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Advancing Additive Manufacturing Through Artificial Intelligence–Powered, High-Throughput, Nondestructive Characterization and Process Optimization

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CRADA Final Report - NFE-19-07705

OAK RIDGE National Laboratory

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Electrification and Energy Infrastructure Division

ADVANCING ADDITIVE MANUFACTURING THROUGH ARTIFICIAL INTELLIGENCE–POWERED, HIGH-THROUGHPUT, NONDESTRUCTIVE CHARACTERIZATION AND PROCESS OPTIMIZATION

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ABBREVIATIONS

AI	artificial intelligence
AM	additively manufactured
AMMT	Advanced Materials and Manufacturing Technologies
AMMTO	Advanced Materials and Manufacturing Technologies Office
CAD	computer-aided design
CRADA	Cooperative Research and Development Agreement
DOE	US Department of Energy
FOV	field of view
GE	General Electric
NDE	nondestructive evaluation
ORNL	Oak Ridge National Laboratory
XCT	x-ray computed tomography

ABSTRACT

This Cooperative Research and Development Agreement (CRADA) between Oak Ridge National Laboratory (ORNL) and ZEISS Industrial Metrology has demonstrated the transformative potential of artificial intelligence (AI)-enabled x-ray computed tomography (XCT) to accelerate the qualification and certification of additively manufactured (AM) parts. At the core of this effort is Simurgh, an AI-powered XCT reconstruction framework jointly advanced by ORNL and ZEISS that integrates computer-aided design (CAD) models, physics-based simulations, and deep learning to overcome the long-standing challenges of metal artifact correction, long scan durations, and limited flaw detectability in dense and geometrically complex components.

Simurgh enables high-throughput, high-quality 3D reconstruction from sparse and fast scans, which reduces XCT acquisition times by more than an order of magnitude and simultaneously improves defect detection limits by up to fourfold compared with industry-standard approaches. This capability reduces scan costs by more than 50%, lowers labor overhead, and makes XCT characterization economically viable for routine industrial use. By enabling reliable flaw detection in minutes rather than hours, Simurgh facilitates real-time feedback loops for process parameter optimization, which was highlighted in a recent *npj Computational Materials* (a *Nature* journal) issue. In the published study, more than 100 alloy coupons were characterized within a single day. This work represents a tenfold acceleration in the development of novel AM alloys and processes compared with conventional workflows.

The ZEISS collaboration has also demonstrated the scalability of Simurgh to diverse application domains, including aerospace, nuclear, automotive, and biomedical components; in these applications, ensuring structural integrity is paramount. By drastically reducing barriers to XCT adoption, this partnership has laid the foundation for digital twins and data-driven certification pipelines and directly addressed bottlenecks in qualifying new materials and designs. Together, ORNL and ZEISS have shown that Simurgh advances the state of the art in nondestructive evaluation and aligns with the broader mission of enabling Industry 4.0 manufacturing ecosystems, in which intelligent, cost-effective, rapid quality assurance is integral to accelerating innovation and ensuring safety in critical applications.

1. SIMURGH: ARTIFICIAL INTELLIGENCE–POWERED X-RAY COMPUTED TOMOGRAPHY RECONSTRUCTION FRAMEWORK FOR X-RAY COMPUTED TOMOGRAPHY

1.1 CHALLENGES IN X-RAY COMPUTED TOMOGRAPHY

X-ray computed tomography (XCT) is a cornerstone nondestructive evaluation (NDE) method for inspecting manufactured components, particularly in safety-critical industries such as aerospace, energy, and biomedical manufacturing. XCT reconstructs a 3D volume from 2D projection images to enable dimensional inspection, flaw detection, and microstructural characterization. However, XCT faces significant challenges when applied to dense metals and complex geometries:

- Artifacts and noise—Beam hardening, scattering, streaks, and blurring (Figure 1) compromise image quality.
- Long scan times—High-density components often require hours of scanning to achieve sufficient detectability limits.
- High cost and computational load—Extended acquisition times and postprocessing increase labor and per-part characterization costs.

These limitations create bottlenecks for qualifying additively manufactured (AM) parts, in which rapid feedback and reliable certification are essential.

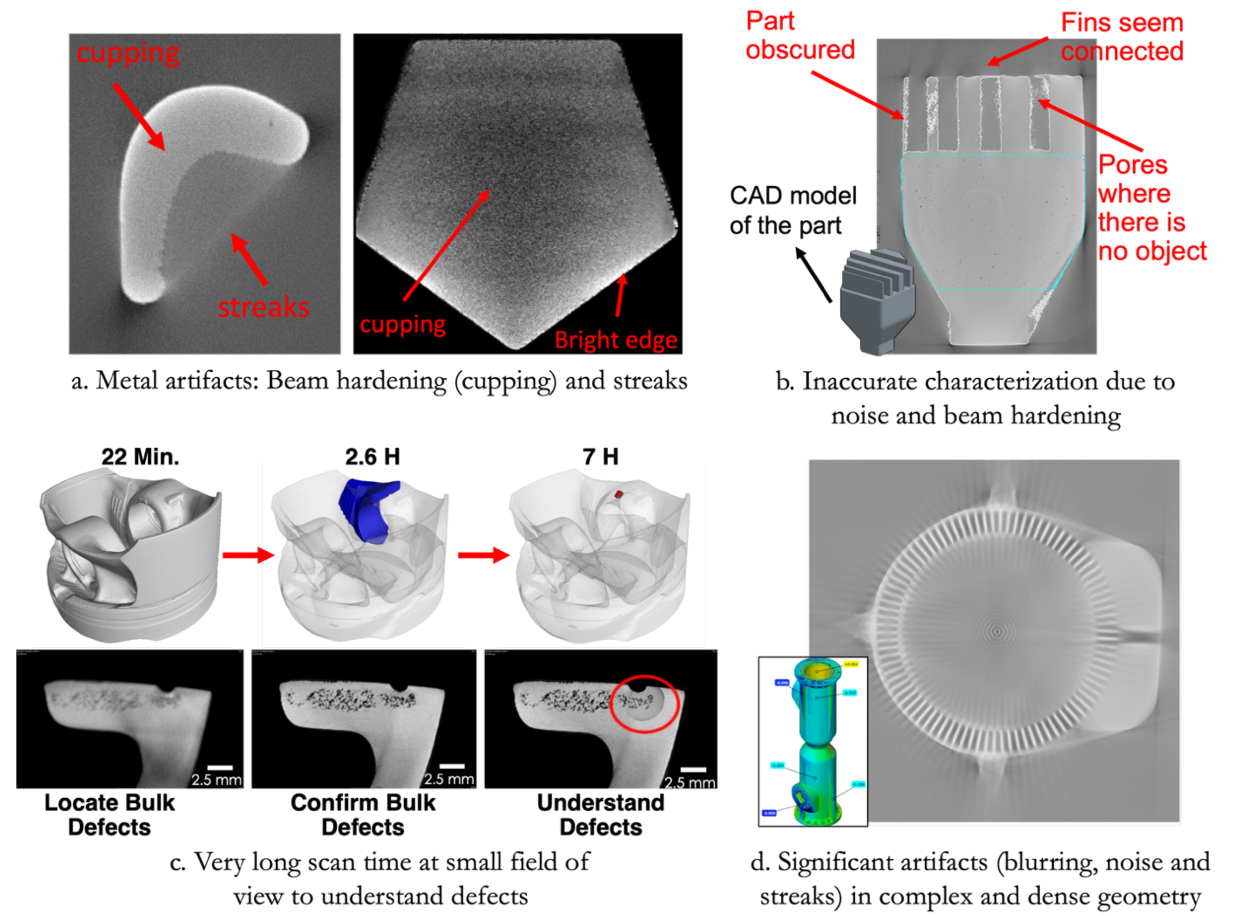


Figure 1. XCT Simurgh challenges current technology standards. (a) Metal artifacts, including beam hardening (cupping/bright edges) and streaks. (b) A slice from a 3D reconstructed part, with white dots indicating detected flaws. Arrows point to the effects of noise (flaws detected where no object is present), beam hardening, metal artifacts (connected fins), and blurring (obscured fin) on characterization accuracy. (c) A metal part that was scanned with three different fields of view (FOVs; see blue and red shaded subvolumes under 2.6H and 7H scans) at different scan times. Bottom row shows a cross section from a quick scan (22 min) with a full FOV to locate defects; a long scan (7 h) with a small FOV was necessary to understand the defects. (d) A slice from an XCT reconstruction of a complex part (inset) and the associated artifacts.

1.2 THE SIMURGH FRAMEWORK

1.2.1 Overview of Simurgh

Simurgh is an artificial intelligence (AI)-powered XCT reconstruction framework designed to overcome the limitations of conventional tomography and enable fast, accurate, and high-throughput characterization. By integrating computer-aided design (CAD) models of scanned parts with physics-based x-ray information, the framework guides deep learning algorithms to reconstruct high-quality volumes from sparse and fast scans and suppresses noise and artifacts [1–6]. To train these models, Simurgh uses a hybrid data generation strategy that combines oversampled reference scans, which are downsampled to sparse views, with synthetic data created from CAD-based phantoms seeded with realistic defect libraries and physics-informed simulations (Figure 2).

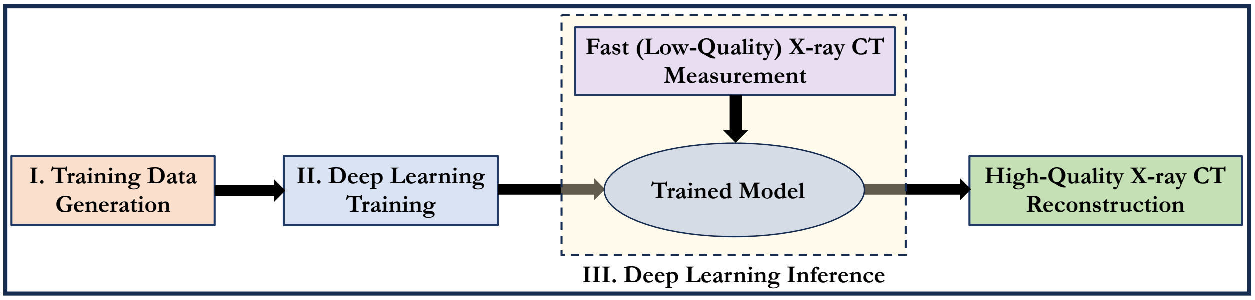


Figure 2. Block diagram showing the flow of data for training and use of the Simurgh deep learning framework for high-quality XCT reconstruction.

At the algorithmic level, Simurgh employs a 2.5D convolutional neural network architecture (Figure 3) that captures volumetric context but remains computationally efficient. Once trained, the framework can rapidly process new XCT scans to produce reconstructions that overcome challenges such as beam hardening and scattering artifacts.

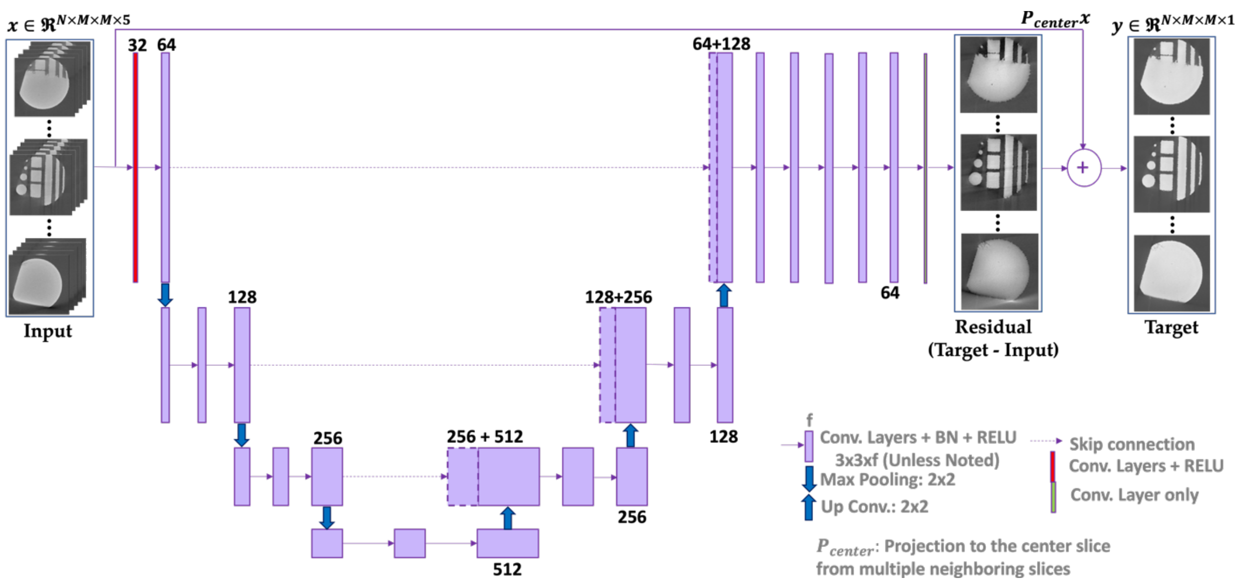


Figure 3. Architecture of the 2.5D convolutional neural network that learns the nonlinear mapping between inferior input and high-quality ground truth pairs.

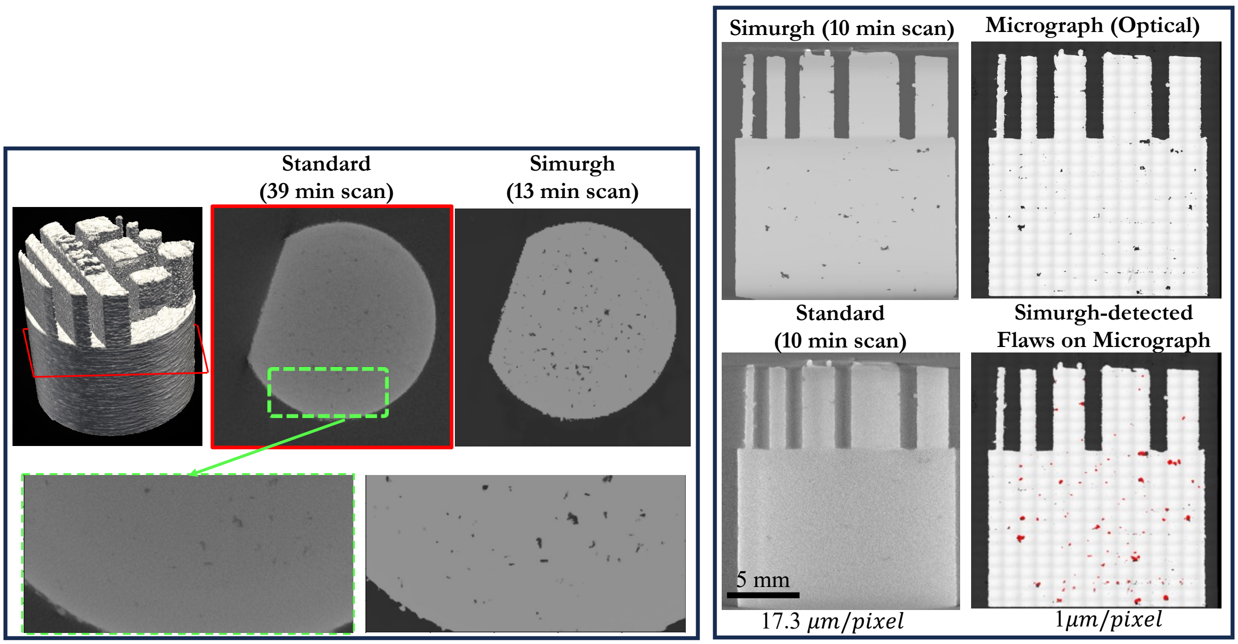
Copyrighted under US Department of Energy (DOE) Invention Reference Number 90000193, Simurgh integrates seamlessly into industrial XCT workflows, including ZEISS scanning services, and represents a major step toward scalable, AI-enabled NDE [7–8].

1.2.2 Verification of Simurgh on Low- and High-Density Alloys

To validate Simurgh against ground truth characterizations, controlled studies were performed on low-density aluminum alloys (AlCe) and high-density nickel-based superalloys (Inconel 718). These cases provided direct comparisons between Simurgh reconstructions, standard industrial XCT algorithms, and independent high-resolution imaging obtained through optical microscopy.

For aluminum alloys (low-density), Simurgh reduced scan times from nearly 40 min to just 13 min and simultaneously improved reconstruction quality (Figure 4a). Standard algorithms blurred small pores and defects, whereas Simurgh provided sharper contrast, enabling clear identification of flaws. Quantitative analysis confirmed that in this regime, Simurgh achieved full detection of defects larger than 50 µm with a threefold reduction in scan time compared with the standard techniques, which required longer scans and still missed finer flaws (Figure 5a).

The benefits were even more pronounced in high-density nickel-based alloys, where conventional reconstructions struggled with severe beam hardening and scattering artifacts. For these alloys, Simurgh produced reconstructions that closely matched independent optical microscopy data (Figure 4b). In a 10 min scan, Simurgh achieved near-complete flaw detection down to approximately 100 µm, whereas standard reconstructions only reliably detected flaws larger than 400 µm, even with much longer scans. Figure 5b illustrates this fourfold improvement in detectability limits, demonstrating that Simurgh accelerated inspection and pushed XCT performance toward the resolution of destructive microscopy.



a. Example from a low-density Al alloy **b. Example from a high-density Ni alloy**

Figure 4. Reconstructions for low- and high-density alloys using standard techniques versus the Simurgh framework. (a) A 3D reconstruction for a low-density aluminum alloy. The slice (red box) through the object compares a standard algorithm with the Simurgh algorithms. An expanded view (dashed green box) compares a region of interest within the slices. The dark black spots in the images are pores and defects in the part. In the standard algorithm's reconstruction, the spots are smeared (blurry), but in the Simurgh reconstruction, they have quite a high contrast. (b) A reconstruction for a low-density nickel alloy. To verify the quality of the reconstruction, the sample was cut and scanned using high-resolution microscopy, then the flaws detected using XCT were compared with the microscopy results. The figure shows the 2D optical microscopy cross section and the corresponding slice from 3D volumes reconstructed from very sparse scans using a standard algorithm and Simurgh. Furthermore, flaws extracted from the Simurgh XCT scan were projected on the 2D microscopy image. Notably, the Simurgh scan for this dense sample was completed in 10 min, but a typical scan of a comparable thick, high-density component takes more than 2 h.

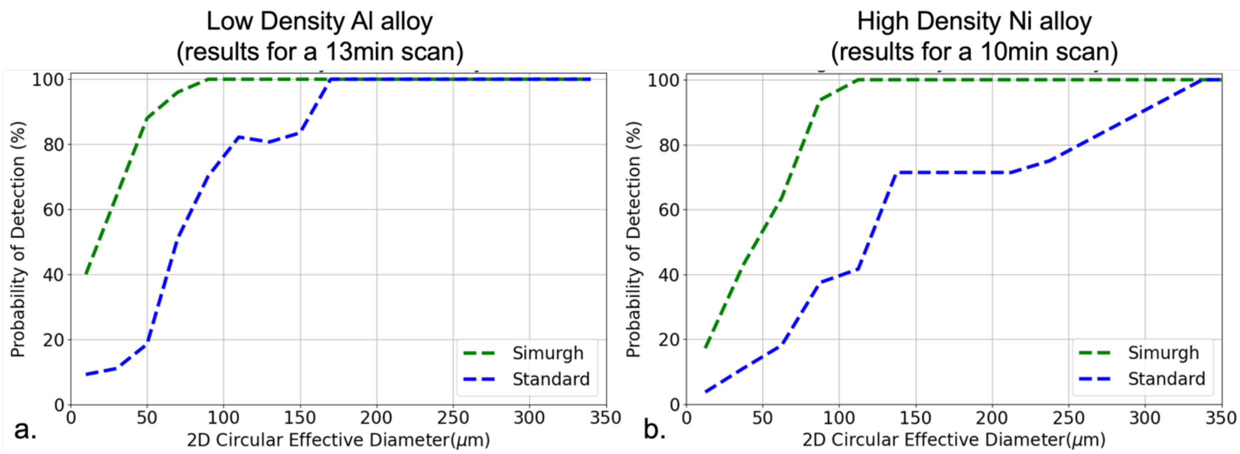


Figure 5. Probability of flaw detection for reconstructions using Simurgh and a standard algorithm. A flaw was considered to be detected in the reconstruction of a fast (sparse) XCT scan if it coincided with a flaw detected by high-resolution microscopy at 1 µm. The plots show results for a (a) low-density aluminum alloy and (b) high-density nickel alloy. Both plots indicate that Simurgh significantly improved flaw detection.

Together, these studies establish that Simurgh delivers high-fidelity flaw detection for both light and dense alloys and significantly reduces scan times without compromising accuracy. By verifying its results against high-resolution microscopy, Simurgh provides the reliability required for industrial adoption in qualification and certification workflows.

2. PROCESS PARAMETER OPTIMIZATION WITH SIMURGH

The integration of Simurgh into XCT workflows has enabled a transformative shift in how process parameters for additive manufacturing are developed and optimized. By delivering high-quality reconstructions from extremely fast scans, Simurgh makes it possible to perform high-throughput, scalable characterization of large batches of parts, each fabricated with different process conditions. As illustrated in Figure 6, entire build plates (120 coupons used here) are designed so that each component is printed with a unique process parameter. These components can then be rapidly scanned, reconstructed, and characterized, which enables quick evaluation of how each parameter set affects porosity, dimensional accuracy, and overall part quality. This level of throughput accelerates parameter studies by more than an order of magnitude compared with traditional XCT methods.

A key innovation of this workflow is that the part design itself allows for isolating the effects of different process parameters and for probing their geometric dependence. Features such as thin fins, inclined bars, and bulk regions exhibit different solidification and porosity behaviors even under identical printing conditions. With Simurgh's consistent, artifact-free reconstructions, these geometry-dependent effects can be systematically evaluated to provide deeper insights into how process windows shift across features.

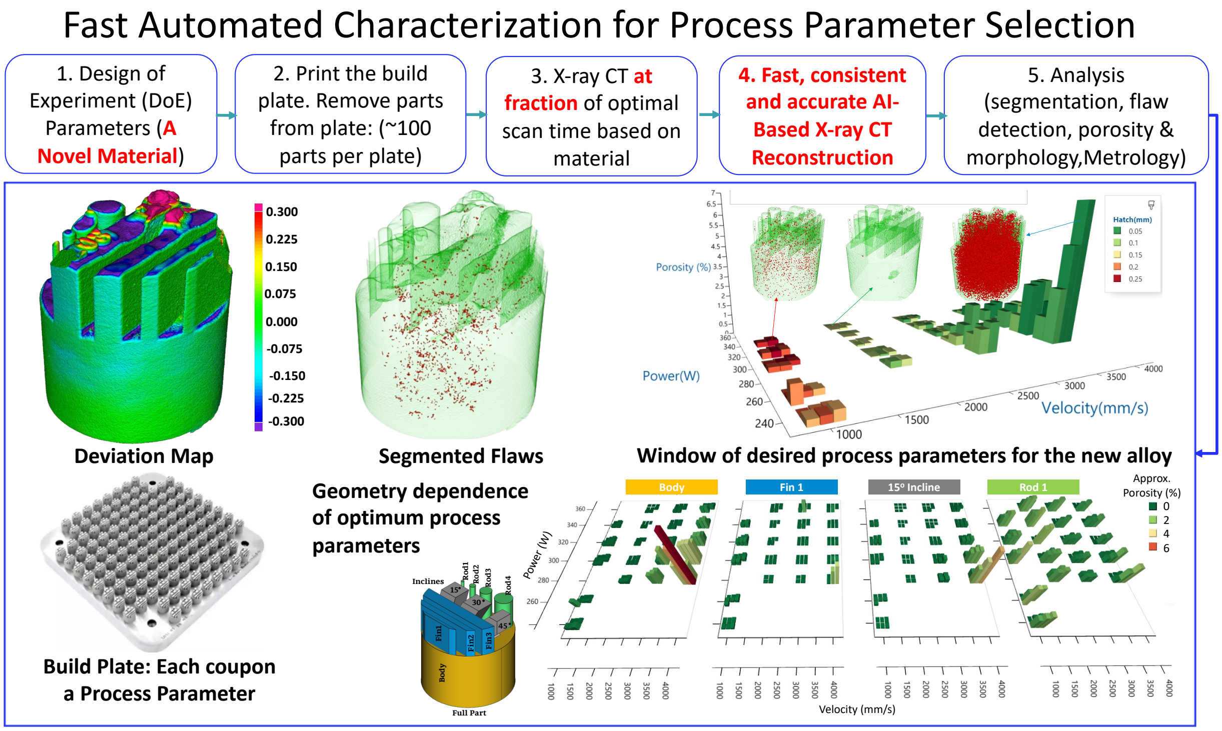


Figure 6. Fast, automated characterization for process parameter selection. A build plate is designed, and each component is printed with a separate printing process parameter. The components are quickly scanned, reconstructed, and characterized, leveraging the algorithms provided. This allows the researchers to quickly evaluate and analyze the effect of process parameters and find regions of ideal process parameters, that result in minimum porosity and geometric deviation among other metrics for ideal printed component. Furthermore, by analyzing these ideal components and their individual geometric features, this study evaluated the effect of geometry on the selection of the ideal region of process parameters.

Equally important, the streamlined nature of Simurgh's output reduces the burden of postprocessing. Conventional reconstructions often require extensive manual intervention and tuning to segment flaws and extract porosity metrics. Simurgh delivers reconstructions that are consistent across large datasets, which enables automated flaw detection and analysis pipelines with minimal human oversight. This combination of fast scans, rapid reconstructions, and automated postprocessing allows researchers and industry partners to identify regions of optimal process parameters, including those leading to minimal porosity and deviation, and validate their reproducibility across diverse part geometries. In doing so in this study, Simurgh revealed for the first time that optimal printing conditions are not universal but can vary depending on component geometry, which is a critical insight for accelerating alloy qualification and industrial adoption of additive manufacturing.

3. BROADER INDUSTRIAL AND PROGRAMMATIC IMPACT

The impact of Simurgh extends well beyond process parameter optimization, shaping DOE mission areas and industrial practices across multiple sectors. Within the DOE Advanced Materials and Manufacturing Technologies Office (AMMTO) and the DOE Office of Nuclear Energy's Advanced Materials and Manufacturing Technologies (AMMT) program, AI-driven NDE frameworks such as Simurgh are central to accelerating the transition to clean energy and strengthening manufacturing competitiveness. By enabling rapid, high-quality XCT characterization of dense and complex components, Simurgh directly supports qualification and certification of advanced materials and promotes energy efficiency, material efficiency, and resilience in domestic supply chains for critical clean energy technologies.

Under the AMMT program, Simurgh has been deployed as a central tool for high-throughput qualification of stainless steels (316L/316H) and advanced alloys. By coupling AI-enabled reconstruction with specialized sample holders, Oak Ridge National Laboratory (ORNL) demonstrated the ability to scan thousands of nuclear-relevant coupons in a fraction of the time required by conventional XCT. More than 400 samples fabricated on the Concept Laser M2 and Renishaw systems were systematically characterized to generate quantitative porosity maps as a function of laser power, scan speed, and hatch spacing. Optimization frameworks further accelerated alloy development by reducing the number of required build iterations, which directly advances the qualification of nuclear-grade materials and components [9].

Industrial adoption has been accelerated through collaborations with ZEISS, Boeing, General Electric (GE), DMG MORI, and other partners. ZEISS has shown that by integrating Simurgh into its XCT-as-a-service platform, the cost of scanning can be reduced from over $750 per part to as little as $330 per part while simultaneously improving reconstruction quality. This cost advantage is complemented by major savings in postprocessing; expert-driven analysis that typically costs $250 per hour is significantly reduced because Simurgh provides consistent, artifact-free reconstructions with minimal manual intervention. Across institutions and companies, Simurgh has already contributed to a market impact of nearly $19 million, which encompasses more than 17,000 scans, related XCT services, and the purchase of three XCT systems by a company dedicated to high-throughput process parameter optimization.

Together, these achievements highlight how Simurgh enables faster and more accurate inspection as well as significant economic and programmatic benefits. By reducing scan costs, accelerating throughput, and simplifying workflows, the framework is driving large-scale adoption of XCT in applications ranging from aerospace and nuclear to additive manufacturing. At the same time, Simurgh provides the foundation for advanced materials discovery, digital manufacturing systems, and qualification pipelines for nuclear energy, reinforcing DOE’s mission to couple cutting-edge AI with advanced manufacturing to deliver sustainable, efficient, and competitive industrial capabilities.

4. CONCLUSION

This Cooperative Research and Development Agreement (CRADA) between ORNL and ZEISS has demonstrated how sustained collaboration between a national lab and industry can deliver transformative advances in NDE and accelerate the deployment of additive manufacturing technologies. Through codevelopment of AI-powered XCT reconstruction tools such as Simurgh, the partnership has achieved step-change improvements in the speed, accuracy, and cost-effectiveness of XCT characterization. These advances now enable high-throughput qualification of AM parts, real-time process parameter optimization, and robust certification workflows that were not previously feasible with conventional methods.

The collaboration has already shown tangible economic and programmatic impacts. ZEISS has integrated these algorithms into its XCT service offerings, cutting scan costs by more than half and reducing dependence on manual postprocessing. ORNL has applied these algorithms in DOE AMMTO and AMMT programs to accelerate alloy qualification and nuclear materials research. Together, these efforts have supported industry partners such as Boeing, GE, and DMG MORI, with applications ranging from aerospace to energy and nuclear systems. This work has generated measurable economic value in the form of reduced inspection costs and increased throughput. The software developed through this CRADA is now licensed by multiple organizations, including the University of Dayton Research Institute, Idaho National Laboratory, National Institute of Standards and Technology, Air Force Research Laboratory, and ZEISS and, in collaboration with the Raytheon Research Center, is used to optimize the printing of Inconel 718 on EOS systems [10–11]. New collaborations and licensing opportunities are also in development with Nikon, EOS, and GE Vernova. These accomplishments were recently recognized with a 2025 R&D 100 Award, underscoring the impact and innovation of the work.

More importantly, this CRADA lays the foundation for something larger: a pathway to industrial ecosystems in which digital manufacturing, AI-enabled inspection, and qualification are tightly integrated. The advances realized through this partnership point toward the development of digital twins for AM parts, data-driven certification pipelines, and Industry 4.0 manufacturing environments in which qualification and certification are faster, more reliable, and more cost-effective. By aligning ORNL's scientific leadership with ZEISS's industrial expertise, the collaboration exemplifies how joint innovation can overcome technical bottlenecks and create scalable, economically viable solutions that will shape the future of advanced manufacturing.

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