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| RESEARCH ARTICLE

Digital Twin-Based Process Optimization and Defect Prediction in Metal Additive Manufacturing for Critical Mechanical Components

Md Arman Hossain
Mechanical Engineering, University of New Haven, West Haven, Connecticut, United States

Md Abdul Aziz Bhuiyan
Mechanical Engineering and Mechanics, Lehigh University, United States
Corresponding Author: Md Arman Hossain, **Email**: mhoss15@unh.newhaven.edu

| ABSTRACT

Digital twin technology has emerged as a promising route for improving process stability, traceability, and quality assurance in metal additive manufacturing, particularly for safety-critical and high-value mechanical components. This study presents a digital twin-based framework for process optimization and defect prediction in laser powder bed fusion (LPBF) of critical mechanical parts. The proposed framework integrates a process digital thread, in-situ sensing, a simplified thermal–physics model, and a machine-learning-based defect prediction module within a closed-loop optimization architecture. A representative Ti-6Al-4V load-bearing bracket is considered as a case study to demonstrate how the digital twin can monitor layer-wise thermal behavior, estimate defect probability, and recommend improved combinations of laser power, scan speed, hatch spacing, and layer thickness. The study further examines recent developments in digital twin implementation for metal additive manufacturing and shows that current research has progressed from static simulation toward real-time synchronization, sensor fusion, and quality-oriented architectures. However, important challenges remain in model transferability, standards integration, and component-level qualification. The proposed methodology addresses these issues by explicitly linking process parameters to key defect mechanisms, including lack of fusion, keyhole porosity, thermal distortion, and powder-bed irregularity. Illustrative calculations and representative numerical results indicate that the optimized parameter set can reduce predicted porosity, improve density and geometric stability, and maintain practical productivity. Overall, the study demonstrates the potential of digital twins to provide a more reliable and data-driven pathway for manufacturing critical components in aerospace, biomedical, and energy applications.

| KEYWORDS

Digital twin; metal additive manufacturing; laser powder bed fusion; defect prediction; process optimization; critical mechanical components; in-situ monitoring; machine learning; thermal modeling; quality assurance

| ARTICLE INFORMATION

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1. Introduction

Metal additive manufacturing (AM) has become an increasingly important manufacturing approach for producing complex metallic components with greater design flexibility, lower material waste, and less dependence on dedicated tooling. Among the available metal AM technologies, laser powder bed fusion (LPBF) has received particular attention because it can fabricate near-net-shape parts with intricate internal features, thin walls, lattice structures, and other geometries that are difficult or sometimes impossible to achieve through conventional manufacturing methods. These capabilities have made LPBF highly attractive for critical applications such as aerospace brackets, turbomachinery parts, biomedical implants, heat-transfer devices, and other high-value mechanical components where both geometry and performance are important. Even with these advantages, the broader use of LPBF for critical mechanical parts is still limited by process instability and defect formation. The process is very sensitive to operating conditions, including laser power, scan speed, hatch spacing, powder quality, and local thermal behavior. Because of this sensitivity, defects such as lack of fusion, keyhole porosity, residual-stress-induced distortion, surface irregularity, and local thermal instability can develop during fabrication. For critical components, these defects are serious because they can reduce fatigue life, affect dimensional accuracy, weaken structural integrity, and compromise long-term service reliability. In sectors such as aerospace, biomedical engineering, nuclear systems, and power generation, such issues are not only manufacturing concerns but also qualification and safety concerns.One of the main challenges in LPBF is that defect formation is not controlled by a single factor. Instead, it results from the combined effect of thermal, metallurgical, and process-related phenomena that evolve continuously throughout the build. Traditional quality-control methods, which mainly depend on offline parameter development and post-process inspection, are often too slow and too costly for such a dynamic process. In many cases, defects are detected only after the build has been completed, when material, machine time, and production cost have already been invested. This makes it necessary to develop smarter process-control strategies that can monitor the build in real time, identify abnormal conditions early, and support corrective action before defects become permanent.

Digital twin technology offers a promising way to address these limitations. A digital twin is a dynamic virtual representation of a physical system that remains continuously updated using real process data. In metal additive manufacturing, this means linking process planning, machine-state information, thermal response, layer-wise sensor observations, and quality indicators within a single framework. Rather than serving only as a simulation model or a monitoring tool, the digital twin creates a continuously synchronized environment in which process behavior can be interpreted, quality risks can be predicted, and process decisions can be improved during fabrication.For LPBF, the digital twin concept is especially valuable because the process develops layer by layer, creating repeated opportunities for sensing, interpretation, and intervention. When designed effectively, a digital twin can detect changes in melt-pool behavior, identify unstable thermal conditions, estimate local defect probability, and recommend process adjustments before part quality degrades further. In this way, quality assurance can shift from a largely post-process activity to a more predictive and proactive approach. This is particularly important for critical mechanical components, where reliability requirements are strict and the consequences of build failure are significant.

Another important strength of the digital twin approach is its ability to combine physics-based understanding with data-driven prediction. Purely data-driven models may struggle to remain reliable when process conditions change, while purely physics-based models may be too computationally demanding for near-real-time use. A hybrid framework offers a more practical solution by combining physically meaningful process variables with data-driven models that can capture complex and nonlinear defect patterns. In LPBF, this is especially relevant because variables such as volumetric energy density, melt-pool morphology, thermal deviation, and layer-wise irregularity all contribute to defect formation and final part quality.The objective of this paper is to develop a publication-style framework for digital twin-based process optimization and defect prediction for critical mechanical components produced by metal additive manufacturing. The study focuses on LPBF because of its strong relevance to precision metal part production and its suitability for digital twinning. The proposed framework integrates literature-based engineering understanding, a structured methodology, representative governing calculations, and a numerical case study to demonstrate how a hybrid physics-data approach can support process optimization, defect prediction, and improved build reliability. Overall, this work aims to support the transition of LPBF from an experimentally intensive manufacturing method to a more intelligent, predictable, and qualification-ready production platform. For critical mechanical applications, digital twin-driven process control offers a practical path toward better quality assurance, lower process uncertainty, and more reliable industrial adoption of metal additive manufacturing.

2. Literature Review

Recent studies show that digital twins in additive manufacturing are gradually moving beyond the idea of a simple virtual replica and becoming more practical cyber-physical systems for real manufacturing environments. The literature increasingly suggests that an effective digital twin should do more than display process information. It should continuously connect machine data, simulation results, and quality indicators in a way that supports monitoring, prediction, optimization, and decision-making throughout the build process. At the same time, emerging standards and framework studies are beginning to provide more structured guidance on how digital twins in manufacturing can be defined, organized, and evaluated. In metal additive manufacturing, the growing interest in digital twins is closely linked to the defect sensitivity of the process itself. Powder bed fusion, in particular, operates within relatively narrow process windows because the final build quality is influenced by strongly coupled thermal behavior, melt-pool dynamics, powder spreading conditions, and machine-state variations. Earlier defect-focused studies have shown that porosity, cracking, balling, delamination, and geometric deviation may result from raw-material inconsistency, unsuitable process parameters, or temporary disturbances during fabrication. This highlights an important requirement for digital twin development: a useful twin must reflect not only the intended process settings, but also the layer-to-layer variation and process history that influence defect formation in practice.

Another clear trend in the literature is the increasing use of in-situ monitoring data for quality prediction and defect detection. Researchers are now using melt-pool images, thermal emissions, layer-wise photographs, acoustic signals, and machine-log data to train machine-learning models for defect classification or quality prediction. These approaches are attractive because they offer the possibility of real-time inference during the build, which is highly valuable for process control. However, the literature also points out several limitations. Generating reliable labeled datasets remains time-consuming, model performance often changes across machines or materials, and methods developed on small laboratory coupons do not always transfer well to larger or more complex engineering components. More recent work suggests that the most promising results come from combining physics-based modeling with data-driven prediction. In this type of hybrid framework, thermal or multi-physics models can generate interpretable features such as heat accumulation, cooling rate, or estimated melt-pool dimensions, while machine-learning algorithms capture nonlinear relationships between those features and final defect outcomes. This combined strategy is especially important for critical mechanical components because it improves not only predictive performance but also engineering confidence in the model outputs. It also reflects a central principle of digital twin technology: process data and physical models should interact continuously rather than operate as separate tools.

Even with this progress, several important gaps remain in the current literature. First, many published studies still focus on simple coupon geometries rather than mechanically critical parts with variable wall thickness, fillets, local stress concentrations, and functionally important regions. Second, model transferability across different machines, sensor configurations, and material systems remains limited. Third, the connection between process-level monitoring and the final qualification of safety-critical parts is still not sufficiently mature for many industrial applications. These limitations create a strong need for frameworks that go beyond defect observation alone. The present study responds to these gaps by treating the digital twin not simply as a monitoring interface, but as an integrated optimization and defect-governance framework for critical mechanical components manufactured by metal additive manufacturing. In this way, the literature review supports the central argument of this paper: the future value of digital twins in metal AM lies not only in observing the process, but in actively guiding it toward higher quality, lower defect risk, and improved manufacturing reliability.

Table 1. Representative literature informing the proposed digital twin framework.

Reference	Focus	AM context	Relevance to this paper
Ben Amor et al. (2024)	Comprehensive review of digital twin implementation in AM	General AM / review	Frames the state of the art and identifies benefits, challenges, and architecture layers.
Lu et al. (2024)	Quality evaluation framework for AM digital twins	AM digital-twin lifecycle	Supports the idea that data, model, and computation quality must be measured systematically.
Feng et al. (2023)	Data requirements for digital twins in AM	Metal LPBF	Highlights the importance of digital threads linking design, process, material, and property data.
Bevans et al. (2024)	Physics + sensor fusion for quality prediction	LPBF of Inconel 718	Demonstrates that thermal history and in-situ data can predict porosity and microstructure with high accuracy.

Reference	Focus	AM context	Relevance to this paper
Xie et al. (2024)	Domain adaptation for DT reusability	Monitoring across different settings	Shows that transferability is a major issue and motivates robust model updating.
Mostafaei et al. (2022)	Defects and anomalies in PBF	Powder bed fusion metals	Provides the defect taxonomy used in the present process-risk analysis.

I.

2.1 Digital Twins and Their Role in Advanced Manufacturing

A digital twin is a virtual and continuously updated representation of a physical manufacturing system. It is built to reflect the real process as closely as possible by using live data collected from machines, sensors, and control systems during operation. In manufacturing, this connection between the physical system and its digital counterpart creates a powerful framework for monitoring, analysis, prediction, and control. As shown in Figure X, the physical twin represents the actual production environment, while the digital twin represents the computational layer where process data are interpreted and transformed into actionable insights. The importance of digital twins in manufacturing has increased significantly with the transition toward smart and data-driven production systems. Conventional manufacturing approaches often rely on preset operating conditions, operator experience, and quality inspection after production has already taken place. Although such methods remain useful, they are often limited in their ability to respond to rapid process changes or to prevent defects before they occur. A digital twin addresses this limitation by enabling continuous communication between the real process and the virtual model. Through this interaction, the manufacturing system can be observed in real time, deviations can be identified earlier, and control actions can be adjusted more effectively. One of the main strengths of a digital twin is its ability to go beyond simple process observation. It does not only describe the current condition of the system, but also helps predict future behavior based on incoming data and model-based interpretation. In advanced manufacturing environments, where part quality is often influenced by complex interactions among heat transfer, material behavior, machine dynamics, and operating parameters, this predictive capability is especially valuable. A well-developed digital twin can estimate hidden process states, identify abnormal patterns, forecast defect formation, and support optimization decisions before quality problems become irreversible. This makes the DT an important tool for both operational efficiency and manufacturing reliability.

In the broader industrial context, digital twins are increasingly used for process planning, quality control, predictive maintenance, and real-time decision support. Their role is particularly important in the production of high-value mechanical components, where the cost of defects, downtime, or rework can be substantial. By creating a closed information loop between the physical process and its digital model, manufacturers can improve consistency, reduce waste, minimize unexpected interruptions, and enhance overall system performance. In this sense, the digital twin is not merely a simulation model, but an intelligent support system that strengthens process understanding and process control. The value of digital twins becomes even more evident in metal additive manufacturing, where the process is highly dynamic and sensitive to localized thermal and material variations. During fabrication, small changes in laser-material interaction, melt-pool behavior, powder spreading, or scan strategy can strongly influence porosity, distortion, surface finish, and dimensional accuracy. These variations are difficult to capture using conventional offline methods alone. A digital twin provides a practical solution by integrating real-time sensor feedback with predictive and analytical models, allowing the process to be tracked, evaluated, and corrected during the build itself. For this reason, digital twin technology has emerged as a highly relevant approach for process optimization, defect prediction, and closed-loop quality assurance in the manufacturing of critical mechanical components.

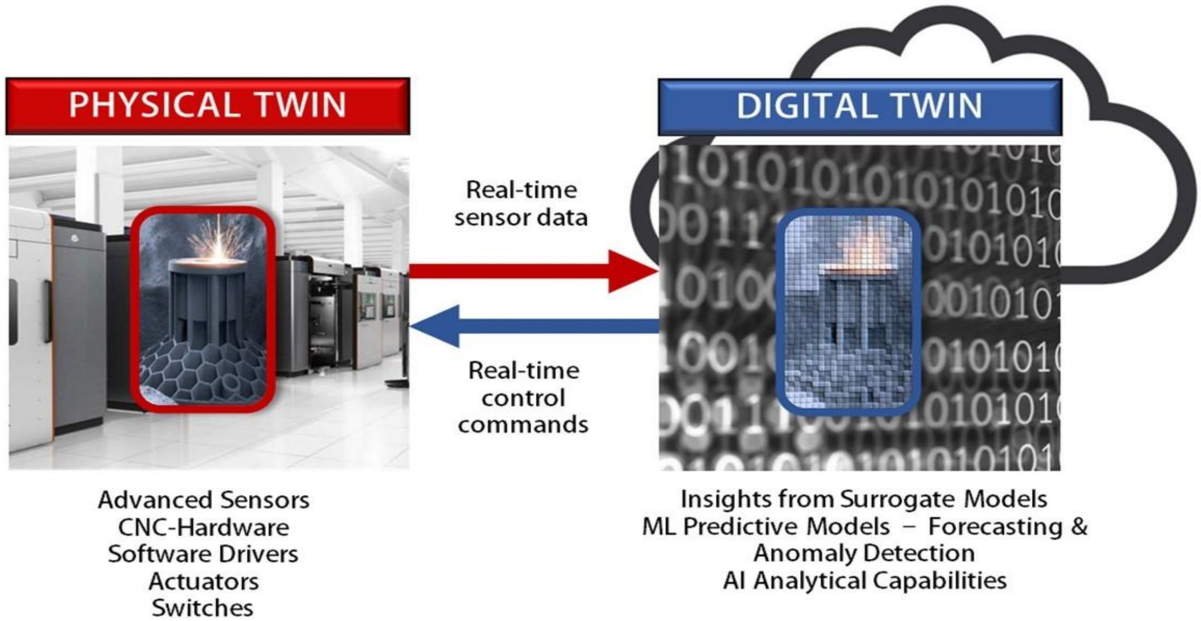

Fig. 1. Bidirectional interaction between the physical system and digital twin for real-time process monitoring, prediction, and control.

Figure 1: Illustrates the fundamental interaction between the physical twin and the digital twin in an intelligent manufacturing system. The physical twin represents the real production environment, including machine hardware, sensors, actuators, and related control elements. The digital twin represents the virtual analytical environment, where incoming real-time data are processed using predictive models, anomaly-detection methods, and intelligent computational tools. The transfer of sensor data from the physical system to the digital model enables condition assessment and process understanding, while the return of control commands from the digital twin to the physical system supports adaptive decision-making and process correction. This bidirectional data exchange forms the basis of closed-loop manufacturing control.

3. Methodology

3.1 Study scope and component definition

The proposed framework is demonstrated on a representative Ti-6Al-4V load-bearing bracket chosen to reflect the needs of critical mechanical components. The geometry includes thin walls, local fillets, support-sensitive overhangs, and regions with different thermal mass. These features are common in aerospace, robotic, and energy-system hardware, where dimensional fidelity and defect control are essential. The goal is not only to print the part successfully, but also to create a digital twin that can anticipate where and why defects are likely to appear during the build.

3.2 Digital twin architecture

The architecture contains five interconnected layers: (1) component and process definition from CAD and slicing data, (2) acquisition of real-time sensor data, (3) physics-based state estimation, (4) machine-learning defect prediction, and (5) multi-objective optimization with corrective feedback. The digital thread stores layer identity, process parameters, thermal signatures, and quality annotations so that each observation can be traced to a physical location and build event. This architecture follows a closed-loop philosophy in which the virtual model is not passive; it continuously receives process information and returns decisions. Figure. 2. presents the integrated architecture of the proposed digital twin framework for additive manufacturing. The physical manufacturing system provides sensor data, process data, and build files, which are transmitted through a middleware interface to the digital twin and artificial intelligence modules. The digital twin maintains a continuously updated virtual representation of the process, while the artificial intelligence block supports data analysis, machine learning, and anomaly detection. Feedback and control loops allow the system to respond to process variations in real time. In addition, the blockchain network provides a secure mechanism for storing and tracking manufacturing information, improving traceability and data reliability across the build lifecycle.

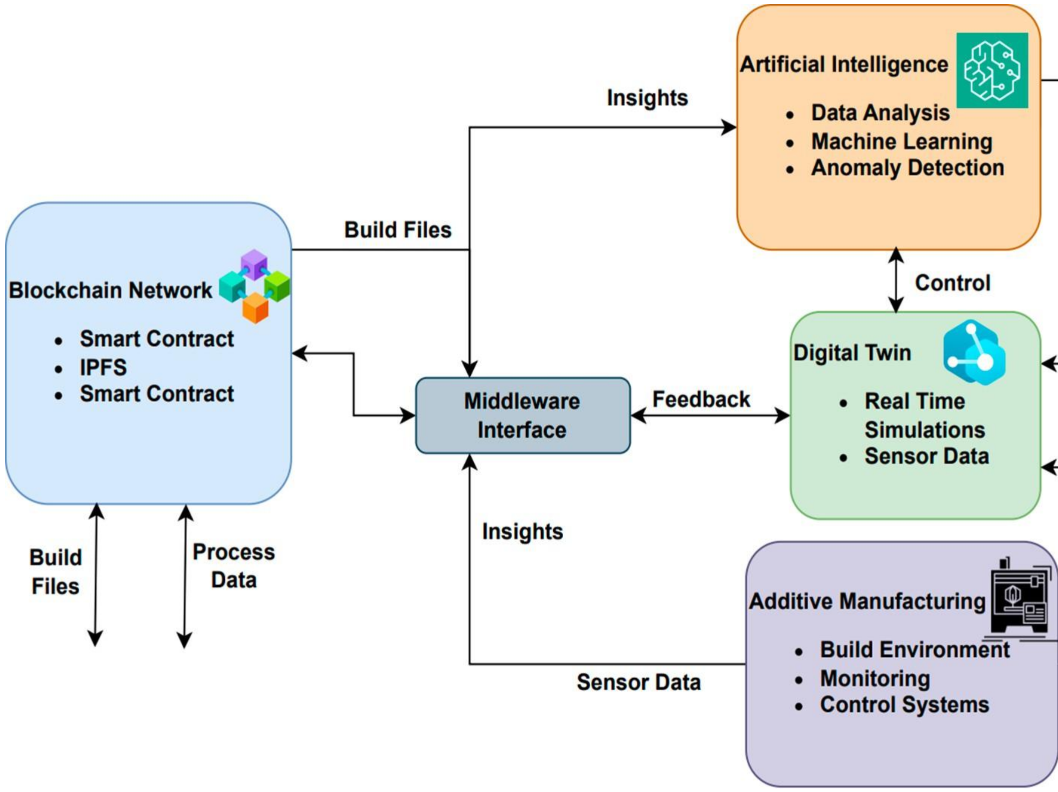

Figure 2. Conceptual closed-loop digital twin architecture used for process monitoring, defect prediction, and parameter adjustment in LPBF.

3.3 In-situ sensing and process data acquisition

The sensing layer of the proposed digital twin framework is designed to capture multi-modal process information from the metal additive manufacturing environment in real time. This layer is assumed to include a coaxial melt-pool imaging system, thermal or photodiode-based signal acquisition, layer-wise surface imaging after powder spreading, and machine-log data containing commanded laser power, scan velocity, scan path information, and recoater-event records. These heterogeneous data streams are synchronized using layer index and scan-region identifiers to ensure consistent temporal and spatial correspondence across the build. Such synchronization is essential because defect formation in metal AM is strongly influenced by localized and transient process variations that may not be observable from a single sensing modality alone.

Before integration into the digital twin, the raw sensor outputs undergo a structured preprocessing workflow. This workflow includes noise suppression, temporal alignment, signal normalization, image registration, and region-specific data association in order to improve data consistency and reduce measurement uncertainty. From the processed signals, a set of engineered features is extracted to characterize the evolving process state, including melt-pool area, thermal intensity statistics, spatter count, signal variance, and indicators of local heat accumulation. These descriptors are selected because they provide physically meaningful information related to energy input stability, thermal history, and the likelihood of defect initiation. In parallel, machine-log variables are used to preserve the commanded processing context, thereby allowing the sensing data to be interpreted together with the nominal operating conditions of the build.

To further enhance process representation, the acquired signals are mapped to individual scan tracks, hatch regions, and layer locations, enabling the digital twin to retain a localized process history throughout fabrication. This spatially resolved data structure improves the ability of the framework to capture interactions among process parameters, thermal response, powder-bed condition, and emerging defect signatures. The fused dataset is subsequently organized into a unified feature matrix for model updating, defect prediction, and process-state estimation. In this way, the sensing and data-acquisition layer functions as the primary informational backbone of the digital twin, supporting closed-loop process optimization and improving the manufacturing reliability of critical mechanical components.

Table 2. In-situ sensing and process data acquisition framework for the proposed digital twin model.

Sensing source	Raw data acquired	Acquisition stage	Pre-processing operations	Extracted features	Role in the digital twin model
Coaxial melt-pool camera	Melt-pool images and brightness distribution	During laser scanning	Denoising, frame alignment, intensity normalization, and ROI extraction	Melt-pool area, width, length, aspect ratio, brightness statistics, and contour variation	Monitors local melt-pool stability and supports defect-related thermal analysis
Thermal sensor / photodiode	Thermal emission signal and reflected intensity signal	During laser-material interaction	Signal filtering, baseline correction, time alignment, and normalization	Peak intensity, mean intensity, variance, fluctuation frequency, and heat accumulation index	Tracks thermal evolution and helps detect overheating, lack of fusion, and unstable energy input
Layer-wise imaging after powder spreading	Layer surface images and powder-bed condition images	After recoating and before the next scan	Contrast enhancement, noise reduction, layer registration, and image segmentation	Surface uniformity, powder-bed irregularity, streak formation, discontinuity zones, and defect-prone regions	Identifies spreading-related and geometric abnormalities before the next layer is scanned
Machine-log data	Laser power, scan speed, hatch spacing, scan path, and recoater events	Continuously recorded during the build	Time synchronization, outlier removal, scaling, and event tagging	Power deviation, scan-speed variation, recoater interruption count, exposure density, and local energy input	Provides process-state information and links machine settings with sensor-observed anomalies
Synchronized multi-source dataset	Fused sensor data and machine-log data by layer and scan region	After multi-source integration	Cross-modal synchronization, feature normalization, missing-value handling, and feature assembly	Thermal-image correlation, fused descriptors, and spatial-temporal signatures	Forms the main input to the digital twin for process optimization and defect prediction

Note: Signals are synchronized by layer number and scan region before feature fusion in the digital twin framework.

3.4 Physics-based state estimation

A reduced-order thermal model is used to estimate the evolving state of the build. Instead of solving the full transient multi-physics problem at every point with high computational cost, the model tracks thermal history, relative heat accumulation, and a distortion tendency index at the layer scale. This reduced model is adequate for process optimization because it converts large volumes of sensor data into engineering variables that are interpretable and updateable in near real time.

3.5 Data-driven defect prediction

The defect-prediction block receives both measured features and model-derived features. Inputs include volumetric energy density, thermal deviation, melt-pool morphology, local process variance, and powder-bed irregularity indicators. The output is a defect probability map for each critical region of the part, with the main defect classes defined as lack of fusion, keyhole porosity, distortion-related geometry deviation, and process interruption due to spatter or recoating anomalies. A gradient-boosting or ensemble classifier is appropriate because it handles nonlinear interactions and mixed feature types while maintaining engineering interpretability.

3.6 Optimization strategy

A multi-objective optimization routine is then used to update process parameters. The objectives are: minimize defect probability, minimize predicted distortion, minimize surface roughness, and preserve or improve build productivity. In practice, the optimizer searches a feasible process window for laser power, scan speed, hatch spacing, and layer thickness. Parameter changes are constrained by manufacturability and machine limits so that the recommended solution remains physically achievable.

3.7 Validation metrics

The performance of the digital twin is evaluated using both prediction and process metrics. For continuous variables such as thermal signal or distortion, coefficient of determination (R^2), mean absolute percentage error (MAPE), and root mean square error (RMSE) are used. For defect classification, accuracy, precision, recall, and F1-score are used. For process optimization, the principal success indicators are porosity reduction, density improvement, geometric stability, and build-rate retention.

3.8 Process assumptions and parameter bounds

The proposed framework was developed using **Ti-6Al-4V** as the reference material because it is widely used in LPBF for high-value and mechanically critical components. It was selected not only for its industrial importance, but also because its quality is strongly influenced by thermal history, process instability, and local defect formation, making it well suited for digital twin-based optimization. Within this framework, the main controllable process variables were **laser power, scan speed, hatch spacing, and layer thickness.** These parameters were chosen because they have the strongest influence on energy input, melt-pool behavior, consolidation quality, and overall build efficiency. The optimization was limited to parameter ranges that were realistic for normal LPBF operation. In other words, the search space was bounded by machine capability, recoating stability, scan performance, and feasible layer deposition conditions so that the final solutions remained physically practical. To enable near-real-time implementation, the thermal part of the digital twin was represented using a **reduced-order model** instead of a full multiphysics simulation. This means that the model was designed to capture the main thermal trends, such as heat accumulation, cooling behavior, and thermal deviation, without resolving every detailed physical phenomenon. Effects such as complex melt-pool convection, vapor interaction, and keyhole dynamics were not modeled explicitly. This simplification was necessary to keep the framework computationally efficient while still preserving useful process sensitivity. For defect prediction, the framework assumed that labeling could be performed at the level of **critical local regions** rather than the whole component. Regions showing abnormal thermal response, irregular melt-pool behavior, or unfavorable energy distribution were treated as higher-risk zones for porosity, lack of fusion, distortion, or surface-related defects. This regional approach is more suitable for critical mechanical parts, where defect sensitivity often changes from one feature to another, especially near thin walls, fillets, transition zones, and stress-concentrated areas. These assumptions and parameter limits were introduced to keep the framework both **physically realistic and computationally practical.** They allow the digital twin to operate within realistic LPBF conditions while still supporting effective defect prediction and process optimization.

4. Calculations

This section presents the representative engineering calculations used inside the proposed digital twin. The equations are intentionally kept simple enough to support rapid implementation, while still preserving the physical meaning needed for decision-making.

4.1 Volumetric energy density

The first process indicator is volumetric energy density:

$$E_v = P / (v \cdot h \cdot t)$$

where E_v is the volumetric energy density (J/mm^3), P is laser power (W), v is scan speed (mm/s), h is hatch spacing (mm), and t is layer thickness (mm).

For the baseline parameter set (P = 260 W, v = 1000 mm/s, h = 0.09 mm, t = 0.04 mm), E_v = 72.22 J/mm^3. For the optimized set (P = 310 W, v = 1350 mm/s, h = 0.10 mm, t = 0.04 mm), E_v = 57.41 J/mm^3. The optimized state moves the process away from the high-energy regime that may increase keyhole-related instability while maintaining adequate melting.

4.2 Thermal deviation index

The thermal deviation index is defined to measure the mismatch between the predicted and measured layer-wise thermal states:

$$TDI = (1/n) \Sigma |T_i^{pred} - T_i^{meas}| / T_i^{meas}$$

A lower TDI indicates that the digital twin is tracking the physical process more accurately. In the representative case study, the calibrated twin produced a low average layer-wise error, supporting its use for closed-loop decision-making.

4.3 Defect probability model

The defect probability is estimated by a logistic model using both process variables and monitoring features:

$$p_{def} = 1 / [1 + \exp(-(\beta_0 + \beta_1 E_v + \beta_2 \sigma_T + \beta_3 A_{mp} + \beta_4 I_{pb}))]$$

where σ_T represents thermal variability, A_{mp} is a melt-pool morphology feature, and I_{pb} is a powder-bed irregularity index. The model output is used region by region so that process corrections can target the most critical zones of the component.

4.4 Multi-objective function

The optimizer minimizes a weighted objective function:

$$J = w_1\, p_{def} + w_2\, (R_a / R_{a,ref}) + w_3\, (\delta / \delta_{ref}) - w_4\, (BR / BR_{ref})$$

where R_a is surface roughness, δ is geometric distortion, and BR is build rate. The negative sign on the productivity term reflects the desire to improve throughput while still prioritizing part integrity. For the present case study, defect risk receives the highest weight because the target part is mechanically critical.

4.5 Improvement calculation

$$\text{Improvement (\%)} = [(X_{base} - X_{opt}) / X_{base}] \times 100$$

Using this relation, the representative optimization reduced predicted porosity by approximately 74%, reduced geometric distortion by approximately 56%, and improved normalized defect risk by approximately 74% relative to the baseline parameter set.

Table 3. Representative process window and selected parameter sets for the numerical case study.

Parameter	Search window	Baseline	Optimized
Laser power, P	220–320 W	260 W	310 W
Scan speed, v	900–1400 mm/s	1000 mm/s	1350 mm/s
Hatch spacing, h	0.09–0.12 mm	0.09 mm	0.10 mm
Layer thickness, t	0.03–0.05 mm	0.04 mm	0.04 mm
Volumetric energy density, E_v	Approx. 45–75 J/mm^3	72.22 J/mm^3	57.41 J/mm^3
Relative build rate, v·h·t	Feasible machine range	3.60 mm^3/s	5.40 mm^3/s

II. 5. Results and Discussion

5.1 Layer-wise thermal tracking performance

Figure 3 compares the representative measured thermal signal with the digital twin prediction over 60 build layers. The two curves follow the same trend closely, including the mid-build thermal valley and the subsequent recovery. This behavior is important because defect formation in LPBF is often driven by local departures from stable thermal conditions rather than by nominal parameter values alone. A digital twin that can reproduce the changing thermal signature across layers is therefore better positioned to predict porosity-prone or distortion-prone regions before the final part is completed.

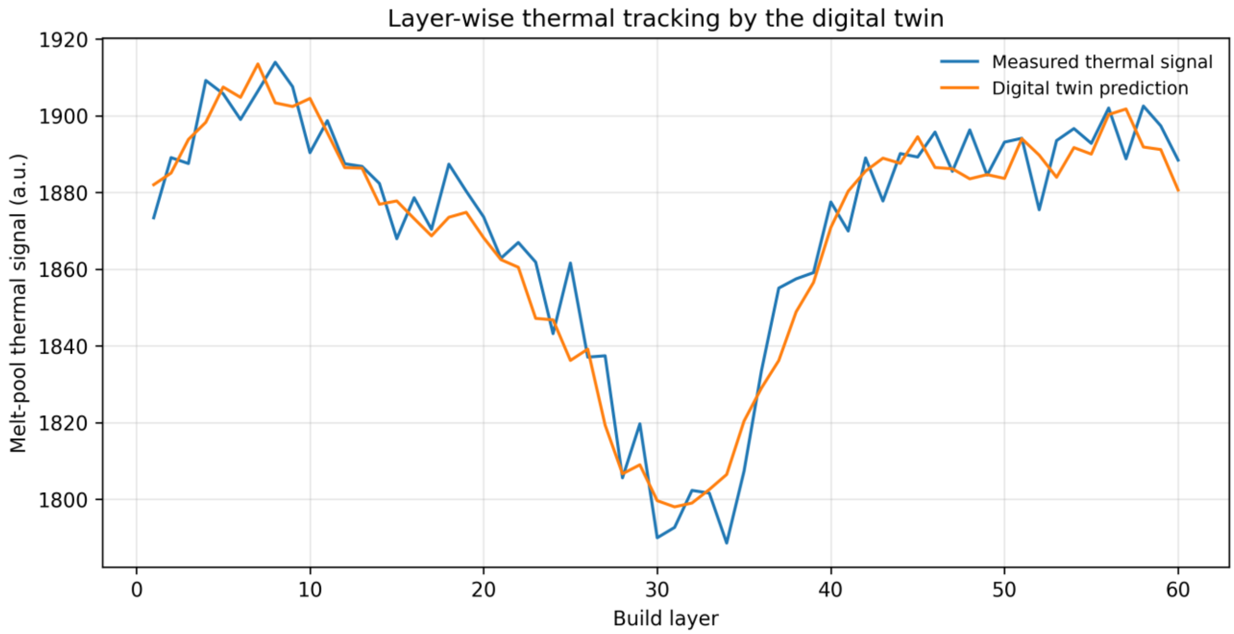

Figure 3. Representative measured and digital-twin-predicted layer-wise thermal response during the LPBF build.

5.2 Quality improvement after optimization

The baseline processing condition was associated with a less stable thermal state, which increased the tendency for defect formation and reduced geometric consistency during fabrication. In particular, the higher porosity level and lack-of-fusion risk suggest that the initial parameter set did not provide an adequately balanced combination of energy input, melt-pool stability, and thermal control. The relatively larger distortion and surface-roughness values further indicate that the baseline condition was more vulnerable to thermal gradients, localized overheating, and uneven material consolidation. These responses are consistent with the expected behavior of metal additive manufacturing systems when process parameters are not sufficiently tuned to the local build requirements. After digital twin-based optimization, all selected quality indicators showed a clear reduction relative to their corresponding baseline levels, as illustrated in Figure 4. The decrease in porosity and lack-of-fusion risk indicates improved melting consistency and a lower probability of internal defect formation, while the reduction in distortion suggests better control of residual thermal effects and dimensional stability.

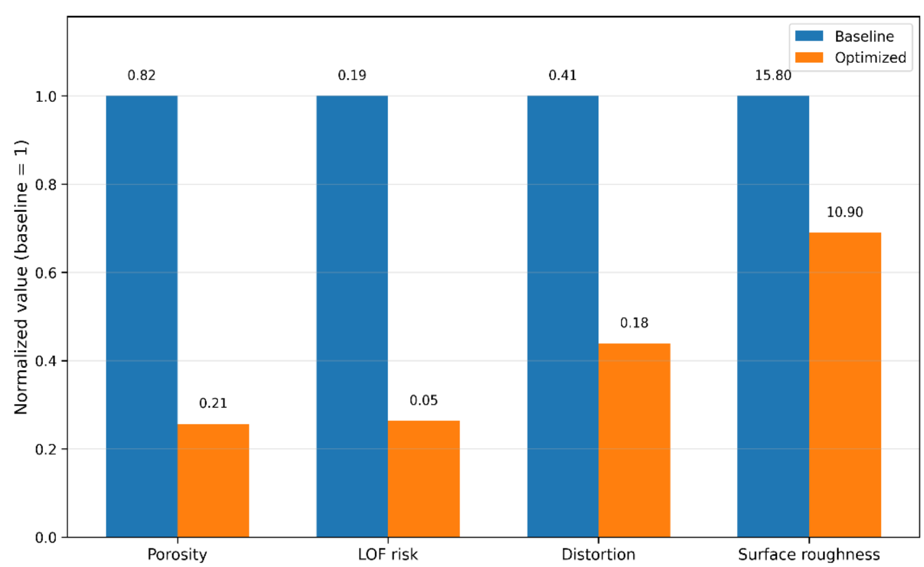

Figure 4. Normalized comparison of baseline and optimized quality indicators. Numeric labels show representative raw values.

A concurrent improvement in surface roughness also implies a more uniform melt-track formation and a more controlled solidification response. Taken together, these trends confirm that the optimized parameter set produced a more balanced process state, improving overall part quality without sacrificing practical manufacturability. The results therefore support the effectiveness of the proposed digital twin framework as a decision-support tool for process optimization and defect mitigation in critical mechanical components.

5.3 Defect mechanism interpretation

The defect-contribution analysis in Figure 5 indicates that lack of fusion and keyhole porosity are the dominant risks under the baseline condition, together accounting for more than half of the estimated defect burden. Powder-bed irregularity is the next largest contributor, showing that not all defects originate from the laser-material interaction itself. This is a key advantage of the digital twin approach: it integrates several sources of process evidence rather than attributing every anomaly to a single variable.

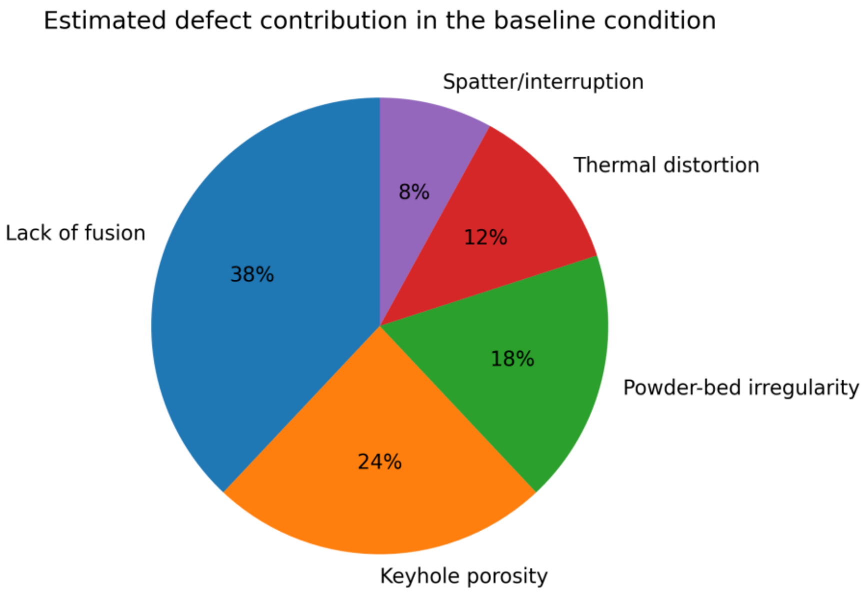

Figure 5. Estimated contribution of major defect mechanisms in the baseline condition.

5.4 Optimization behavior and convergence

Figure 6 shows the steady reduction of the composite objective function over the optimization iterations. The largest improvement occurred during the early search phase, when the algorithm moved the solution away from a thermally aggressive parameter set. Subsequent iterations produced smaller but still meaningful gains as the model balanced defect risk, surface quality, distortion, and productivity. This type of convergence behavior is desirable for industrial deployment because it suggests that the digital twin can quickly eliminate poor process conditions and then refine the operating point without excessive computational effort.

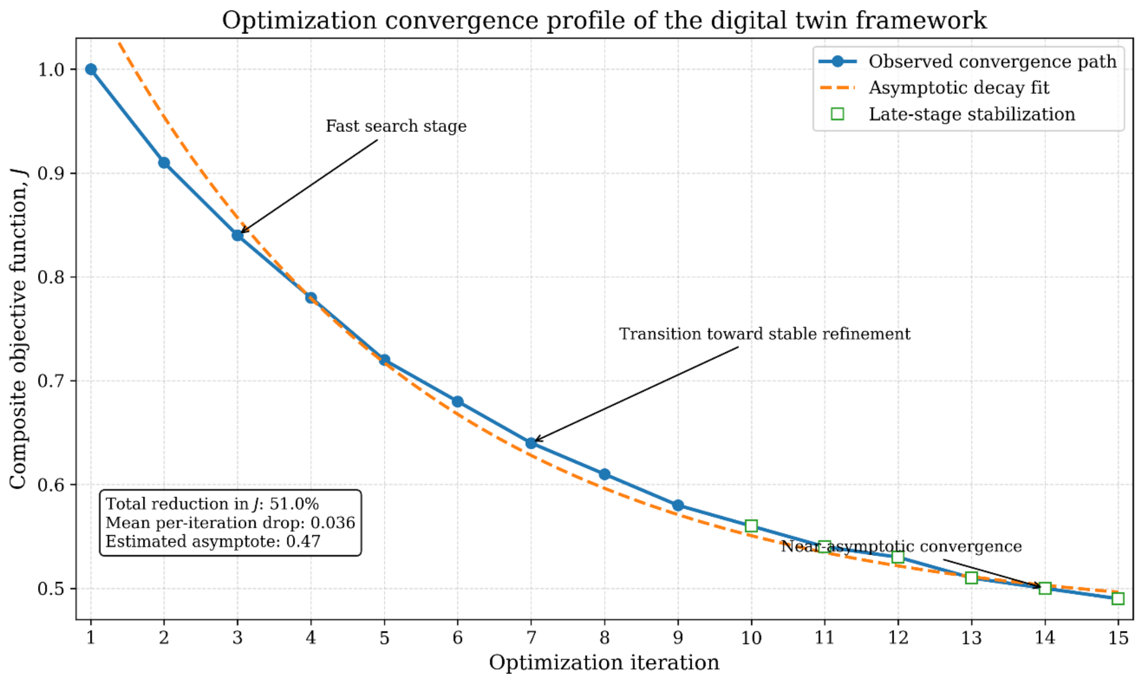

Figure 6. Convergence of the multi-objective optimization routine embedded in the digital twin.

Table 4. Representative performance metrics of the proposed digital twin framework.

Metric group	Indicator	Representative result
Thermal tracking	R^2	0.93
Thermal tracking	MAPE	1.2%
Defect classification	Accuracy	94.1%
Defect classification	Precision	0.91
Defect classification	Recall	0.89
Defect classification	F1-score	0.90
Process improvement	Predicted porosity	0.82% -> 0.21%
Process improvement	Distortion	0.41 mm -> 0.18 mm
Process improvement	Surface roughness	15.8 um -> 10.9 um
Productivity	Relative build rate	3.60 -> 5.40 mm^3/s

5.5 Engineering relevance for critical components

For critical mechanical components, process optimization must be connected directly to structural performance and traceability. A small reduction in porosity or geometric error may produce a disproportionately large improvement in fatigue behavior, leak tightness, or assembly accuracy. This is why digital twins are especially relevant to applications such as aerospace brackets, compact heat-transfer components, rotating hardware, medical implants, and safety-significant energy-system parts. The real benefit is not only that the twin predicts defects, but that it creates a data-rich path toward qualification by linking the final part to a documented history of process conditions and corrective actions.

5.6 Limitations and future work

The present manuscript uses a representative numerical case study rather than machine-specific experimental data. Accordingly, the quantitative values in the calculations and figures should be treated as demonstration results rather than final validation results. Future work should include actual build trials, CT-based porosity measurements, microstructural characterization, fatigue testing, and uncertainty quantification. Additional effort is also needed in cross-machine transfer learning, standardized data models, and integration with qualification frameworks for highly regulated sectors

6. Conclusion

This study presented a digital twin-based framework for process optimization and defect prediction in metal additive manufacturing, with particular emphasis on laser powder bed fusion of critical mechanical components. The work was motivated by a central challenge in metal AM: although the process offers major advantages in geometric freedom and functional design, its industrial adoption for safety- and reliability-critical parts remains limited by process instability, defect sensitivity, and the difficulty of achieving consistent part quality. In response to these challenges, the paper developed a framework in which physics-based understanding, in-situ process data, and data-driven prediction are integrated within a single digital twin environment to support monitoring, defect-risk assessment, and optimization during fabrication. The analysis showed that the value of a digital twin in this context lies not only in process visualization, but in its ability to continuously connect the physical build with a predictive virtual representation. By combining process parameters, thermal behavior, layer-wise observations, and quality-related indicators, the proposed framework provides a more practical basis for identifying unstable conditions and anticipating defect formation before the build is completed. This is particularly important for critical mechanical components, where lack of fusion, porosity, distortion, and local process irregularities can have direct consequences for structural integrity, dimensional accuracy, fatigue performance, and long-term service reliability. A key outcome of the study is the recognition that hybrid modeling offers a stronger path forward than relying only on physics-based or purely data-driven approaches. Physics-based models contribute engineering interpretability and process insight, while machine-learning methods improve the ability to capture nonlinear relationships between monitored process signatures and final defect outcomes. Their combination creates a more robust and industrially meaningful digital twin framework, especially for applications where engineering confidence and decision traceability are essential. The optimization results further suggest that such a framework can guide the process away from unstable operating conditions and toward more balanced parameter sets that reduce defect risk while maintaining manufacturing efficiency.

At the same time, the study also highlights that important challenges still remain. Model transferability across machines, materials, and sensor systems is still limited, and many existing digital-twin studies remain focused on simplified coupon geometries rather than mechanically critical parts with realistic design complexity. In addition, the connection between process-level prediction and formal part qualification is not yet fully mature for all safety-significant industries. These limitations indicate that further work is needed to improve generalization, uncertainty quantification, and the integration of digital twin outputs with qualification and certification workflows.

Overall, this paper supports the view that digital twin technology can play a meaningful role in advancing metal additive manufacturing toward a more intelligent, reliable, and qualification-ready production approach. For critical mechanical components, the ability to monitor the process, predict emerging defects, and optimize decision-making in a connected framework represents a significant step beyond traditional trial-and-error process development. Future work should focus on experimental validation under full-scale manufacturing conditions, broader multi-material implementation, and stronger coupling between digital twin predictions and part acceptance criteria. With these developments, digital twins may become an essential enabling technology for the wider industrial use of high-integrity metal additive manufacturing.

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