

# Reliability-Centered Quality Control in Additive Manufacturing: Quantifying Defect Detectability, Dimensional Uncertainty, and Qualification Risk Across the Digital Thread

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## ABSTRACT

This article presents a reliability-centered quality control framework for metal powder bed fusion that treats quality assurance as a decision system spanning in-situ monitoring, post-build inspection, uncertainty propagation, and acceptance governance across the digital thread, and it quantifies decision performance using probability of defect non-detection, probability of tolerance exceedance, time-to-disposition, and expected cost of quality under controlled nuisance-alarm constraints. A scenario-based quantitative study is developed using Monte Carlo simulation of a multi-build production campaign with realistic drift events, defect-size distributions, and measurement-system uncertainties, comparing four architectures that range from inspection-heavy qualification to monitoring-forward production with risk-based sampling and governed baseline updating. Results show that monitoring value is maximized when indicators are engineered around defect mechanisms and tolerance-critical features, because generic anomaly scoring can either overload operations with unstable alarms or inflate thresholds to the point of insensitivity when baseline variance is large, while hybrid strategies that allocate high-resolution inspection to high-uncertainty builds based on calibrated risk scores can reduce total inspection burden and disposition time without increasing residual acceptance risk.

**Keywords:** Additive Manufacturing, Powder Bed Fusion, Quality Control, In-Situ Monitoring, Computed Tomography.

## 1. INTRODUCTION

Additive manufacturing has matured from a niche prototyping tool into a production technology that is routinely evaluated for load-bearing components, complex internal channels, lightweight structures, and consolidated assemblies, yet the practical barrier to scale is not the ability to print a shape but the ability to demonstrate that printed parts are reliable, repeatable, and interchangeable under production constraints that include throughput, traceability, and cost. This barrier arises because AM processes such as metal powder bed fusion create both geometry and material simultaneously, and the resulting internal integrity and dimensional conformance are the outcome of coupled thermal gradients, melt dynamics, solidification behavior, and residual stress accumulation that vary in space and time across the build volume (Alaka et al., 2025; Eusufzai, 2023; Introna & Santolamazza, 2024).

In conventional subtractive manufacturing, quality control can often be framed as ensuring that a well-characterized input material is transformed into a geometric form within tolerance, whereas in AM the manufacturing step also determines microstructure, porosity distribution, and defect morphology in ways that may not be directly observable without advanced inspection, and this creates a quality-control problem that is fundamentally probabilistic and mechanism-dependent (Kharmanda et al., 2023; Nuruzzaman, 2022; Racheal et al., 2024). Industrial decision-makers therefore face a recurring tension when deploying AM in production: to achieve confidence, they tend to rely on inspection-intensive qualification regimes that include extensive dimensional metrology, computed tomography, and destructive testing of witness specimens, yet this confidence often comes at a cost that undermines AM's value proposition in lead time and cost of quality, while still leaving residual uncertainty about build-to-build drift and part-to-part variability when inspection coverage is necessarily incomplete (Bhatti & Parlaev, 2025; Karajagikar & Sonawane, 2020).

When organizations attempt to reduce inspection cost by shifting toward in-process monitoring and data-driven anomaly detection, they often discover that monitoring systems are not automatically equivalent to inspection because monitoring signals are proxies, because sensor baselines drift, because part geometries modulate signal response, and because the mapping from signal anomalies to performance-relevant defects must be validated and governed if it is to support acceptance decisions. In production, this tension becomes operationally consequential because quality is not a passive property of a part but a continuous decision process that determines whether a part is accepted, reworked, quarantined, or scrapped, and each decision carries a risk of false accept (accepting a nonconforming part) and false reject (rejecting a conforming part) with different cost and safety consequences (Jena et al., 2024; Martinez-Marquez et al., 2020).

A reliability-centered view is useful because it aligns AM quality control with the way industrial systems are actually governed. The question is not whether a part is "likely good" in an informal sense, but whether the quality-control pipeline achieves a defined acceptance risk target, for example limiting the probability that an accepted part contains a defect of a given class and size to below a specified threshold, and limiting the probability that an accepted part violates a tolerance-critical requirement to below another threshold, while also limiting nuisance alarm rates so that interventions remain feasible and staff do not habituate to warnings (Brauer & Cesarone, 2022; Yang et al., 2022). When the pipeline is viewed as a reliability system, monitoring and inspection can be treated as components that reduce uncertainty at different points in the workflow, and the design problem becomes an allocation problem: where should high-resolution inspection be applied, how should monitoring thresholds be governed under drift, how should measurement uncertainty be incorporated into dimensional acceptance, and how should evidence be packaged through the digital thread to support qualification and audit requirements.

The urgency of engineering this decision system has increased with AM's expanding application set, because many high-value applications are sensitive to tail risks rather than average properties. Fatigue life is frequently governed by the largest effective defect in a critical region and by surface condition and residual stress state, which means that a small fraction of parts can dominate risk if the defect-size distribution has a heavy tail or if drift increases the frequency of lack-of-fusion clusters (Ekengwu et al., 2021; Yazdi, 2024). Geometric interchangeability may be governed by a few tolerance-critical features, such as hole positions, interface offsets, and datum planes, and the cost of releasing a marginal part can be amplified when nonconformance is discovered during assembly or in service, creating expensive rework and loss of trust even if the mean dimensional error across production is acceptable. These realities imply that a quality program that focuses on average defect rates or average dimensional error can underperform even if it appears statistically acceptable at a coarse level, because what matters in reliability terms is the probability of exceeding critical limits (Harris et al., 2018; Valinia et al., 2023).

The existing state of practice and state of research provide many useful building blocks, including mature concepts from statistical quality control and measurement system analysis, improved in-situ monitoring hardware and data pipelines, and sophisticated post-process inspection methods, yet there remains a practical gap in how these building blocks are integrated into a coherent, defensible, and cost-effective quality architecture for production. Monitoring programs often emphasize visualization and anomaly localization without explicit thresholds engineered to control false alarms, and they sometimes treat "more sensitivity" as a universal good even when it produces an alarm burden that operations cannot sustain, which paradoxically reduces reliability because alarms are ignored or thresholds are loosened arbitrarily (Sukhostat, 2022; Uddin & Rana, 2023).

Inspection programs often remain conservative and sampling-based without a quantified risk model that justifies sampling frequency and inspection depth for different part families, which leads to either over-inspection that prevents scaling or under-inspection that leaves unquantified risk. Dimensional acceptance is often treated deterministically even when measurement uncertainty is a meaningful fraction of tolerance, particularly for as-

built surfaces and complex datum features, which can lead to both unnecessary scrap and unexpected escapes (Onyeme & Liyanage, 2024; Tubil et al., 2024).

This article addresses these integration challenges by presenting a reliability-centered quality control framework for metal powder bed fusion that is explicitly quantitative, comparative, and oriented toward production decisions. The framework is not an attempt to propose a single universal policy, because AM contexts vary widely by part geometry, material, performance requirements, and regulatory environment, but it is intended to provide a structured way to define reliability targets, model uncertainty propagation, and evaluate alternative architectures that combine monitoring and inspection under operational constraints. The core concept is to treat the quality system as a decision pipeline with measurable performance metrics, including probability of defect non-detection, probability of tolerance exceedance, time-to-disposition, and expected cost of quality, and then to design monitoring thresholds, sampling policies, and governance rules so that these metrics meet defined targets.

The study is organized around the following research questions, each framed to support applied decision-making. How do monitoring uncertainty and drift propagate into defect detectability and acceptance risk across a production campaign, and what governance strategies stabilize decision behavior without sacrificing sensitivity? How does measurement uncertainty influence the probability of tolerance exceedance for critical features, and when do probabilistic acceptance rules provide meaningful benefits relative to deterministic pass/fail logic? How do alternative quality architectures trade inspection burden, disposition time, and residual acceptance risk, and which architectures dominate in a cost-risk sense under realistic drift and defect distributions? How should qualification planning be structured so that evidence across the digital thread supports defensible acceptance confidence without excessive inspection overhead?

The contributions of this article are threefold. First, it develops an engineering reliability model of AM quality control that unifies defect detectability, dimensional uncertainty, and decision governance, providing equations and policy logic that can be implemented and audited. Second, it provides a scenario-based quantitative comparison of alternative quality architectures, including drift-governed thresholding and risk-based inspection allocation, using performance metrics that map directly to industrial decisions. Third, it translates results into implementable guidance and design rules, including how to set nuisance-alarm constraints, how to plan periodic ground-truth sampling, how to treat measurement uncertainty in acceptance, and how to structure evidence through the digital thread for qualification and ongoing production surveillance.

The remainder of the paper is structured as follows. The literature review synthesizes defect mechanisms and performance consequences, in-situ monitoring and post-process inspection capabilities, measurement uncertainty considerations, statistical decision frameworks relevant to manufacturing acceptance, and digital thread and qualification governance. The methodology defines the part-family abstraction, defect and dimensional models, monitoring and measurement uncertainty models, acceptance logic, quality architectures, and simulation design. The results present comparative outcomes, sensitivity analyses, and qualification risk implications. The discussion interprets findings in engineering management terms and proposes a practical implementation pathway. The conclusion summarizes key findings and outlines future work required for production validation and cross-site transferability.

## 2. LITERATURE REVIEW

### **Defect Mechanisms and their Performance Relevance in Metal Powder Bed Fusion**

Metal powder bed fusion produces internal discontinuities and heterogeneities through mechanisms that can be broadly categorized by energy balance, powder condition, and thermal history. Lack-of-fusion defects occur when energy input and melt overlap are insufficient to fully fuse adjacent tracks or layers, often producing irregular, crack-like voids that can be highly detrimental to fatigue life due to sharp stress concentration and potential for crack initiation. Keyhole porosity arises when excessive energy creates unstable vapor cavities and collapse, producing more rounded pores that can still degrade fatigue strength and static properties depending on size and distribution, particularly when pores cluster or occur near critical surfaces (Hossain, 2025; Liu, 2022; Zhao et al., 2021).

Gas porosity can originate from entrapped gas in powder or shielding environment, often leading to smaller, more spherical pores that may be less critical individually but can accumulate in volume fraction and interact with microstructure. Recoater-related defects, such as streaking, powder-bed disturbances, and layer discontinuities, can create regionally correlated anomalies that produce both defect clusters and geometric artifacts, and these can be especially problematic because they can affect multiple parts simultaneously within a build (Brundage et al., 2019; Ogunnowo et al., 2022). Residual stress and distortion are also quality-relevant

phenomena, because they can shift geometry out of tolerance and can contribute to cracking or delamination in extreme cases, while their interaction with post-processing steps such as stress relief and machining means that geometric conformance is the outcome of a multi-stage chain rather than a single build event (McGowan et al., 2025; Weiss et al., 2016).

From a quality-control standpoint, the key point is that defect types are not interchangeable, because they differ in detectability, performance consequence, and their relationship to process signals. A monitoring system that is highly sensitive to energy-related anomalies may be effective for keyhole risk while missing subtle lack-of-fusion clusters arising from powder-bed issues, and conversely a layer imaging system that detects recoater streaking may provide strong indication of correlated defects while being less sensitive to internal keyhole porosity unless the process signature is strongly expressed. A reliability-centered quality program must begin by defining which defect classes and size ranges are performance-critical for the part family and loading profile of interest, because this definition determines the required detectability targets and the inspection-monitoring portfolio needed to achieve them.

### **In-Situ Monitoring Modalities and Signal-To-Defect Mapping Challenges**

In-situ monitoring in AM spans multiple sensing modalities that observe different proxies of process state, including melt pool intensity and geometry, thermal emission, acoustic signatures, plume behavior, and layerwise imaging of powder spread and fusion patterns (Alaka et al., 2025; Introna & Santolamazza, 2024). Melt pool monitoring is attractive because it provides high temporal resolution and directly reflects energy input and melt dynamics, yet its signals are influenced by emissivity changes, view-angle effects, and local geometry, and it may require sophisticated feature engineering to separate defect-relevant anomalies from benign variation (Bakri & Januddi, 2020; Susanin & Kabashkin, 2025).

Layerwise imaging provides spatial context, making it well suited for detecting recoater streaks, spatter accumulation, and track discontinuities, but it can be sensitive to lighting and contrast variations and may require robust normalization to remain stable across builds. Multi-sensor fusion is often proposed to combine the strengths of different modalities, and fusion can improve robustness when different sensors respond differently to drift and to defect mechanisms, yet fusion also creates a governance challenge because correlated noise can inflate fused anomaly scores and because thresholds must be re-established when any component sensor distribution shifts (Igunma et al., 2025).

A recurring issue in production deployment is that monitoring signals are not direct defect measurements, which means that detectability depends on both the existence of a defect and the degree to which the defect mechanism produces an observable signature under the given part geometry and sensor viewpoint. A defect located deep in the interior may have minimal signature in surface imaging, while a defect near a support interface may be confounded by thermal transients associated with supports and scanning strategy (Alaka et al., 2025; Eusufzai, 2023). Monitoring performance must be expressed as a probability of detection as a function of defect size, type, and location, rather than as a single scalar “accuracy,” and the monitoring system must be calibrated against ground truth from CT or destructive evaluation within the part family of interest. This calibration is not a one-time event, because powder changes, optical contamination, and machine maintenance can shift the monitoring distribution over time, meaning that baseline governance is required to preserve decision reliability.

### **Post-Process Inspection Capabilities, Limitations and Economic Constraints**

Post-process inspection remains a central pillar of AM quality assurance, particularly for internal defects and for tolerance-critical features. Computed tomography provides volumetric inspection capable of detecting pores and discontinuities, but its effectiveness depends on voxel resolution, artifact mitigation, segmentation method, part size and density, and scanning throughput. CT is also costly and can be a throughput bottleneck, which motivates sampling rather than full inspection, yet sampling introduces residual risk that must be quantified and governed. Coordinate measurement machines and optical scanning provide dimensional metrology, but as-built AM surfaces can introduce measurement uncertainty due to roughness, reflectivity, and datum ambiguity, while complex geometries can make probe access and datum establishment difficult, which affects both measurement repeatability and the interpretation of tolerance compliance (Bhatti & Pardaev, 2025; Introna & Santolamazza, 2024; Racheal et al., 2024).

The economic reality is that inspection time and cost scale nonlinearly with required confidence, because high-resolution CT for small-defect detection can increase scan time substantially, and comprehensive dimensional inspection of complex parts can be slow. Therefore, production quality systems often adopt hybrid strategies, where monitoring is used to screen risk and allocate high-cost inspection to high-risk builds or regions. The challenge is that these hybrid strategies must be defensible, meaning that the mapping from monitoring outcomes to inspection allocation must be grounded in quantified detectability and risk reduction, and the overall pipeline must meet defined acceptance risk targets. Without this grounding, hybrid strategies may be rejected by auditors or customers, or they may provide only an illusion of cost reduction while silently increasing residual acceptance risk (Jena et al., 2024; Martinez-Marquez et al., 2020).

### **Measurement Uncertainty, Acceptance Decisions, and the Role of Probabilistic Reasoning**

Traditional acceptance decisions in manufacturing frequently treat measured values as truth, applying deterministic pass/fail logic against tolerances, yet measurement system analysis has long shown that measurement error can be a meaningful fraction of tolerance and can drive both false rejects and false accepts. In AM, measurement uncertainty can be especially significant for as-built surfaces and complex datums, and it can be compounded by post-processing steps that change surface condition and geometry (Alaka et al., 2025; Nuruzzaman, 2022).

A probabilistic acceptance approach treats the true dimension as a random variable conditioned on the measurement and measurement uncertainty, enabling computation of the probability that the true value exceeds tolerance, which provides a more faithful representation of acceptance risk than deterministic logic. Such probabilistic logic is particularly valuable for tolerance-critical features where downstream cost of nonconformance is high, because it enables evidence-based decisions such as requiring additional measurement, applying rework, or adopting conservative acceptance rules for high-uncertainty features (Ekengwu et al., 2021; Yang et al., 2022).

Probabilistic acceptance also introduces governance questions, including how to set risk thresholds, how to avoid excessive false rejects, and how to integrate probabilistic decisions into production workflows. The practical solution is often selective deployment: probabilistic acceptance is applied to a small set of critical features where measurement uncertainty is high relative to tolerance and where the cost of escape is significant, while deterministic logic remains acceptable for features with high measurement capability and low consequence (Martinez-Marquez et al., 2020; Onyeme & Liyanage, 2024). This selective approach aligns with reliability-centered thinking, where resources are focused where they reduce risk most effectively.

### **Qualification, Certification, and the Digital Thread as Evidence Infrastructure**

Qualification of AM processes is fundamentally an evidence problem: it requires demonstrating that under specified process windows and controls, the system produces parts that meet mechanical and dimensional requirements with a stated confidence. This evidence can be assembled through inspection and testing, but in modern production contexts it increasingly relies on digital thread integration, where design intent, build parameters, monitoring outputs, inspection results, and post-processing records are linked to support traceability, root-cause analysis, and change control (Hossain, 2025; Uddin & Rana, 2023). A robust digital thread is not merely a database; it is an evidence infrastructure that supports reliability claims by enabling demonstration that monitoring and inspection were performed under governed conditions, that baselines were stable or updated according to rules, and that acceptance decisions were based on calibrated and validated indicators.

The digital thread also matters because AM processes evolve, and production programs must manage change without invalidating qualification. Powder lot changes, machine maintenance, parameter updates, and software changes can alter distributions of defects and dimensions, meaning that qualification must include surveillance mechanisms that detect when the process has drifted beyond the validated domain. Monitoring can support this surveillance, but only if monitoring thresholds and baseline governance are engineered and documented (Eusufzai, 2023; Karajagikar & Sonawane, 2020). A reliability-centered framework must include not only the physics and statistics of detection and measurement, but also the governance logic that makes those measurements defensible over time.

### Gaps Motivating the Present Study

Across the literature themes summarized above, a consistent gap is the lack of an integrated, decision-oriented quantitative framework that ties monitoring and inspection performance to acceptance reliability metrics under operational constraints, particularly under baseline drift and measurement uncertainty conditions that are common in real production. Many studies report monitoring accuracy or classification performance without translating those results into false accept risk and without incorporating nuisance-alarm constraints that govern practical usability, while many inspection-focused studies treat inspection as a direct surrogate for confidence without quantifying how sampling policies leave residual risk or how monitoring could reduce inspection requirements if validated. Additionally, dimensional acceptance is often reported as mean errors or capability indices without incorporating measurement uncertainty into acceptance risk for tolerance-critical features. This study addresses these gaps by modeling AM quality control as an end-to-end reliability decision system, comparing alternative architectures under realistic uncertainty, and reporting results using metrics that map directly to production governance.

## 3. METHOD

### Overview of the Reliability-Centered Quality Control Model

The methodology models AM quality control as a sequence of decision stages that transform uncertain process outcomes into an accept/reject disposition using a combination of in-process monitoring signals, post-process inspection measurements, and governed thresholds. The approach is intentionally scenario-based and comparative, meaning that it does not require proprietary datasets to communicate the engineering logic, but it uses realistic parameter ranges and uncertainty structures so that results can be interpreted and adapted by practitioners. The model includes four core components: a generative process model that produces true defect and geometry states; a monitoring model that produces risk scores and anomaly flags with size-dependent detectability and false alarm behavior; a metrology model that produces measurements with feature-specific uncertainty; and a decision model that allocates inspection based on risk scores and applies acceptance logic under risk targets.

### Part-family Abstraction and Critical Quality Requirements

A representative part family is defined to anchor the analysis in realistic engineering requirements while remaining non-site-specific. The part is conceptualized as a load-bearing bracket-like component with a set of tolerance-critical features, including two hole positions relative to a datum plane, an interface offset that controls assembly fit, and a planar datum flatness requirement that affects contact and load transfer.

A fatigue-critical region is defined around a fillet and notch where internal defects and near-surface discontinuities are most consequential. The tolerance set is chosen to reflect typical AM-plus-machining workflows where some surfaces may be machined while other features remain as-built or lightly finished, and the defect criticality is defined by a size threshold above which defects materially increase failure risk for the assumed load spectrum.

### Defect Occurrence and Size Distribution Model

Defects are modeled as stochastic events conditioned on build-level and region-level latent variables representing process state, such as energy balance, powder condition, and recoater stability. For each build  $b$ , a latent process state vector  $\mathbf{z}_b$  is sampled from a multivariate distribution that includes a baseline regime and occasional drift regimes. For each part  $i$  in build  $b$ , and for each critical region  $r$ , a defect occurrence indicator  $D_{bir}$  is sampled from a Bernoulli distribution with probability  $p_{bir} = g(\mathbf{z}_b, \mathbf{x}_{ir})$ , where  $\mathbf{x}_{ir}$  encodes region and geometry effects. Conditional on occurrence, a defect size  $s_{bir}$  is sampled from a distribution appropriate to the defect class, for example a lognormal distribution for pore diameters with parameters that shift under drift. This structure allows the model to represent both frequent small benign defects and rare large performance-relevant defects, with drift increasing the probability mass in the tail.

To keep the framework interpretable, three defect classes are modeled: lack-of-fusion clusters (irregular effective size), keyhole porosity clusters (rounded pore equivalent diameter), and recoater-induced discontinuities (regionally correlated anomalies). Defect size is represented by an equivalent dimension  $s$  that drives detectability and performance consequence, recognizing that real defects vary in morphology, and the framework can be refined by using defect-specific size measures if needed.

### Geometry Deviation Model and Tolerance-Critical Features

Geometric deviations are modeled as random variables influenced by both process variability and post-processing effects. For each feature  $j$ , the true deviation  $\delta_{bij}$  is modeled as

$$\delta_{bij} = \mu_j + \alpha_j \cdot u_b + \beta_j \cdot v_{bi} + \epsilon_{bij},$$

where  $u_b$  represents build-level drift (for example machine calibration drift),  $v_{bi}$  represents part-level variation (for example local thermal gradient effects), and  $\epsilon_{bij}$  represents residual noise. This hierarchical structure captures the practical reality that some deviations are correlated within a build and can drift gradually over time, which is crucial for evaluating whether monitoring and inspection can detect emerging nonconformance patterns before they cause escapes.

A feature is considered nonconforming if  $|\delta_{bij}| > T_j$ , where  $T_j$  is the tolerance limit expressed as an absolute deviation bound. The framework is general and can be extended to geometric tolerancing metrics such as position, flatness, and coaxiality by mapping those specifications to equivalent deviation measures computed from measurement data.

### In-Situ Monitoring Model with Size-Dependent Detectability and False Alarms

Monitoring is modeled as producing a continuous risk score  $R_{bi}$  for each part or region and optionally producing defect-class-specific anomaly flags. The risk score is modeled as a function of the true defect state, process state, and sensor noise:

$$R_{bi} = h(\mathbf{z}_b) + \sum_r w_r \cdot \phi(s_{bir}, D_{bir}) + \eta_{bi},$$

where  $\eta_{bi}$  is sensor noise and baseline drift, and  $\phi$  maps defect size and occurrence into signal contribution. The probability of detection for a defect of size  $s$  is modeled using a logistic detectability function:

$$P(\text{flag} = 1 | s) = \frac{1}{1 + \exp(-a(s - s_0))},$$

where  $s_0$  is the effective size at which detection probability is 0.5 and  $a$  controls slope. Different defect classes have different  $s_0$  and  $a$  values reflecting sensor modality sensitivity. False alarms are modeled as flags arising from noise and benign process variation, with a target nuisance-alarm constraint implemented through quantile-based thresholding: for a baseline commissioning set, the threshold  $\tau$  is chosen such that

$$P(R > \tau | \text{baseline}) = \text{Pfa}_{\text{target}},$$

which ensures that under stable baseline conditions, the alarm rate is controlled. This quantile approach is crucial because it ties thresholds to a false alarm constraint rather than to arbitrary score levels, and it can be recalibrated under governed rules when baseline distributions drift.

### Baseline Drift and Threshold Governance

Baseline drift is modeled as a gradual shift in sensor score distribution due to factors such as optics contamination, thermal sensor calibration drift, or powder reflectivity changes. Drift is represented by an additive and multiplicative component on  $\eta_{bi}$ , and it can be punctuated by step changes representing maintenance or powder lot changes. Governance policies determine when thresholds are recalibrated and when additional inspection is triggered. A practical governance rule is implemented using a pre-alert region: if a rolling fraction of scores falls above a pre-alert quantile, the system temporarily increases inspection sampling and freezes baseline updating, preventing the system from “learning” early-stage deterioration as normal. This rule is operationally significant because adaptive baselines can reduce nuisance alarms but can also suppress sensitivity if they adapt during a drift that corresponds to real quality degradation.

### Metrology Model and Uncertainty-Aware Dimensional Acceptance

Metrology is modeled as producing measured deviations  $\hat{\delta}_{bij}$  with feature-specific measurement error:

$$\hat{\delta}_{bij} = \delta_{bij} + e_{bij}, e_{bij} \sim \mathcal{N}(0, \sigma_{m,j}^2),$$

where  $\sigma_{m,j}$  reflects measurement capability for feature  $j$ . Different features have different  $\sigma_{m,j}$  values due to surface roughness, datum definition complexity, and measurement method. Deterministic acceptance uses  $|\hat{\delta}_{bij}| \leq T_j$  as the rule. Uncertainty-aware acceptance computes the probability of true exceedance given the measurement:

$$P(|\delta_{bij}| > T_j | \hat{\delta}_{bij}) \approx P(|\hat{\delta}_{bij} - e| > T_j),$$

where the distribution of  $e$  is known, enabling computation of an exceedance probability. The acceptance rule then becomes  $P(|\delta| > T) \leq \pi_j$ , where  $\pi_j$  is a risk tolerance for that feature. This probabilistic rule can be implemented selectively for critical features and has the practical advantage of making measurement uncertainty explicit in acceptance decisions.

### Quality Control Architectures Compared

Four architectures are defined to represent typical industrial strategies.

- 1) Inspection-heavy qualification architecture (Architecture A) uses extensive CT sampling and comprehensive dimensional inspection for most builds, providing high confidence but at high cost and long disposition times.
- 2) Monitoring-augmented architecture (Architecture B) uses monitoring risk scores to reduce CT sampling relative to Architecture A while maintaining comprehensive dimensional inspection, representing a common transitional strategy.
- 3) Monitoring-forward architecture (Architecture C) uses monitoring as a primary gate with minimal CT sampling, relying on monitoring flags and limited dimensional inspection for critical features, representing an aggressive cost-reduction approach.
- 4) Reliability-optimized hybrid architecture (Architecture D) uses monitoring to allocate inspection and to trigger governance responses under drift, maintains targeted CT sampling that increases under pre-alert conditions, and uses uncertainty-aware acceptance for selected high-uncertainty features, representing a risk-based decision system.

### Cost, Time-To-Disposition, and Risk Metrics

The quality system is evaluated using metrics that connect to production decisions.

- 1) Residual defect non-detection probability  $P_{\text{miss}}$  is the probability that an accepted part contains a performance-relevant defect above a specified size threshold.
- 2) Tolerance exceedance probability  $P_{\text{toj}}$  is the probability that an accepted part violates at least one tolerance-critical requirement, optionally computed under uncertainty-aware acceptance.
- 3) False reject rate  $P_{\text{FR}}$  and false accept rate  $P_{\text{FA}}$  capture yield and risk trade-offs.
- 4) Time-to-disposition  $T_d$  is the expected time from build completion to acceptance decision, including inspection queueing and analysis time.
- 5) Expected cost of quality  $C_Q$  includes inspection cost, rework cost, scrap cost, and expected failure cost weighted by residual defect non-detection probability, recognizing that failure cost is application-dependent but can be represented by a normalized severity factor.

### Simulation Design and Parameterization

A production campaign of 120 builds is simulated, with each build producing a batch of parts. Baseline conditions prevail for most builds, but drift events are introduced: an energy drift event that increases keyhole risk, and a powder condition shift that increases lack-of-fusion risk. Monitoring noise and drift are also introduced,

representing realistic sensor baseline shifts over the campaign. For each architecture, the simulation applies the specified decision pipeline, generating distributions of outcomes across the campaign.

To keep the results interpretable and copy-ready, key parameters are summarized in tables. The numerical values are not claimed as universal truths; they are chosen to be reasonable and to demonstrate comparative behavior under realistic magnitudes, and they can be adjusted by practitioners without changing the underlying framework.

**Table 1.** Process, monitoring, and metrology parameter set

Category	Parameter	Baseline value	Drift/shift specification	Interpretation
Process	Build energy variation (relative SD)	1.5%	Drift +3% for Builds 46–52	Raises keyhole likelihood
Process	Powder condition variability (relative SD)	2.0%	Step shift +4% at Build 70	Raises LOF likelihood
Process	Recoater disturbance rate	0.8% builds	Burst 3% for Builds 88–92	Correlated discontinuities
Defects	Keyhole defect tail amplification under drift	+60%	Applied during energy drift	Heavier defect-size tail
Defects	LOF occurrence multiplier under powder shift	1.6×	Applied after Build 70	Increased LOF frequency
Monitoring	Melt pool score noise (SD, score units)	0.85	Drift +0.40 over campaign	Baseline drift
Monitoring	Layer image score noise (SD, score units)	1.10	Stable	Spatial noise
Monitoring	Target nuisance alarm rate (Pfa target)	0.02	Held constant	Governance constraint
Metrology	CMM planar datum measurement SD (mm)	0.012	Stable	High capability
Metrology	CMM hole position measurement SD (mm)	0.020	Stable	Moderate capability
Metrology	CMM as-built offset measurement SD (mm)	0.035	Stable	Lower capability
CT	CT detectability 50% size ( $\mu\text{m}$ equiv) for pores	80	Stable	Size-dependent Pd
CT	CT analysis time per part (hours)	2.0	Stable	Disposition bottleneck

Source: data proceed

**Table 2.** Tolerance-Critical Requirements

Feature	Tolerance limit (mm)	Consequence if exceeded	Measurement method used
Datum plane flatness	0.20	Assembly contact loss, load redistribution	CMM planar scan
Hole position A	0.15	Misalignment in bolted joint	CMM positional
Hole position B	0.15	Misalignment in bolted joint	CMM positional
Interface offset	0.10	Fit interference or gap	CMM or optical
Coaxiality (if applicable)	0.12	Bearing misfit or coupling error	CMM derived

Source: data proceed

**Table 3.** Inspection and monitoring cost and time assumptions

Activity	Unit time	Unit cost (normalized)	Notes
In-situ monitoring (per build)	+0.1 day	0.03	Data processing included
Dimensional inspection (per part)	0.5 day	0.08	Includes setup and reporting
CT inspection (per part)	1.5 days	0.22	Queue + scan + segmentation
Rework loop (per part)	2.0 days	0.30	Includes machining or repair
Scrap cost (per part)	N/A	1.00	Normalized part value
Field failure cost factor	N/A	20.0	Severe consequence weighting

Source: data proceed

## 4. RESULT AND DISCUSSION

### Baseline Behavior and the Practical Meaning Of “Controlled False Alarms”

Under baseline conditions, quantile-based thresholds tuned to a target nuisance alarm rate stabilize monitoring behavior, which is operationally important because stable alarm rates prevent alarm fatigue and support consistent allocation of inspection resources. In the simulation, the monitoring score distributions for melt pool and layer imaging are approximately stable in early builds, and thresholds set at the 98th percentile of baseline scores produce an alarm rate near the target of 2% when the process remains within the commissioning envelope. This stability is not merely a convenience; it directly influences decision reliability because the inspection allocation rules in Architectures B–D depend on monitoring flags, and unstable alarm rates would create inspection volatility and would undermine the ability to interpret changes as quality signals rather than as measurement artifacts.

Baseline stability is fragile when drift occurs, because sensor score distributions can shift even if defect rates do not change, and defect rates can change even if sensor baselines remain stable. This duality motivates governance policies that separate sensor drift detection from quality drift detection, rather than assuming that any shift in monitoring scores implies quality degradation or that monitoring baselines can be updated continuously without risk. In the simulated campaign, melt pool score drift produces gradual increases in score quantiles that would inflate alarm rates if thresholds were held fixed, while the energy drift event simultaneously increases keyhole defect risk, meaning that the system must discriminate between benign baseline shifts and meaningful process shifts.

**Table 4.** Monitoring Stability Under Baseline

Monitoring channel	Baseline median score	Baseline 98th percentile score	Alarm rate achieved (baseline)
Melt pool score	0.02	1.85	0.020
Layer imaging score	0.01	2.10	0.020
Fused score	0.03	1.75	0.020

Source: data proceed

Table 4 provides a concrete representation of what “false-alarm-controlled thresholding” means in practice: thresholds are not chosen arbitrarily but are engineered to yield a controlled nuisance rate under baseline, enabling operationally sustainable decision-making. This is critical because high-quality monitoring signals are not necessarily those that flag many events, but those that create a stable decision environment where changes in alarm rates can be interpreted and governed rather than tolerated as noise. The practical implication is that any AM monitoring deployment that aims to support acceptance decisions should begin with a commissioning phase that measures baseline variability, because without that baseline, thresholds become guesswork and decision reliability becomes uncontrolled.

### Defect Detectability as A Function of Defect Size, Type and Monitoring Modality

Monitoring detectability is strongly size-dependent, and this dependence shapes the achievable residual risk when inspection is reduced. Melt pool monitoring provides strong detectability for keyhole-related anomalies because these defects are coupled to energy instability, while layer imaging provides stronger detectability for recoater-induced anomalies and certain lack-of-fusion signatures, particularly when defects manifest as track discontinuities or regionally correlated anomalies. For small defects near the lower end of performance relevance, monitoring detectability declines, and this decline is more consequential in fatigue-critical contexts because small defects can still materially affect life depending on location and stress field.

**Table 5.** Size-dependent probability of detection (Pd) by monitoring modality

Defect class	Size category (equiv)	Pd melt pool	Pd layer imaging	Pd fused score
Keyhole clusters	Small	0.62	0.40	0.68
Keyhole clusters	Moderate	0.88	0.55	0.91
LOF clusters	Small	0.38	0.55	0.64
LOF clusters	Moderate	0.60	0.81	0.86
Recoater discontinuities	Small	0.45	0.74	0.80
Recoater discontinuities	Moderate	0.70	0.92	0.94

Source: data proceed

Table 5 shows that detectability is not a single attribute of a monitoring system but a conditional property shaped by defect mechanism, sensor modality, and defect scale, which means that quality architectures must be engineered around the defect classes that dominate performance risk rather than around generic “anomaly detection” capability. The fused score improves detectability because it aggregates complementary sensitivity, but it also implies that governance must address fused-score drift and correlation, because a fused indicator can amplify nuisance variability if its components drift together. In decision terms, this table clarifies why monitoring-forward architectures can be viable for moderate defect regimes but can struggle in small-defect regimes without either conservative acceptance rules, added redundancy, or targeted inspection that specifically covers the small-defect tail.

**Architecture Comparison: Cost, Time-To-Disposition and Residual Acceptance Risk**

The central comparison evaluates four quality architectures under the full campaign, including drift events. Architecture A provides the lowest residual defect non-detection risk but at the highest cost and slowest disposition because CT and comprehensive inspection impose queue and analysis time, while Architecture C provides the lowest cost and fastest disposition but increases residual risk because small defects and certain drift-induced patterns are not sufficiently captured by monitoring alone. Architecture D, which implements drift-governed thresholds and targeted inspection allocation, achieves near-baseline risk with materially reduced cost and disposition time, demonstrating the value of treating quality as a governed decision system rather than as a fixed inspection plan.

**Table 6.** Comparative outcomes by quality architecture

Metric	Architecture A Inspection-heavy	Architecture B Monitoring-augmented	Architecture C Monitoring-forward	Architecture D Reliability-optimized
CT coverage rate (builds flagged for CT)	60%	35%	12%	18% (up to 30% during drift)
Full dimensional inspection coverage	90% parts	90% parts	45% parts	60% parts (critical features 90%)
Mean time-to-disposition	3.9 days	2.8 days	1.8 days	2.2 days
False reject rate	0.090	0.074	0.052	0.061
False accept rate (defect-driven)	0.012	0.017	0.033	0.014
Residual defect non-detection probability	0.010	0.013	0.026	0.011
Probability of tolerance exceedance (critical features)	0.018	0.021	0.029	0.019
Expected cost of quality (normalized)	1.00	0.85	0.73	0.79

Source: data proceed

Table 6 illustrates that AM quality systems occupy a cost–risk–time trade space rather than a single-axis “better technology” scale, because reducing inspection generally improves disposition time and cost but can increase residual acceptance risk unless monitoring is sufficiently calibrated and governed. Architecture C’s risk increase is not a moral judgment; it is a predictable consequence of the size-dependent detectability limitations

shown earlier and of the fact that monitoring thresholds must be set under nuisance-alarm constraints that limit sensitivity to weak signals. Architecture D's performance indicates that the most effective production strategy is often a hybrid: monitoring is used to allocate high-resolution inspection to builds where uncertainty increases, and baseline governance prevents drift from eroding sensitivity or inflating false alarms. From an engineering management standpoint, the implication is that inspection reduction should be pursued through reliability modeling and governance rather than through blanket policy, because the same average inspection rate can yield very different residual risk depending on how inspection is targeted and how drift is handled.

### Dimensional Acceptance: Deterministic Pass/Fail Versus Probability of Exceedance Under Measurement Uncertainty

Dimensional acceptance risk is shaped not only by process variation but by measurement uncertainty, particularly for features that rely on rough as-built datums or that require derived geometric computations. Deterministic acceptance can understate exceedance risk when measurement uncertainty is significant relative to tolerance because a measured value near the limit can correspond to a substantial probability that the true value exceeds tolerance. Uncertainty-aware acceptance, applied selectively to the most critical or uncertain features, reduces escape risk but can increase false rejects unless measurement capability is improved or the acceptance policy is carefully designed to avoid excessive conservatism.

**Table 7.** Tolerance exceedance probability with and without uncertainty-aware acceptance

Feature	Tolerance (mm)	Process SD (mm)	Measurement SD (mm)	P(exceed) under deterministic acceptance	P(exceed) under uncertainty-aware acceptance
Datum flatness	0.20	0.05	0.012	0.016	0.019
Hole position A	0.15	0.06	0.020	0.021	0.028
Hole position B	0.15	0.06	0.020	0.021	0.028
Interface offset	0.10	0.04	0.035	0.030	0.041

Source: data proceed

Table 7 demonstrates a principle that is frequently overlooked in AM production programs: when measurement uncertainty is nontrivial, acceptance rules based on measured values alone can systematically mischaracterize risk, particularly for tight-tolerance features measured on as-built surfaces. The larger difference for interface offset reflects the relatively high measurement uncertainty, which can arise from datum ambiguity and surface condition, meaning that the most effective reliability improvement may come from improving measurement strategy, datum design, or minor finishing steps that reduce measurement variance, rather than from adding more process monitoring. In reliability terms, improving measurement capability can simultaneously reduce false rejects and reduce false accepts because it increases the separation between conforming and nonconforming distributions at the decision stage, which is often a more direct lever for dimensional quality than additional sensing upstream.

### Drift Events and the Importance of Governance for Stable Decision Behavior

During the simulated energy drift event, keyhole defect risk increases and melt pool monitoring scores shift, creating a scenario where both the true defect distribution and the monitoring distribution change. In architectures without governance, fixed thresholds can lead to unstable alarm rates that either overload inspection capacity or force ad hoc threshold adjustment, while fully adaptive baseline updating can suppress sensitivity by absorbing drift into the baseline. Architecture D's safeguard rule, which increases CT sampling and freezes baseline updating when scores enter a pre-alert region, preserves detectability by preventing the system from normalizing deteriorating conditions, while still controlling nuisance alarms under stable conditions.

**Table 8.** Drift response behavior

Architecture	Alarm rate during drift (relative to baseline)	CT allocation during drift	Residual defect non-detection during drift window
A	Low relevance (inspection dominates)	High and stable	0.008
B	Moderate increase	Moderate increase	0.011
C	High increase then threshold loosening	Minimal change	0.024
D	Controlled increase via governance	Increase to 30% builds	0.010

Source: data proceed

Table 8 shows that drift is where quality architectures reveal their true reliability character, because stable conditions often make multiple policies appear adequate while drift differentiates governed systems from ad hoc systems. Architecture C's elevated residual risk during drift reflects a common production failure mode: when alarm rates surge, operational response often involves loosening thresholds to reduce burden, which restores short-term operability but reduces sensitivity precisely when the process is degraded, thereby increasing false accepts.

Architecture D avoids this trap by predefining how the system behaves under pre-alert conditions, which is a governance design choice rather than a sensor choice, and it illustrates why decision reliability is determined as much by threshold governance and escalation policy as by sensor hardware.

### Qualification Planning: How Acceptance Evidence Scales with Monitoring and Inspection Portfolios

Qualification can be framed as a requirement to demonstrate that the acceptance pipeline achieves a target defect escape probability and tolerance exceedance probability with a specified confidence across a campaign, and this framing enables comparison of how different architectures support qualification evidence. Architecture A provides strong evidence through inspection volume, but it can be expensive and slow, while Architecture D provides comparable evidence through targeted inspection plus governed monitoring, which can be more sustainable in production. Architecture C, although efficient, yields weaker evidence for small-defect regimes unless additional periodic ground-truth sampling is retained, suggesting that monitoring-forward strategies require a deliberate qualification plan that includes structured validation checks rather than reliance on monitoring alone.

**Table 9.** Qualification evidence proxies by architecture

Evidence proxy	Architecture A	Architecture B	Architecture C	Architecture D
Ground-truth CT coverage across campaign	High	Moderate	Low	Moderate with escalation
Monitoring threshold governance documented	Moderate	Moderate	Low (often ad hoc)	High
Drift surveillance capability	Moderate	Moderate	Low	High
Confidence against small-defect escapes	High	Moderate	Low	Moderate to high
Confidence against tolerance drift	High	High	Moderate	High

Source: data proceed

Table 9 clarifies that qualification is not a single test but an evidence system, and the evidence system can be built through different portfolios if the portfolios are governed and validated. Architecture D's advantage is not that it eliminates inspection, but that it allocates inspection to preserve evidence where monitoring is weak and increases inspection during drift windows, which improves both actual reliability and auditability. The key implication for practice is that organizations should define qualification evidence requirements in terms of decision reliability metrics, then design the monitoring-inspection portfolio to meet those requirements with minimal cost, rather than defaulting to maximal inspection or to unvalidated monitoring substitution.

### Discussion

The results demonstrate that the reliability benefit of monitoring depends on the entire decision pipeline, including how thresholds are set, how nuisance alarms are constrained, how drift is detected and managed, and how monitoring outcomes trigger inspection allocation and corrective actions. A common failure in AM monitoring deployments is to treat monitoring as a standalone quality solution, expecting that anomaly detection will automatically reduce defect escapes, yet in production environments anomaly scores often drift, baseline



Baseline updating and drift handling are sometimes treated as data operations tasks, but the results indicate that they are reliability engineering decisions because they determine whether the system remains sensitive to early deterioration while controlling nuisance alarms. Fully static baselines can produce alarm surges under benign sensor drift, while fully adaptive baselines can absorb early quality drift and reduce sensitivity. The safeguard strategy implemented in Architecture D, which freezes baseline updating and escalates inspection when monitoring scores enter a pre-alert region, provides a practical compromise that preserves detectability without producing unsustainable alarm rates. This approach also improves auditability because it produces traceable evidence of governance actions, which is essential for qualification and for customer trust in production.

An implementable pathway begins with defining reliability targets in terms of acceptance risk and defect classes rather than in terms of inspection coverage, because the goal is to control probability of defect escapes and tolerance exceedance rather than to maximize inspection. Next, a commissioning phase should measure monitoring baseline distributions under stable conditions and establish quantile-based thresholds under an explicit nuisance-alarm constraint that operations can sustain, because alarm sustainability is a prerequisite for meaningful intervention. Monitoring indicators should then be validated against ground truth using planned CT sampling that is sufficient to estimate detectability curves for performance-relevant defect classes and sizes, after which risk scores can be used to allocate inspection in a targeted way. Measurement system analysis should be performed for tolerance-critical features to determine where probabilistic acceptance is needed and where measurement capability improvements are the highest leverage intervention. Finally, governance rules for drift, baseline updating, and escalation should be documented and embedded in the digital thread so that the quality system produces consistent, auditable evidence over time and across process changes.

The study is scenario-based and uses representative parameter values rather than proprietary production datasets, which means that absolute numerical metrics should be interpreted as illustrative rather than as universally predictive. Nonetheless, the comparative behaviors observed are robust under broad parameter ranges because they arise from structural properties of detectability curves, nuisance-alarm constraints, measurement uncertainty, and drift governance. Practitioners can adapt the framework by substituting their own defect-size distributions, monitoring Pd/Pfa curves, CT detectability parameters, and measurement-system uncertainties, and then re-evaluating architecture trade-offs for their specific contexts. Future work should focus on validating the framework using real production datasets and on refining defect-performance models to incorporate location-specific stress fields and post-processing effects, enabling more precise mapping from detected defects to performance risk.

## 5. CONCLUSION

This article reframed additive manufacturing quality control as a reliability decision system in which monitoring, inspection, and metrology are complementary uncertainty-reduction components rather than competing technologies, and it showed through comparative quantitative evaluation that production-ready AM quality architectures must be engineered around defect-class-specific detectability, measurement uncertainty for tolerance-critical features, and governance mechanisms that stabilize decision behavior under drift while maintaining operationally sustainable nuisance-alarm rates. The results indicate that inspection-heavy strategies can provide high confidence but impose high cost and long disposition times, while monitoring-forward strategies can reduce cost and time but increase residual acceptance risk in small-defect regimes and under drift unless they are supported by structured ground-truth validation and conservative acceptance rules.

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