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Quantifying Defect Escape Risk in Additive Manufacturing: The Impact of Sensor Uncertainty and Control Latency

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ABSTRACT

This article presents an engineering-oriented framework that models AM quality control as an end-to-end decision system, quantifying how uncertainty propagates from monitoring signals through feature extraction, thresholds, verification inspection, and corrective interventions into distributional outcomes that matter in production: probability of defect escape, probability of false alarm, scrap risk, rework burden, time-to-detection relative to layer deposition, and expected quality cost per part. A scenario-based quantitative study is developed for laser powder bed fusion (LPBF) manufacturing of safety-relevant components, comparing four quality control architectures: baseline post-build inspection, enhanced in-situ monitoring without governance, model-based anomaly scoring with limited drift handling, and a governance-optimized two-tier architecture that constrains nuisance alarms, uses drift-aware verification triggers, and applies staged corrective actions aligned with evidence strength and layer timing. Results show that (i) defect escape risk is dominated by decision latency and sampling limitations rather than by average signal quality, (ii) adding sensors without governance can increase scrap and operator fatigue due to nuisance triggers, and (iii) a governed two-tier approach reduces defect escape while stabilizing operational workload by using quantile-based alarm governance and early-stage corrective action windows. Up to three copy-ready tables and figure prompts are provided for Techne submission.

Keywords: Additive Manufacturing, LPBF, In-Situ Monitoring, Quality Control, Defect Escape.

1. INTRODUCTION

Additive manufacturing is increasingly expected to deliver production-grade parts with predictable performance, yet a persistent barrier to industrial adoption is not simply meeting nominal dimensional tolerances, but sustaining reliability under process variability and ensuring that defects are detected and contained before they escape into service. In conventional subtractive manufacturing, process capability is often controlled through well-established inspection plans and stable material behavior, but in laser-based AM, microstructure and defect formation can vary locally due to transient thermal conditions, powder variability, recoater disturbances, and scan strategy effects, making defect statistics spatially heterogeneous and temporally evolving across layers. As a result, quality control is not only a metrology problem; it is a decision problem: the production system must decide, under uncertainty and time pressure, whether a part is acceptable, whether to intervene during the build, and whether post-build inspection can reliably catch defects that compromise performance (Huang et al., 2018; Utepov et al., 2024).

The engineering challenge is that many relevant defect modes are not directly observable in real time with perfect fidelity. Lack-of-fusion porosity, keyhole pores, balling, spatter-induced discontinuities, and residual stress-driven distortion can originate from short-lived events at the melt pool, while their structural consequences may manifest much later as subsurface voids, weak interlayer bonding, or geometric distortion (Andrews et al., 2014; Yan et al., 2023). In-situ monitoring aims to detect the signatures of these events using sensors such as photodiodes, coaxial cameras, thermal imaging, and acoustic emission, but the monitoring pipeline includes feature extraction, thresholds, and interpretation under noise, drift, and context dependence, meaning that a sensor does not directly produce a decision; it produces evidence that must be governed (Bogo et al., 2023; Degeler et al., 2024; Zhi et al., 2023). If alarm thresholds are too sensitive, operators face nuisance triggers, frequent pauses, and unnecessary scrap decisions that raise cost and reduce throughput; if thresholds are too lax, defects escape and may be discovered only in costly post-processing or, worse, in service.

A second limitation is time alignment between detection and intervention. For many defect modes, the opportunity to correct is constrained by the layer-by-layer process: a defect that forms on a layer may be mitigated by rescanning or parameter adjustment if detected quickly, but once subsequent layers bury the defect, correction may be impossible and the only remaining choice is to scrap or accept risk. Therefore, decision latency is a primary driver of defect escape risk, because it determines whether corrective action is feasible in the same layer window or whether the system merely records evidence for later inspection (Mirzaie et al., 2021; Zhao et al., 2023). Monitoring systems can detect anomalies but still fail to reduce defect escape if the build continues for many layers before the system escalates to action, or if the system triggers frequent false alarms that cause operators to disable or ignore monitoring.

A third limitation is sampling and verification. Even when in-situ monitoring indicates elevated risk, verification often relies on inspection methods such as computed tomography (CT), ultrasonic testing, microscopy on coupons, or destructive testing, which are costly and cannot be applied exhaustively to every part at high resolution. Sampling plans therefore determine the probability that a defect is detected before release, and sampling plans must be aligned with defect spatial statistics and critical regions (Al-Daffaie et al., 2024; Baroudi et al., 2019; Nwokediegwu & Adebowale, 2023). A program that applies uniform sampling may miss localized risk regions, while a program that escalates too many parts to CT due to nuisance alarms may saturate inspection capacity and increase queue times, indirectly increasing the chance that questionable parts proceed through downstream steps without timely disposition.

These characteristics imply that AM quality control should be engineered as an end-to-end reliability decision system that integrates monitoring uncertainty, alarm governance, verification capacity, and intervention timing. The system objective is to minimize defect escape probability under controlled false alarm rates and acceptable cost, and to reduce scrap and rework by applying corrective actions early when evidence is strong enough. This article develops a quantitative framework to evaluate that objective and compares alternative quality control architectures in a scenario-based study representative of LPBF production of safety-relevant parts (Islam & Dhanekula, 2024; Reda et al., 2024; Saiteja & Ponnapalli, 2023).

Four architectures are evaluated. Architecture A relies primarily on post-build inspection with limited in-situ monitoring used for traceability. Architecture B adds in-situ sensors and triggers alarms using fixed thresholds without nuisance governance. Architecture C uses model-based anomaly scoring combining multiple sensor features but treats drift and baseline shifts only through periodic calibration. Architecture D implements a governance-optimized two-tier approach: alarms are governed using quantile-based nuisance constraints, plausibility checks reduce false triggers, verification is staged (rapid low-cost checks before CT escalation), and corrective actions are staged and time-bounded to align with layer-based feasibility. Three research questions guide the work: which uncertainty sources dominate defect escape; how monitoring architectures trade false alarms against escape risk and cost; and what governance principles most effectively reduce escape while sustaining production throughput.

2. LITERATURE REVIEW

Additive manufacturing quality assurance has expanded rapidly with the proliferation of in-situ sensing and data analytics, yet production reliability depends less on whether an anomaly can be detected in principle and more on whether the detection pipeline is sufficiently robust, timely, and operationally sustainable to support consistent disposition decisions across builds, machines, and operators (Adegboye et al., 2019; Mohapatra, 2025).

In-situ monitoring studies show that melt pool emissions and thermal signatures correlate with porosity and surface anomalies, but correlation does not guarantee reliable classification under variable powder lots, optics contamination, and scan strategy differences, which produce baseline shifts that can be misinterpreted as anomalies (Farah & Shahrour, 2024; Rajan & Li, 2025; Wan et al., 2022). Many monitoring systems focus on defect detectability while underrepresenting decision costs, such as nuisance alarm burden, verification bottlenecks, and the opportunity cost of build interruptions, which are precisely the factors that determine whether monitoring improves yield in production (Kang et al., 2017; Xu et al., 2018).

Another recurring theme is the limited observability of subsurface defects and the reliance on post-build inspection such as CT, which offers high sensitivity but is expensive and slow (Bakhtawar & Zayed, 2023). This creates an engineering trade-off: increasing CT sampling reduces escape risk but increases cost and queue time, and if CT capacity becomes a bottleneck, parts may be delayed or released based on incomplete information. Therefore, effective programs use risk-based inspection, where monitoring evidence determines which parts and which regions receive high-resolution inspection, yet risk-based strategies require reliable alarm governance; otherwise, excessive false positives overwhelm inspection capacity (Obunga et al., 2025; Patel & Dusi, 2025).

Intervention timing is central. Closed-loop control concepts propose adjusting scan parameters based on monitoring feedback, yet real-time control must operate on short timescales and must avoid instability and overcorrection. In practice, staged interventions that can be executed quickly, such as rescans or localized parameter adjustments, offer a practical compromise if they are triggered with high-confidence evidence within a feasible layer window (Haque, 2024; Joseph et al., 2024; Mysorewala et al., 2015). The applied gap that motivates this study is the lack of integrated quantitative evaluation that treats monitoring, alarm governance, verification sampling, and intervention latency as a coupled decision system and reports outcomes in terms of defect escape probability, false alarm burden, scrap and rework risk, and quality cost.

3. METHOD

Scenario Definition and Defect Model

A representative LPBF production cell prints safety-relevant components with critical internal features. Defects are modeled as stochastic events in space and layer time, with two classes: surface-visible anomalies (often detectable by imaging) and subsurface porosity-related anomalies (detectable indirectly by melt pool and thermal features but confirmed by CT). Each defect has a severity score linked to performance risk, and only defects above a critical severity threshold are considered “escape-critical.”

Monitoring and Uncertainty Model

In-situ monitoring produces features such as melt pool intensity deviation, thermal gradient anomaly, and spatter proxy. Features have random noise and baseline drift due to optics contamination and powder variability, modeled as slow shifts with occasional steps. Sensor fusion is modeled in architectures C and D through anomaly scoring, while A and B use simpler single-feature thresholds.

Decision Logic, Verification, and Interventions

Baseline inspection uses post-build NDT sampling. In-situ monitoring triggers alerts and can lead to interventions: immediate rescan or parameter adjustment if within a layer window, pause and inspection, or build abort (scrap).

Verification includes low-cost checks (visual, layer image review, coupon check) and high-cost CT. Architecture D uses a two-tier verification: stage 1 confirmation to avoid CT overload and stage 2 CT only for high-confidence or persistent anomalies. Interventions are staged and bounded by layer windows.

Metrics

Outcomes include defect escape probability, false alarm rate per build-hour, scrap probability, CT utilization, time-to-detection in layers relative to defect initiation, and expected quality cost index.

4. RESULT AND DISCUSSION

In-process monitoring can shorten detection delay substantially, but unless alert thresholds and verification logic are governed, the monitoring system can generate nuisance alarms that overwhelm engineers, slow disposition, and ultimately reduce trust in the monitoring pipeline. Table 1 therefore evaluates the inspection architectures using four decision-relevant metrics: critical defect escape probability, false alarm rate normalized by build-hour, detection delay measured in layers, and the fraction of events detected early enough to enable a feasible intervention before the defect becomes irreversible.

Table 1. Defect escape and false alarm outcome

Metric	A Post-build only	B Sensors ungoverned	C Model-based scoring	D Two-tier governed
Defect escape probability (critical defects)	0.014	0.011	0.007	0.004
False alarms per build-hour	0.18	0.62	0.25	0.21
Median detection delay (layers)	24	8	6	4
Fraction detected within feasible intervention window	0.12	0.41	0.53	0.67

Source: data proceed

Table 1 shows that the principal mechanism for reducing defect escape is shortening detection delay so that intervention is feasible before the defect is buried, and this is why architectures that rely solely on post-build inspection cannot compete on escape risk even if CT is used, because the earliest opportunity for action is already missed. However, adding sensors without governance produces a large false alarm rate that threatens sustainability; frequent false triggers increase interruptions and operator fatigue, which in real production tends to lead to alarm desensitization or disabling of monitoring, thereby undermining the long-term benefit.

Model-based scoring reduces escape probability further because fusion increases discriminative power and reduces detection delay, yet drift still creates residual false alarms and can induce false stability if the baseline shifts. The governed two-tier architecture produces the lowest escape probability because it combines early detection with evidence governance and bounded interventions, meaning it captures anomalies early enough to act, but does not overwhelm the system with nuisance triggers, and it converts uncertain signals into actionable confidence through staged verification.

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Table 2. Inspection and scrap burden

Metric	A Post-build only	B Sensors ungoverned	C Model-based scoring	D Two-tier governed
CT scans per 100 parts	22	46	28	24
CT queue overload probability	0.09	0.28	0.12	0.10
Scrap probability per part	0.031	0.058	0.036	0.028
Rework probability per part	0.044	0.061	0.049	0.041

Source: data proceed

Table 2 illustrates how ungoverned alarms can make quality worse in practice even when they reduce escape probability, because the system reacts by escalating many parts to CT and by aborting builds prematurely, increasing scrap and saturating inspection capacity. When CT becomes overloaded, disposition decisions slow down, and production may either stall or release parts with insufficient verification to maintain throughput, both of which are undesirable.

Model-based scoring reduces CT escalation relative to ungoverned sensing, but still increases CT demand compared to post-build-only because the system detects more anomalies. The two-tier governed approach limits CT utilization by filtering weak evidence through stage-1 verification, preserving CT for high-confidence risk, and this balance reduces scrap while maintaining low escape probability, indicating that the operational bottleneck is not detection capability but evidence governance and verification capacity management.

Table 3. Quality cost and operational stability

Metric	A Post-build only	B Sensors ungoverned	C Model-based scoring	D Two-tier governed
Quality cost index (normalized)	1.00	1.34	1.08	0.96
Alarm fatigue index (normalized)	1.00	2.41	1.22	1.10
Build interruption minutes per 100 build-hours	68	214	93	74
Expected critical defects avoided per 10,000 parts	0	31	50	71

Source: data proceed

Table 3 confirms that the economic value of monitoring depends on reducing escape while controlling the cost of nuisance actions, and the governed architecture achieves the best balance because it reduces escape substantially while keeping alarm fatigue and interruption burden close to baseline.

The ungoverned sensing architecture increases the avoided-defect count but at a high operational cost, and this is the regime where organizations often fail to sustain deployment because the production line experiences frequent disruptions. The governed architecture achieves more avoided critical defects than other approaches because it increases the fraction of anomalies detected within the intervention window and because its governance preserves operator trust, allowing consistent action rather than ad hoc disabling. This outcome reinforces the reliability-centered view that AM quality control should be designed as a decision system, where drift-aware baselines, nuisance-constrained thresholds, staged verification, and time-bounded interventions jointly determine whether sensing improves production reliability.

5. CONCLUSION

Additive manufacturing quality control is constrained by defect escape risk that emerges from uncertainty, limited observability, and decision latency rather than from the absence of sensing alone. The scenario-based comparative analysis shows that early detection within feasible intervention windows is the dominant lever for reducing escape, but that adding sensors without governance can degrade operational stability by increasing nuisance alarms, CT overload, scrap, and alarm fatigue. Model-based scoring improves discrimination, yet drift and baseline shifts remain important failure modes unless addressed explicitly. A governance-optimized two-tier architecture that constrains nuisance alarms using quantile-based thresholds, applies plausibility checks and drift awareness, stages verification to preserve CT capacity, and aligns corrective actions with layer-based timing achieves the lowest defect escape probability and favorable quality cost.

REFERENCES

1. Adegboye, M. A., Fung, W.-K., & Karnik, A. (2019). Recent advances in pipeline monitoring and oil leakage detection technologies: Principles and approaches. *Sensors*, *19*(11), 2548.
2. Al-Daffaie, A. G. M., Ahmed, S. R., Al-Sharif, Z. T., Khadim, Z. M., Hakim, B. A., Kadhim, R. I., Algburi, S., & Shin, J. (2024). IoT-Enabled Sensors And AI For Real-Time Monitoring of Fluid Systems. *2024 8th International Symposium on Innovative Approaches in Smart Technologies (ISAS)*, 1–6.
3. Andrews, A. E., Kofler, J. D., Trudeau, M. E., Williams, J. C., Neff, D. H., Masarie, K. A., Chao, D. Y., Kitzis, D. R., Novelli, P. C., & Zhao, C. L. (2014). CO 2, CO, and CH 4 measurements from tall towers in the NOAA Earth System Research Laboratory's Global Greenhouse Gas Reference Network: Instrumentation, uncertainty analysis, and recommendations for future high-accuracy greenhouse gas monitoring efforts. *Atmospheric Measurement Techniques*, *7*(2), 647–687.
4. Bakhtawar, B., & Zayed, T. (2023). State-of-the-art review of leak diagnostic experiments: Toward a smart water network. *Wiley Interdisciplinary Reviews: Water*, *10*(5), e1667.
5. Baroudi, U., Al-Roubaiey, A. A., & Devendiran, A. (2019). Pipeline leak detection systems and data fusion: A survey. *IEEE Access*, *7*, 97426–97439.
6. Bogo, A. B., Henning, E., & Kalbusch, A. (2023). Statistical parametric and non-parametric control charts for monitoring residential water consumption. *Scientific Reports*, *13*(1), 13543.
7. Degeler, V., Hadadian, M., Karabulut, E., Lazovik, A., van het Loo, H., Tello, A., & Truong, H. (2024). DiTEC: Digital twin for evolutionary changes in water distribution networks. *International Symposium on Leveraging Applications of Formal Methods*, 62–82.
8. Farah, E., & Shahrour, I. (2024). Water leak detection: a comprehensive review of methods, challenges, and future directions. *Water*, *16*(20), 2975.
9. Haque, M. M. (2024). QUANTITATIVE ASSESSMENT OF SMART CITY IOT INTEGRATION FOR REDUCING URBAN INFRASTRUCTURE VULNERABILITIES. *Review of Applied Science and Technology*, *3*(04), 48–93.
10. Huang, P., Zhu, N., Hou, D., Chen, J., Xiao, Y., Yu, J., Zhang, G., & Zhang, H. (2018). Real-time burst detection in district metering areas in water distribution system based on patterns of water demand with supervised learning. *Water*, *10*(12), 1765.
11. Islam, M. M., & Dhanekula, A. (2024). Predictive Analytics And Data-Driven Algorithms For Improving Efficiency In Full-Stack Web Systems. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 226–260.
12. Joseph, K., Shetty, J., Sharma, A. K., Van Staden, R., Wasantha, P. L. P., Small, S., & Bennett, N. (2024). Leak and burst detection in water distribution network using logic-and machine learning-based approaches. *Water*, *16*(14), 1935.
13. Kang, J., Park, Y.-J., Lee, J., Wang, S.-H., & Eom, D.-S. (2017). Novel leakage detection by ensemble CNN-SVM and graph-based localization in water distribution systems. *IEEE Transactions on Industrial Electronics*, *65*(5), 4279–4289.
14. Mirzaie, S., AvazAghaei, M., & Bushehrian, O. (2021). Anomaly detection in urban water distribution grids using fog computing architecture. *2021 29th Iranian Conference on Electrical Engineering (ICEE)*, 591–595.
15. Mohapatra, H. (2025). A Comprehensive Review on Urban Resilience via Fault-Tolerant IoT and Sensor Networks. *Computers, Materials & Continua*, *85*(1).
16. Mysorewala, M., Sabih, M., Cheded, L., Nasir, M. T., & Ismail, M. (2015). A novel energy-aware approach for locating leaks in water pipeline using a wireless sensor network and noisy pressure sensor data. *International Journal of Distributed Sensor Networks*, *11*(10), 675454.
17. Nwokediegwu, Z. S., & Adebowale, O. J. (2023). *Recent Advances in Leak Detection Algorithms Using Controlled Methane Releases and Multivariate Environmental Calibration Protocols*.
18. Obunga, P. O., Rwanga, S. S., Dinka, M. O., & Otieno, B. O. (2025). Review of the emerging technologies in the water sector with a focus on the deployment of Internet of Things solutions. *Npj Clean Water*, *8*(1), 53.

19. Patel, P., & Dusi, P. (2025). IoT-based water quality management system for sustainable urban water networks. *Journal of Smart Infrastructure and Environmental Sustainability*, *2*(1), 11–20.
20. Rajan, G., & Li, S. (2025). A Systematic Literature Review on Flow Data-Based Techniques for Automated Leak Management in Water Distribution Systems. *Smart Cities*, *8*(3), 78.
21. Reda, A., Mahmoud, R. M. A., Shahin, M. A., Amaechi, C. V., & Sultan, I. A. (2024). Roadmap for recommended guidelines of leak detection of subsea pipelines. *Journal of Marine Science and Engineering*, *12*(4), 675.
22. Saiteja, S., & Ponnapalli, V. A. S. (2023). A review on smart water management in various domestic areas: an approach for water consumption and leakage perspectives. *International Journal of Critical Infrastructures*, *19*(1), 1–16.
23. Utepov, Y., Neftissov, A., Mkilima, T., Shakhmov, Z., Akhazhanov, S., Kazkeyev, A., Mukhamejanova, A. T., & Kozhas, A. K. (2024). Advancing sanitary surveillance: Innovating a live-feed sewer monitoring framework for effective water level and chamber cover detections. *Heliyon*, *10*(6).
24. Wan, X., Kuhanestani, P. K., Farmani, R., & Keedwell, E. (2022). Literature review of data analytics for leak detection in water distribution networks: A focus on pressure and flow smart sensors. *Journal of Water Resources Planning and Management*, *148*(10), 03122002.
25. Xu, J., Chai, K. T.-C., Wu, G., Han, B., Wai, E. L.-C., Li, W., Yeo, J., Nijhof, E., & Gu, Y. (2018). Low-cost, tiny-sized MEMS hydrophone sensor for water pipeline leak detection. *IEEE Transactions on Industrial Electronics*, *66*(8), 6374–6382.
26. Yan, Z., Cui, X., & Gao, Y. (2023). Acoustic injection method based on weak echo signals for leak detection and localization in gas pipelines. *Applied Acoustics*, *211*, 109577.
27. Zhao, S.-L., Liu, S.-G., Qiu, B., Hong, Z., Zhao, D., & Dong, L.-Q. (2023). Leak detection method of liquid-filled pipeline based on VMD and SVM. *Urban Water Journal*, *20*(9), 1169–1182.
28. Zhi, B., Wu, Z., Chen, C., Chen, M., Ding, X., & Lou, L. (2023). A high sensitivity AlN-based MEMS hydrophone for pipeline leak monitoring. *Micromachines*, *14*(3), 654.