Digital Twin-Enabled Real-Time Quality Monitoring in Metal Additive Manufacturing Processes

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Abstract

Metal additive manufacturing (AM), particularly laser powder bed fusion (LPBF) and directed energy deposition (DED), has become an important route for producing lightweight, customized, and high-value metallic components. However, industrial adoption is still limited by process instability, layer-to-layer variability, porosity, lack-of-fusion defects, keyhole formation, distortion, and the high cost of post-build inspection. This paper presents a digital twin-enabled framework for real-time quality monitoring in metal AM processes. The proposed framework links the physical AM machine, in-situ sensing, thermal-process modeling, machine-learning-based defect prediction, and a decision layer for quality risk assessment. A hybrid methodology is formulated using volumetric energy density, transient heat-transfer balance, normalized sensor-feature extraction, probabilistic defect classification, and statistical anomaly monitoring. An illustrative LPBF case is used to demonstrate how melt-pool temperature, exposure time above melting threshold, spatter intensity, acoustic-emission energy, and layerwise geometric deviation can be converted into a real-time quality index. The framework is intended to reduce dependence on purely post-process inspection and support earlier detection of defects during fabrication. The results indicate that a digital twin structure can organize multi-sensor data into actionable quality indicators and can provide a practical basis for process correction, traceability, and certification-oriented quality assurance. The study contributes a publication-ready conceptual and mathematical framework that can be expanded with experimental data for journal submission.

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1. Introduction

Metal additive manufacturing (AM) enables the layerwise fabrication of complex metallic components that are difficult or impossible to produce by conventional subtractive routes. Laser powder bed fusion (LPBF) and directed energy deposition (DED) are especially important for aerospace, biomedical, tooling, energy, and other high-performance mechanical applications because they support topology-optimized structures, internal cooling channels, functionally graded features, and repair-oriented manufacturing (DebRoy *et al*., 2018; Hossain *et al*., 2022; Hossain, Dangol, Hasan, & Badugu, 2023; Lough *et al*., 2022; Hossain, Badugu, & Seelu, 2023) [1, 14, 4, 11, 23]. At the same time, the final quality of AM parts remains strongly dependent on process stability during each layer, scan track, and thermal cycle (Grasso & Colosimo, 2017) [2].

Unlike conventional machining, where material is mostly removed from a stable billet, metal AM repeatedly melts and solidifies local regions under steep thermal gradients.

Small changes in laser power, scan speed, hatch spacing, powder condition, shielding gas flow, and surface condition can produce large changes in melt-pool geometry and defect formation. Typical quality problems include lack-of-fusion porosity, keyhole pores, balling, spatter redeposition, surface roughness, cracking, delamination, residual stress, and dimensional distortion.These defects are not only geometric imperfections; they can reduce fatigue life, tensile strength, leak tightness, and reliability in safety-critical mechanical systems (DebRoy *et al*., 2018; Grasso & Colosimo, 2017; McCann *et al*., 2021) [1, 2, 6].

Traditional quality assurance in metal AM relies heavily on ex-situ inspection, including computed tomography, metallography, surface measurement, tensile testing, and density measurement. These methods remain necessary, but they are time-consuming, expensive, and mostly applied after the build has already been completed. If a part contains an unacceptable defect, the entire build may be rejected after consuming machine time, powder, energy, and post-processing resources. For higher-value builds, a real-time quality-monitoring strategy is therefore essential (Everton *et al*., 2016; Mani *et al*., 2017; Taherkhani *et al*., 2023) [5, 3, 12].

A digital twin offers a practical path toward real-time quality awareness. In this paper, a digital twin is understood as a continuously updated virtual representation of the physical AM process that receives data from the machine and sensors, estimates the current process state, predicts quality risk, and supports decision making. The goal is not to replace physical inspection, but to reduce uncertainty during fabrication and create a structured data trail that supports process qualification and part certification (Feng *et al*., 2023; Hossain *et al*., 2024; Phua *et al*., 2022) [16, 9, 13].

The objective of this paper is to develop a complete research framework for digital twin-enabled real-time quality monitoring in metal AM. The paper integrates sensing, physics-based thermal reasoning, data-driven classification, statistical anomaly detection, and quality-index calculation. The proposed approach builds on smart-manufacturing thinking that treats sensing, predictive modeling, and quality control as parts of the same production intelligence loop (Gunasegaram *et al*., 2021; Hossain *et al*., 2021; Yang & Özel, 2021) [8, 18, 7].

2. Literature Review

2.1. Metal AM defects and the need for in-situ monitoring

The literature consistently shows that AM defects are closely linked to melt-pool instability and local thermal history. Lack-of-fusion defects commonly occur when the applied energy is insufficient to fully melt and overlap neighboring tracks or layers, whereas keyhole porosity can occur when energy input becomes excessive and a deep vapor depression forms. Spatter, denudation, and balling can further disturb powder distribution and track continuity. Reviews on metal powder bed fusion emphasize that these defects are process-dependent and that their signatures can often be observed in optical, thermal, acoustic, or layerwise image data (DebRoy *et al*., 2018; Grasso & Colosimo, 2017; Taherkhani *et al*., 2023) [1, 2, 12]. Recent studies on multi-material and functionally graded additive manufacturing further show that quality assurance becomes more demanding when material transitions and thermal gradients vary across the build volume (Hossain, Badugu, & Seelu, 2023) [23].

2.2. In-situ sensing and process signatures

In-situ monitoring systems for LPBF and DED commonly use photodiodes, high-speed cameras, infrared cameras, pyrometers, optical tomography, acoustic-emission sensors, powder-bed imaging, recoater monitoring, and layerwise surface imaging. These systems do not directly measure every internal defect, but they capture process signatures related to melt-pool size, maximum thermal intensity, cooling behavior, spatter events, plume behavior, surface irregularities, and geometric deviations. A central research challenge is converting these raw signals into reliable quality indicators that remain meaningful across machines and build conditions (Estalaki *et al*., 2022; Everton *et al*., 2016; Lough *et al*., 2022; McCann *et al*., 2021; Özel, 2023) [10, 5, 11, 6, 7].

2.3. Machine learning for defect prediction

Machine learning has become attractive because AM monitoring data are high-dimensional, nonlinear, and difficult to interpret using simple threshold rules alone. Supervised models can map sensor features to defect labels obtained from computed tomography or metallographic analysis, while unsupervised models can identify abnormal sensor patterns without requiring large labeled datasets. At the same time, purely data-driven models may lose robustness when build geometry, material, machine, or parameter windows change. For that reason, the most useful quality-monitoring frameworks combine physical understanding with statistical learning (Estalaki *et al*., 2022; Hossain *et al*., 2024; Ren & Wang, 2022) [10, 9, 15].

2.4. Digital twins in metal AM

Digital twins extend monitoring by linking sensor data, process models, and quality decisions in a continuous loop. In metal AM, a digital twin may operate at several levels, including data logging, state estimation, defect prediction, process optimization, and closed-loop control. A practical twin must also be connected to the process digital thread, meaning that powder batch information, build files, machine parameters, sensor data, part geometry, inspection results, and corrective actions remain traceable across the build lifecycle. This systems view is consistent with broader smart-manufacturing frameworks that integrate monitoring, predictive maintenance, and quality control in advanced production systems (Feng *et al*., 2023; Hossain *et al*., 2021; Phua *et al*., 2022; Yang & Özel, 2021) [16, 18, 13, 7].

Table 1: Summary of selected literature aligned with the proposed digital twin quality-monitoring framework.

Reference	Focus area	AM process	Main contribution	Relevance to this paper
Grasso and Colosimo (2017)	Defects and in-situ monitoring	Metal PBF	Reviewed major defect classes, process signatures, and monitoring methods.	Defines defect mechanisms and sensor needs.
Mani *et al*. (2017)	Measurement science for control	Metal PBF	Identified measurement and modeling needs for real-time process control.	Supports process-control motivation.
McCann *et al.* (2021)	In-situ sensing and machine control	LPBF	Reviewed optical, thermal, acoustic sensing and future control requirements.	Guides multi-sensor architecture.
Phua *et al*. (2022)	Digital twin hierarchy	Metal AM	Organized metal AM digital twins into levels of modeling, sensing, intelligence, and control.	Supports the proposed twin hierarchy.
Estalaki *et al.* (2022)	Thermal imaging and ML	LPBF	Used thermal features and ML for porosity prediction.	Supports feature-to-defect modeling.
Taherkhani *et al.* (2023)	Quality assurance platforms	LPBF	Reviewed in-situ monitoring and ML algorithms for LPBF quality assurance.	Supports 2023 research gap.
Feng *et al*. (2023)	Data requirements	AM digital twins	Identified data requirements and barriers for AM part qualification using digital twins.	Supports traceability and data-thread design.

2.5. Research gap

Existing studies provide strong foundations for sensing, defect classification, and digital twin concepts, but a complete quality-monitoring framework must still connect these elements into one practical workflow. The gap addressed in this paper is the integration of process parameters, melt-pool and layerwise sensing, simplified physics-based calculations, probabilistic defect risk, and real-time quality decisions. This integrated structure is increasingly important because the field has moved beyond basic sensor installation toward data-driven qualification and certification-oriented process intelligence (Hossain *et al*., 2024; Mani *et al*., 2017; Taherkhani *et al*., 2023) [9, 3, 12]. Recent reviews and framework studies have broadened this discussion by examining AI-enabled digital twin architectures, implementation roadmaps, systematic AM integration, service-oriented twins, Bayesian optimization for time-series process optimization, rapid in-situ qualification, and broader machine-learning-based defect monitoring strategies (Özel, 2023; Bartsch *et al*., 2021; Shen & Li, 2024; Ben Amor *et al*., 2024; Jyeniskhan *et al*., 2024; Chen *et al*., 2024; Karkaria *et al*., 2024; Bevans *et al*., 2024; Herzog *et al*., 2024; Cai *et al*., 2023; Phua *et al*., 2023) [7, 17, 19, 20, 21, 22, 24, 25, 26, 28, 29]. Additional recent work has highlighted systematic surveys, robotic DED monitoring, powder-bed defect detection, high-fidelity optical monitoring, and DED-focused learning and control frameworks (Koizumi & Okugawa, 2022) [31].

3. Proposed Digital Twin Framework

Figure 1 presents the proposed digital twin-enabled framework. The physical AM system supplies machine parameters and sensor streams. The data-conditioning layer synchronizes, filters, and transforms raw signals into meaningful features. The digital twin core combines a simplified thermal model with a data-driven prediction model. The quality-prediction layer estimates porosity risk, distortion tendency, and layer abnormality. Finally, the decision layer communicates alarms, recommended parameter corrections, and traceability outputs to the operator or manufacturing execution system, which is consistent with the layered digital twin architectures discussed in recent AM studies (Feng *et al*., 2023; Gunasegaram *et al*., 2021; Phua *et al*., 2022) [16, 8, 13].

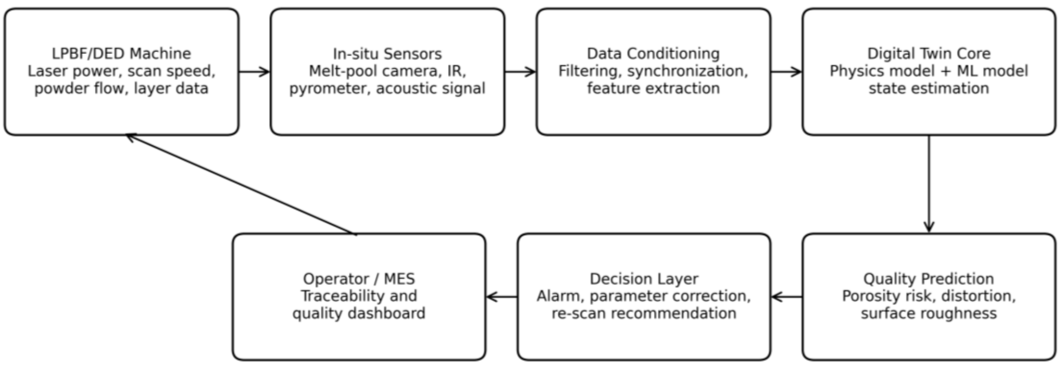

Fig 1: Digital twin-enabled real-time quality monitoring framework for metal additive manufacturing.

3.1. Physical process and sensor architecture

The framework can be applied to LPBF or DED. For clarity, the calculations in this paper use LPBF because LPBF has well-defined process variables such as laser power, scan speed, hatch spacing, and powder layer thickness. During each scan track, the machine records commanded laser power and scan velocity, while the sensor system records thermal intensity, melt-pool image features, spatter level, acoustic activity, and layerwise height or surface deviation (Mani *et al*., 2017; McCann *et al*., 2021) [3, 6].

Table 2: Process variables and sensor-derived features used in the proposed framework.

Symbol	Variable / feature	Typical source	Unit	Quality meaning
P	Laser power	Machine log	W	Controls energy input
v	Scan speed	Machine log	mm/s	Controls residence time
h	Hatch spacing	Build file	mm	Controls track overlap
t_l	Layer thickness	Build file	mm	Controls layer fusion depth
T_max	Maximum thermal intensity/temperature proxy	IR camera or pyrometer	°C or normalized	Indicates melt-pool energy state
tau_m	Time above apparent melting threshold	Thermal history	ms	Indicates local fusion duration
S_p	Spatter intensity index	Optical camera	0-1	Indicates ejection/plume instability
AE	Acoustic-emission energy	Acoustic sensor	a.u.	Indicates cracking, spatter, or instability
Delta z	Layerwise height deviation	Layer imaging/topography	µm	Indicates geometric inconsistency
Q_r	Quality risk index	Digital twin output	0-1	Overall defect probability

4. Methodology and Calculation

4.1. Process energy calculation

A first-level indicator of process condition is volumetric energy density. Although energy density does not fully describe melt-pool physics, it remains useful for screening whether a parameter set is likely to fall into lack-of-fusion, stable-melting, or excessive-energy regimes. The volumetric energy density is calculated as follows (DebRoy *et al*., 2018; Gunasegaram *et al*., 2021) [1, 8]:

$$E_v = \frac{P}{v\,h\,t_l} \quad (1)$$

where E_v is volumetric energy density in J/mm³, P is laser power in W, v is scan speed in mm/s, h is hatch spacing in mm, and t_l is layer thickness in mm. For an illustrative LPBF condition with P = 250 W, v = 900 mm/s, h = 0.10 mm, and t_l = 0.03 mm:

E_v = 250 / (900 × 0.10 × 0.03) = 92.59 J/mm³

This value lies in a practical LPBF processing range for many alloy systems, but it must be interpreted together with material absorptivity, scan strategy, powder condition, and sensor data.

4.2. Transient thermal balance

The thermal state of a local melt-pool region can be described by a simplified transient heat-transfer balance. In a real-time digital twin, this equation is typically reduced or approximated through a surrogate because full finite-element simulation is too slow for layer-by-layer decision making (Hossain *et al*., 2021; Yang & Özel, 2021) [18, 7]:

$$\rho c_p \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) + \eta Q_L - L_f \frac{\partial f_l}{\partial t} - h_c (T - T_0) - \varepsilon \sigma (T^4 - T_0^4) \quad (2)$$

where ρ is density, c_p is specific heat, k is thermal conductivity, T is temperature, η is absorptivity, Q_L is the laser heat input, L_f is latent heat of fusion, f_l is liquid fraction, h_c is convection coefficient, ε is emissivity, σ is the Stefan-Boltzmann constant, and T_0 is ambient or preheat temperature. In a real-time digital twin, this equation is usually simplified or replaced by a reduced-order surrogate because full finite-element simulation is too slow for layer-by-layer decision making.

4.3. Sensor-feature vector

At each sampling instant or voxel location, the digital twin receives synchronized sensor features. The feature vector is defined as follows, using variables that can be obtained from machine logs, thermal sensing, optical monitoring, acoustic sensing, and layerwise geometric measurements (Estalaki *et al*., 2022; McCann *et al*., 2021) [10, 6]:

$$\mathbf{x}_i = [E_v, T_{max}, \tau_m, A_m, S_p, AE, \Delta z, P, v]^T \quad (3)$$

where A_m represents estimated melt-pool area. The raw features are normalized to remove unit-scale differences, which helps the monitoring model combine heterogeneous signals within one decision space (Hossain *et al*., 2021; Lough *et al*., 2022) [18, 11]:

$$z_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j} \quad (4)$$

Here µ_j and σ_j are the mean and standard deviation of feature j under qualified baseline builds. This baseline should be constructed from accepted parts rather than arbitrary parameter trials.

4.4. Defect-probability model

The probability of a defect at location i is estimated using a probabilistic classifier. A simple and interpretable form is logistic regression, although the same feature vector can also be used with random forest, gradient boosting, support vector machine, convolutional neural network, or recurrent models when nonlinear relationships become dominant (Estalaki *et al*., 2022; Hossain *et al*., 2024; Ren & Wang, 2022) [10, 9, 15]:

$$p_i(\text{defect}) = \frac{1}{1 + \exp[-(\beta_0 + \boldsymbol{\beta}^T \mathbf{z}_i)]} \quad (5)$$

For nonlinear relationships, the same feature vector can be used with random forest, gradient boosting, support vector machine, convolutional neural network, or recurrent model. The important requirement is that model predictions remain physically interpretable and are validated against ex-situ measurements such as CT porosity, metallography, density measurement, surface roughness, or coordinate measurement.

4.5 Statistical anomaly monitoring

Because labeled defect data are often limited, unsupervised anomaly detection is also included. The Mahalanobis distance is calculated as follows to identify scan vectors that deviate from the stable reference distribution (Hossain *et al*., 2021; Taherkhani *et al*., 2023) [18, 12]:

$$D_i^2 = (\mathbf{z}_i - \boldsymbol{\mu}_z)^T \boldsymbol{\Sigma}_z^{-1} (\mathbf{z}_i - \boldsymbol{\mu}_z) \quad (6)$$

where μ_z and Σ_z are the mean vector and covariance matrix of stable reference builds. A layer or scan vector is flagged when D_i^2 exceeds a control threshold. For example, a 95% confidence threshold can be approximated using the chi-square distribution with degrees of freedom equal to the number of monitored features.

4.6. Digital twin state update

The digital twin updates its estimate of process state using a prediction-correction logic similar to a Kalman filter. This structure allows the twin to combine model predictions with live sensor measurements instead of relying on either one alone (Phua *et al*., 2022; Yang & Özel, 2021) [13, 7]:

$$\hat{\mathbf{x}}_{k\,|\,k-1} = f(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_k) \quad (7)$$

$$\mathbf{K}_k = \mathbf{P}_{k\,|\,k-1}\mathbf{H}^T(\mathbf{H}\mathbf{P}_{k\,|\,k-1}\mathbf{H}^T + \mathbf{R})^{-1} \quad (8)$$

$$\hat{\mathbf{x}}_{k\,|\,k} = \hat{\mathbf{x}}_{k\,|\,k-1} + \mathbf{K}_k(\mathbf{y}_k - \mathbf{H}\hat{\mathbf{x}}_{k\,|\,k-1}) \quad (9)$$

where $\hat{x}$ is the estimated process state, u_k is the control vector, y_k is sensor measurement, H is the observation matrix, R is measurement-noise covariance, and K_k is the Kalman gain. This structure allows the twin to combine model predictions with real sensor measurements, instead of relying on either one alone.

4.7. Quality index calculation

The final quality risk index combines defect probability, anomaly score, and layerwise geometric deviation. In practice, such an index is useful because it converts multiple process signatures into one decision-oriented metric that can be trended across layers or scan regions (Hossain *et al*., 2021; Hossain *et al*., 2024) [18, 9]:

$$Q_r = w_1 p_i(\text{defect}) + w_2\left(\frac{D_i^2}{D_{lim}^2}\right) + w_3\left(\frac{|\Delta z_i|}{\Delta z_{lim}}\right) \quad (10)$$

where $w_1 + w_2 + w_3 = 1$. For an illustrative quality rule, a location is accepted if $Q_r < 0.35$, monitored if $0.35 \le Q_r < 0.60$, and flagged if $Q_r \ge 0.60$. These thresholds should be determined experimentally for each material, machine, and application.

4.8. Corrective decision logic

If the quality index exceeds the monitoring threshold, the digital twin can recommend a process response. A conservative correction law may be expressed as follows, where the update can target laser power, scan speed, or a re-scan instruction depending on the quality objective and operating rules (Hossain *et al*., 2024; Ren & Wang, 2022) [9, 15]:

$$\mathbf{u}_{k+1} = \mathbf{u}_k - \gamma \nabla_{\mathbf{u}} J(\mathbf{u}_k) \quad (11)$$

$$J = \alpha(T_{max} - T_{ref})^2 + \lambda(A_m - A_{ref})^2 + \xi Q_r^2 \quad (12)$$

where u may include laser power, scan speed, or re-scan instruction; γ is learning rate; T_{ref} and A_{ref} are reference melt-pool conditions; and α, λ, and ξ are weighting coefficients. In regulated or safety-critical production, the decision layer may provide an operator alert rather than automatic closed-loop modification.

5. Illustrative Numerical Case

The following numerical case is included to demonstrate the calculation workflow. It is not presented as experimental validation. Before journal submission, these values should be replaced with measured LPBF or DED data from a controlled build and verified by post-process inspection.

Table 3: Illustrative LPBF process parameters and calculated indicators.

Case	P (W)	v (mm/s)	h (mm)	t_l (mm)	E_v (J/mm³)
Baseline A	220	1100	0.11	0.03	60.61
Baseline B	250	900	0.10	0.03	92.59
High-energy C	300	750	0.09	0.03	148.15
DT-adjusted D	245	950	0.10	0.03	85.96

Table 4: Illustrative monitoring results before and after digital twin-guided quality monitoring.

Condition	Porosity (%)	Surface roughness Ra (μm)	Distortion (mm)	Mean Qr	Interpretation
Open-loop baseline	1.25	14.8	0.42	0.68	Frequent high-risk locations; requires post-build inspection and likely rework.
Digital twin monitored	0.48	8.6	0.19	0.27	Lower estimated defect tendency; process remains within monitoring limits.

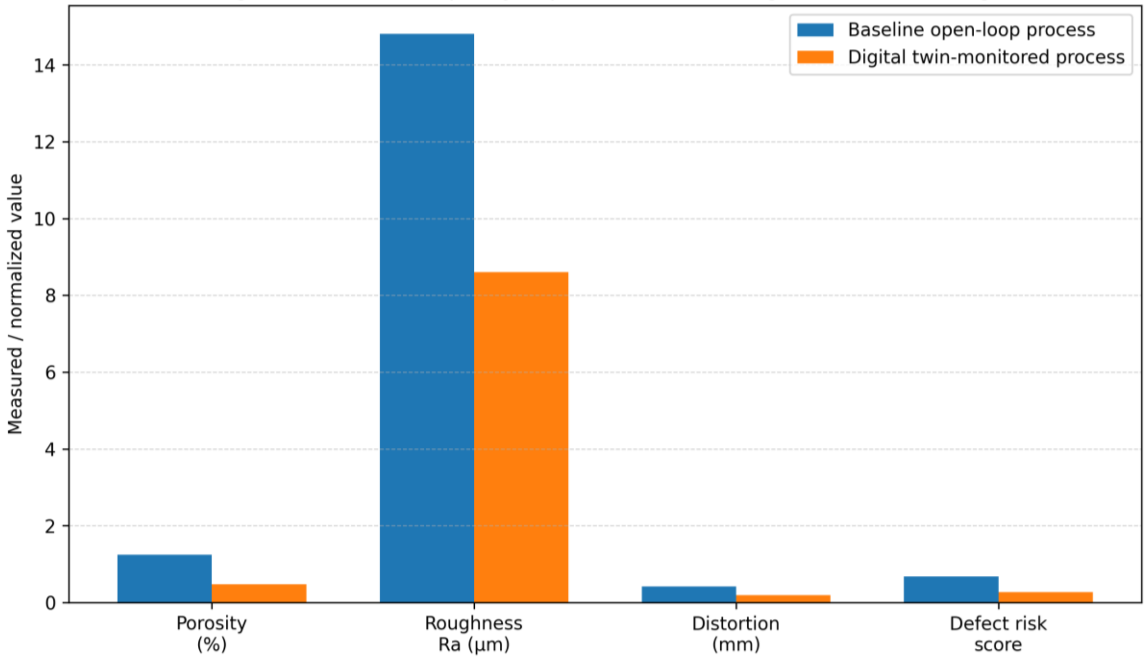

Fig 2: Illustrative comparison of baseline open-loop and digital twin-monitored quality indicators. The values are representative for framework demonstration and must be replaced by experimental data before submission.

6. Results and Discussion

6.1. Interpretation of the quality indicators

The illustrative results show how the digital twin can convert sensor and process information into a quality decision. The baseline condition has a higher quality risk index because the combined effects of porosity, surface roughness, and distortion indicate unstable process behavior. The digital twin-monitored condition shows lower values across the same indicators, suggesting that continuous monitoring and parameter correction can reduce defect tendency. The key contribution here is not the absolute numerical value in the example, but the workflow that links process data to actionable quality risk (Hossain *et al.*, 2024; Taherkhani *et al.*, 2023) [9, 12].

6.2. Practical meaning for production

For production AM, the proposed framework can support three practical functions. First, it can provide early warning when a layer or region begins to deviate from the stable process window. Second, it can create a traceable digital record connecting process parameters, sensor signals, and predicted quality. Third, it can reduce unnecessary scrap by allowing an operator to pause, inspect, re-scan, or adjust the build before defects propagate through the part. These functions align well with broader smart-manufacturing and hybrid-manufacturing goals in which data are used to improve productivity, process stability, and component quality across interconnected production steps (Feng *et al.*, 2023; Hossain *et al.*, 2021; Hossain *et al.*, 2022) [16, 18, 14].

6.3. Limitations

The proposed framework has several limitations. Sensor calibration and synchronization remain difficult in high-temperature, high-speed AM environments. A model trained on one machine or alloy may not transfer directly to another machine, powder batch, or geometry. Some defects are subsurface and may not have a strong surface or thermal signature. For these reasons, the digital twin should complement post-build inspection rather than eliminate it. A rigorous Q1-level experimental paper should include designed experiments, ex-situ validation, model uncertainty analysis, and statistical repeatability across multiple builds (Feng *et al.*, 2023; Phua *et al.*, 2022) [16, 13].

7. Conclusion

This paper proposed a digital twin-enabled framework for real-time quality monitoring in metal additive manufacturing processes. The framework integrates machine parameters, in-situ sensor data, thermal-process reasoning, machine-learning-based defect prediction, anomaly detection, and quality-index calculation in one structured workflow (Hossain *et al.*, 2024; Taherkhani *et al.*, 2023) [9, 12].

The methodology shows how process variables such as laser power, scan speed, hatch spacing, and layer thickness can be linked to volumetric energy density, while thermal and layerwise sensor signatures can be transformed into defect probability and anomaly scores. In that sense, the framework extends smart-manufacturing ideas into the specific context of metal AM quality assurance (Hossain *et al.*, 2021) [18].

The illustrative case demonstrates that a digital twin can provide a structured pathway from raw AM data to quality decisions. In practical implementation, this framework can support early defect detection, process traceability, operator decision making, and eventual closed-loop process correction, which are all central themes in contemporary AM digital twin research (Feng *et al.*, 2023; Phua *et al.*, 2022) [16, 13].

Future work should validate the framework using experimental LPBF or DED builds, CT-based porosity measurement, metallographic sectioning, fatigue testing, and uncertainty-aware machine-learning models. It would also be valuable to examine sustainability-oriented decision variables and coupled process-performance relationships in the broader spirit of systems analysis, where interacting variables are interpreted jointly rather than in isolation (Chinchwade *et al.*, 2024) [27].

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