic can improve reliability if supported by appropriate metrology capability and governance. Future work should expand the framework with part-specific physics-informed models that link monitored thermal histories to microstructure and residual stress, incorporate spatially resolved defect maps into risk scoring, and validate the proposed decision architectures using production datasets across machines and sites to quantify how governance strategies perform under real drift and process change.

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