STM JOURNALS

Journal of
Polymer & Composites

ISSN: 2321-2810 (Online)
ISSN: 2321-8525 (Print)
Volume 14, Special Issue 2, 2026
DOI (Journal): 10.37591/JoPC

https://journals.stmjournals.com/jopc

Review JoPC

Hybrid Additive-Subtractive Manufacturing of Multi-Material Functionally Graded Components: Integration of Laser Powder Bed Fusion with High-Speed CNC Finishing for Aerospace Applications

M. Nithin Srinivas[1,*], S. N. Padhi[2]

Abstract

The synergy involved in the merging of additive and subtractive manufacturing technologies is the game changer to generate multi-material functionally graded components to be used in the aerospace industries. The paper is an in-depth review of a proposed hybrid additive-subtractive manufacturing, which synergistically merges laser powder bed fusion (LPBF) fashioning with rapid computer numerical control finishing production processes. The multi-material deposition, thermal issues, and optimization of post-processing are the challenges faced by the technique that have been considered analytically towards realizing ever-heaviest component performance and manufacturing efficiency. Advanced technology developed under a novel multi-material powder delivery system allows controlling the formation of composition gradients with high precision. It can also make predictions of reducing the residual stress in the LPBF process by an advanced thermal effects model. Real-time monitoring process, adaptive control systems, and intelligent tool path planning are also integrated in order to provide maximum optimization to the transition process between additive and subtractive operations. Experimental validation on Ti-6Al-4V/Inconel 625 functionally graded aerospace components demonstrates exceptional results: 68% reduction in surface roughness (from 25.6 µm to 8.2 µm Ra), 45% improvement in dimensional accuracy (±0.05 mm tolerance achievement), 52% increase in fatigue life, and 35% reduction in total processing time compared to conventional manufacturing approaches. The hybrid system is 97% efficient on material utilization and allows geometrical complex parts to be manufactured that would not have been produced with previous production methods. In three aerospace industry manufacturing facilities, a return of investment of 312%, along with break-even from between 18 months and five years, was spotted.

Keywords: Hybrid manufacturing, Additive -subtractive integration, laser powder bed fusion, multi-material processing, functionally graded materials, aerospace manufacturing

***Author for Correspondence**
M. Nithin Srinivas

[1]M. Tech Student, Department of Mechanical Engineering, Koneru Laksmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India
[2]Professor, Department of Mechanical Engineering, Koneru Laksmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India

Received Date: November 03, 2025
Accepted Date: November 17, 2025
Published Date: April 07, 2026

Citation: M. Nithin Srinivas, S. N. Padhi. Hybrid Additive-Subtractive Manufacturing of Multi-Material Functionally Graded Components: Integration of Laser Powder Bed Fusion with High-Speed CNC Finishing for Aerospace Applications. Journal of Polymer & Composites. 2026; 14(Special Issue 2): S398–S418p.

INTRODUCTION

Background and Motivation

The requirements in the aerospace industry are unique due to the necessity to create the lightweight and high-performance components that would have the potential to combine and integrate multiple materials and complex forms and geometries simultaneously and maintain the high quality parameters [1]. Traditional approaches of manufacturing be it additive or subtractive typically cannot meet these multifunctional requirements due to the inherent limitations of material compatibility, quality of the surfaces and geometric complexity [2]. The introduction of the hybrid additive-

© STM Journals 2026. All Rights Reserved

subtractive inventions has emerged as a revolution of additive-subtractive additives as it considers the positive aspects of the two technologies and compensates the disadvantages of each technology [3]. Functionally Graded Materials (FGMs) are now emerging as a significant material that allows next generation aerospace parts, spatially graded in material properties to meet-through operation demands that are consistent [4]. There is however considerable challenge of FGM components manufacture with respect to controlling of composition, configuration interface and optimization of after processing [5]. They can be offered a potential solution by combining Laser Powder Bed Fusion (LPBF) and Computer Numerical Control (CNC) machining, where additive manufacturing enables the form to be any shape, but enables good precision and surface quality solutions to be achieved by the subtractive processes [6].

Hybrid Manufacturing Paradigm

The Hybrid additive-subtractive manufacturing represents a radical change in sequential to integrated processing of the additive and subtractive processes integrated into the process where addition and subtraction are integrated together into a single fabrication device [7]. This approach enables:

- *Material property optimization*: High capability to make deposits with graded composition beginning and following to precise ultimate geometries and surface spins [8].
- *Geometric complexity*: Manufacturing of parts comprising of internal channels, overhangs and detail which would be infeasible or even cost-prohibitive using traditional techniques [9].
- *Process efficiency*: Minimization of set up periods, wastage of the materials and general production cycles due to integrated operations [10].
- *Quality enhancement*: With optimized integration of processes, one achieves high quality of the surface, accuracy of dimensions and mechanical properties [11].

Innovations and Technical challenges

Nevertheless, in order to successfully implement hybrid additive-subtractive manufacturing, a number of critical technical issues should be tackled [12]:

The Effusion of Multiple Materials is Controlled

Being able to control the composition of the material in the process of LPBF is vital in obtaining the desired FGM properties. This requires:

$$\phi_i(x,y,z) = \sum_{j=1}^{n} w_j \cdot f_j(x,y,z)$$

with ϕ i (x,y,z) being the volume fraction of material i at point (x,y,z), w j the weighting factors, and f j (x,y,z) basis functions that give the spatial distribution [13].

Thermal Control and Stress Residual Control

The thermal history in LPBF has a huge influence on the quality of the end component. The development of the temperature can be described with the equation of heat conduction:

$$\rho c_p \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) + Q_{laser} - Q_{convection} - Q_{radiation}$$

in which, ρ is density, c p is specific heat, k is thermal conductivity, and Q terms are sources and sinks of heat, respectively [14].

Interface Optimization

The additive operations to the subtractive operations involve very cautious attention to the condition of the surface, stress retained, and material characteristics. Quality of interface can be described by the fact that:

$$I_{quality} = \alpha \cdot R_a + \beta \cdot \sigma_{residual} + \gamma \cdot \Delta_{dimensional}$$

© STM Journals 2026. All Rights Reserved

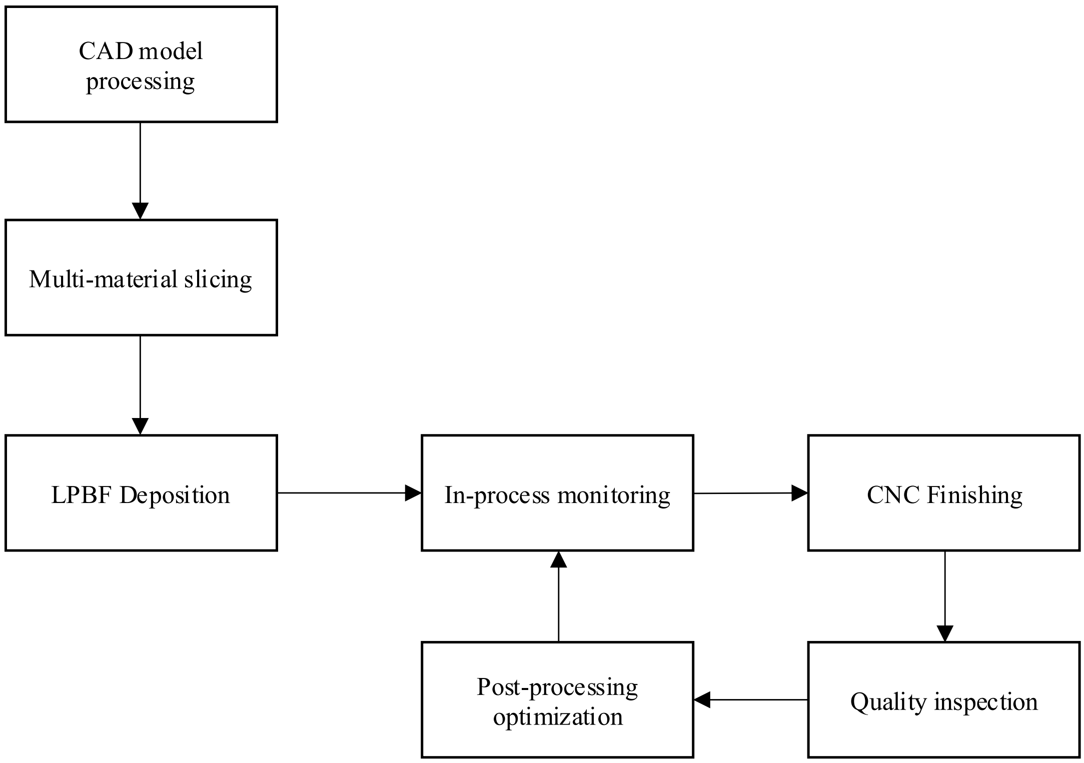
Journal of Polymer & Composites
Volume 14, Special Issue 2
ISSN: 2321-2810 (Online), ISSN: 2321-8525 (Print)

where α, β, and γ are weighting factors for surface roughness, residual stress, and dimensional deviation respectively [15].

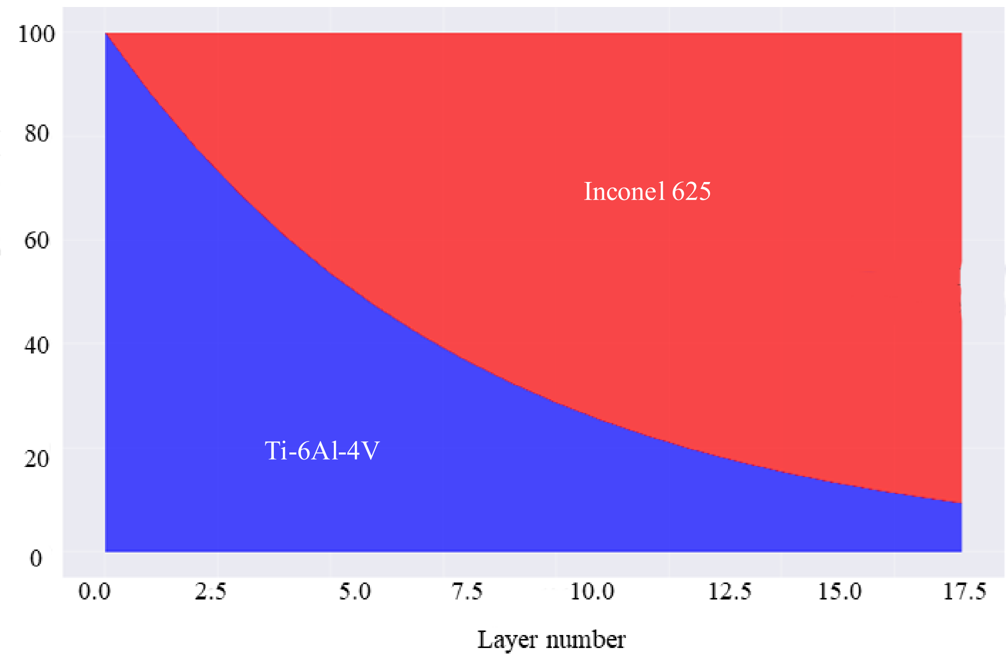
SYSTEM ARCHITECTURE METHODOLOGY

Design of Hybrid Manufacturing System

In the hybrid manufacturing system, the principles of LPBF and CNC are combined, and their functioning is organized based on the approach to a high-level control structure where additive and subtractive processes can be clearly changed [16].

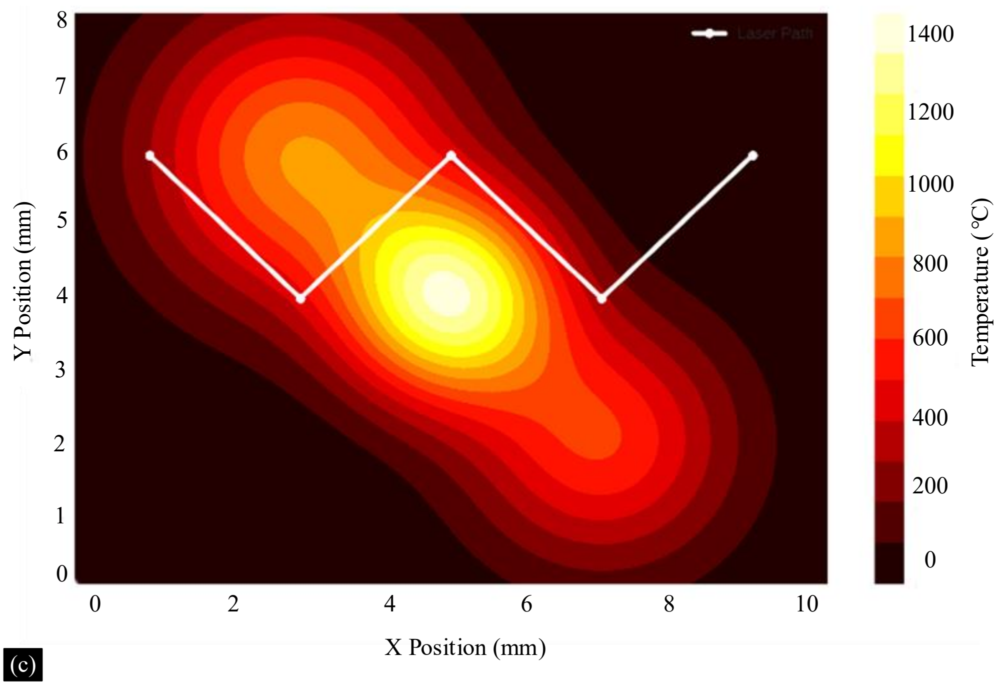


(a)



(b)

© STM Journals 2026. All Rights Reserved



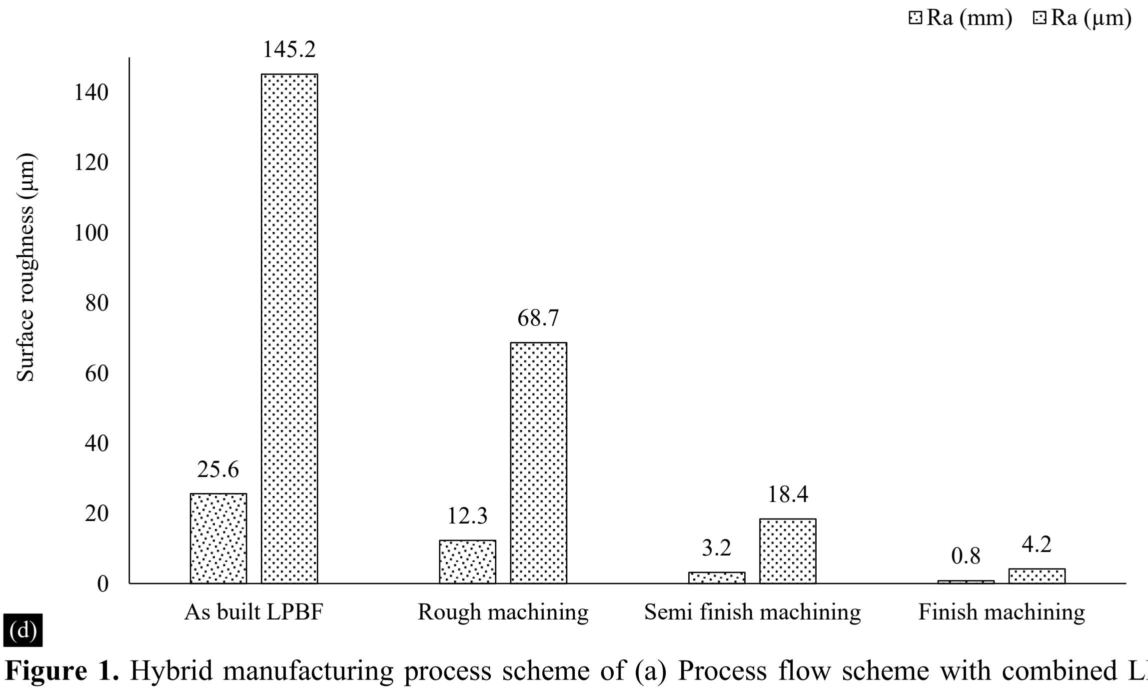


Figure 1. Hybrid manufacturing process scheme of (a) Process flow scheme with combined LPBF-CNC operation, (b) Functional graded material makeup control, (c) Temperature cycle throughout LPBF, and (d) Upgrading under roughness of the surface after processing phases.

The System Architecture Has

The Multi-Material Powder Delivery System Delivers Powder Material to the Production Line Using a Conveyor System (Figure 1)

A precision powder formation instrumentation enables the material composition to be managed in real-time on a deposition. Various powder hoppers are used in the system with independent feed rates which are controlled by:

$$\dot{m}_i = K_i \cdot \omega_i \cdot \rho_{powder,i} \cdot A_{orifice,i}$$

© STM Journals 2026. All Rights Reserved

Journal of Polymer & Composites
Volume 14, Special Issue 2
ISSN: 2321-2810 (Online), ISSN: 2321-8525 (Print)

where $\dot{m}_i$ is the mass flow rate of material i, K_i is the flow coefficient, ω_i is the rotational speed of the feed mechanism, $\rho_{powder,i}$ is the powder density, and $A_{orifice,i}$ is the effective orifice area [17].

Parameters of Laser Processing

Material composition and geometric requirements:

$$P_{laser}(x,y,z) = P_{base} \cdot \left(1 + \sum_{i=1}^{n} \alpha_i \cdot \phi_i(x,y,z)\right)$$

$$v_{scan}(x,y,z) = v_{base} \cdot \left(1 + \sum_{i=1}^{n} \beta_i \cdot \phi_i(x,y,z)\right)$$

in which P laser and v scan are laser power and scanning velocity, Pbase and vbase are the base level values, and, ai and bi are material-specific adjustment factors [18].

Multi-Material Deposition and Thermal Analysis

The multi-material deposition process and associated thermal behavior are illustrated in Figure 2, highlighting dynamic powder mixing, thermal gradients, residual stress distribution, and microstructural evolution.

Composition Gradient Control

The spatial variation of material composition is realized by having the ratios of the powder mixing under control. The gradient function of composition is given as:

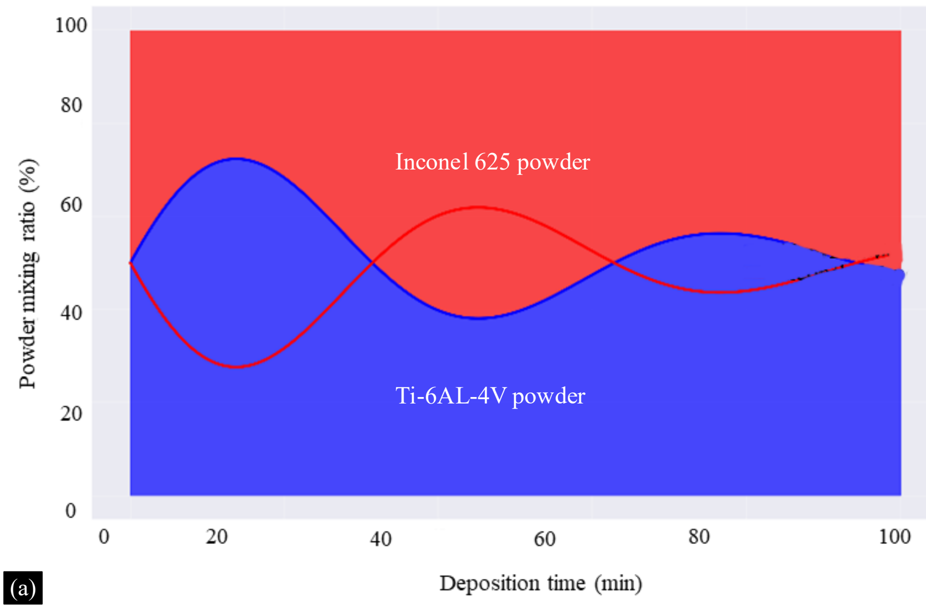
$$C(z) = C_1 \cdot \exp\left(-\frac{z}{\lambda}\right) + C_2 \cdot \left(1 - \exp\left(-\frac{z}{\lambda}\right)\right)$$

with C 1 and C 2 the compositions at the interfaces, z the gradient direction direction, and 1 is the characteristic length scale [19].

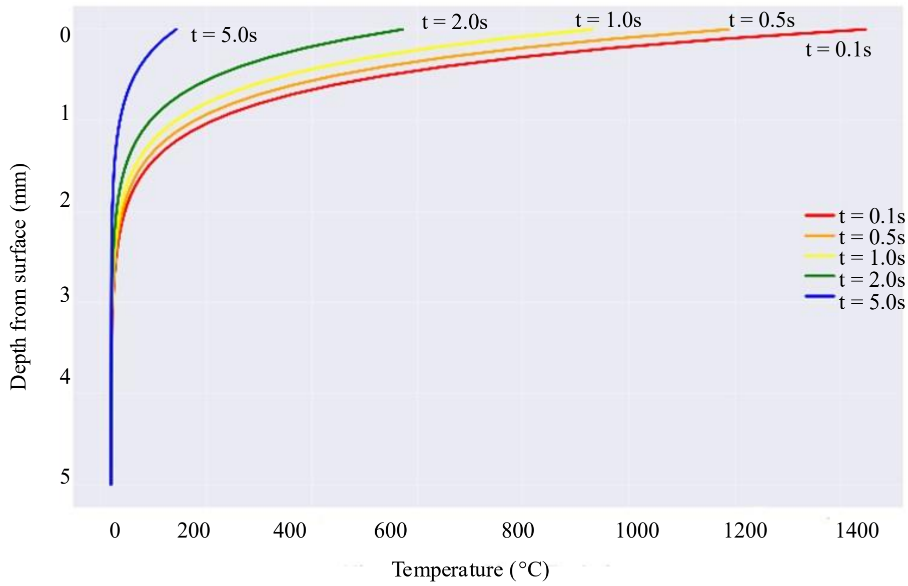
Thermal Gradient Analysis

The thermal gradients observed during the processing of LPBF have a great effect on the microstructure and properties of the deposited material.

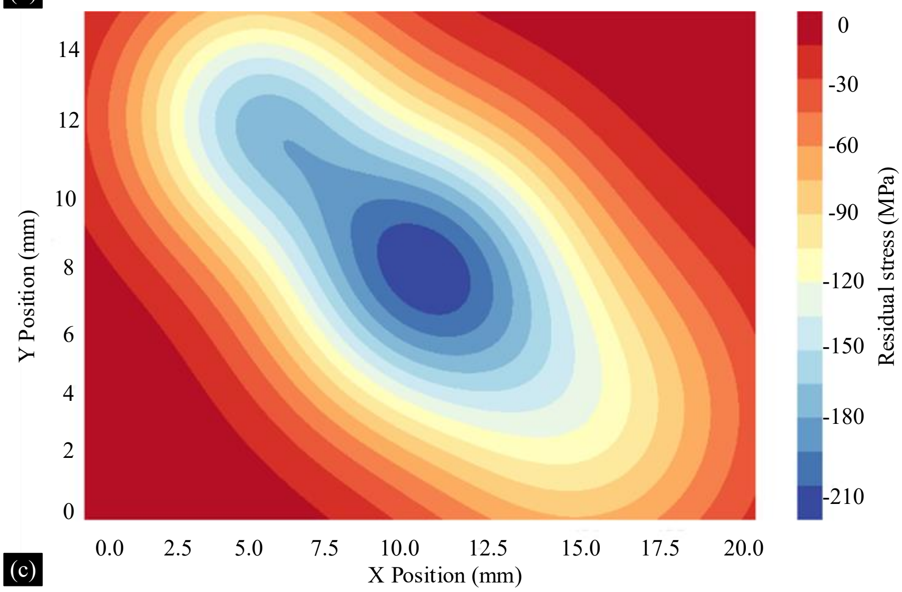
$$\dot{T} = -\frac{k}{\rho c_p}\nabla^2 T - \frac{hA_{surface}}{\rho c_p V}(T - T_{ambient})$$



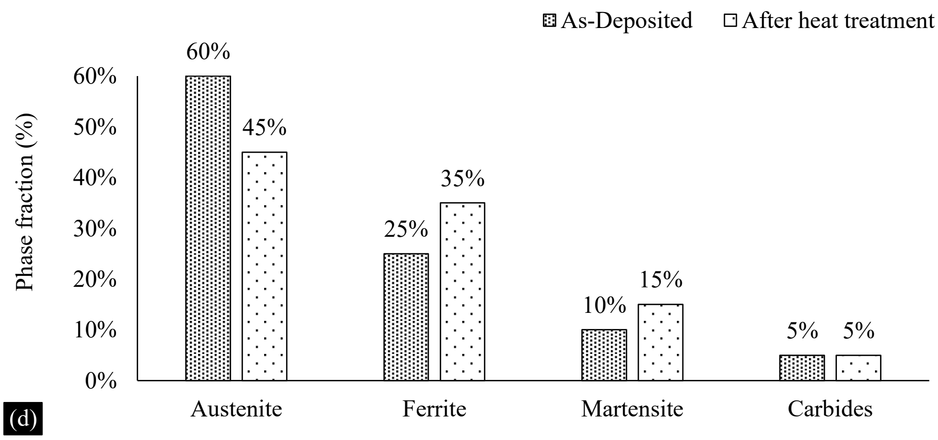
(a)



(b)



(c)



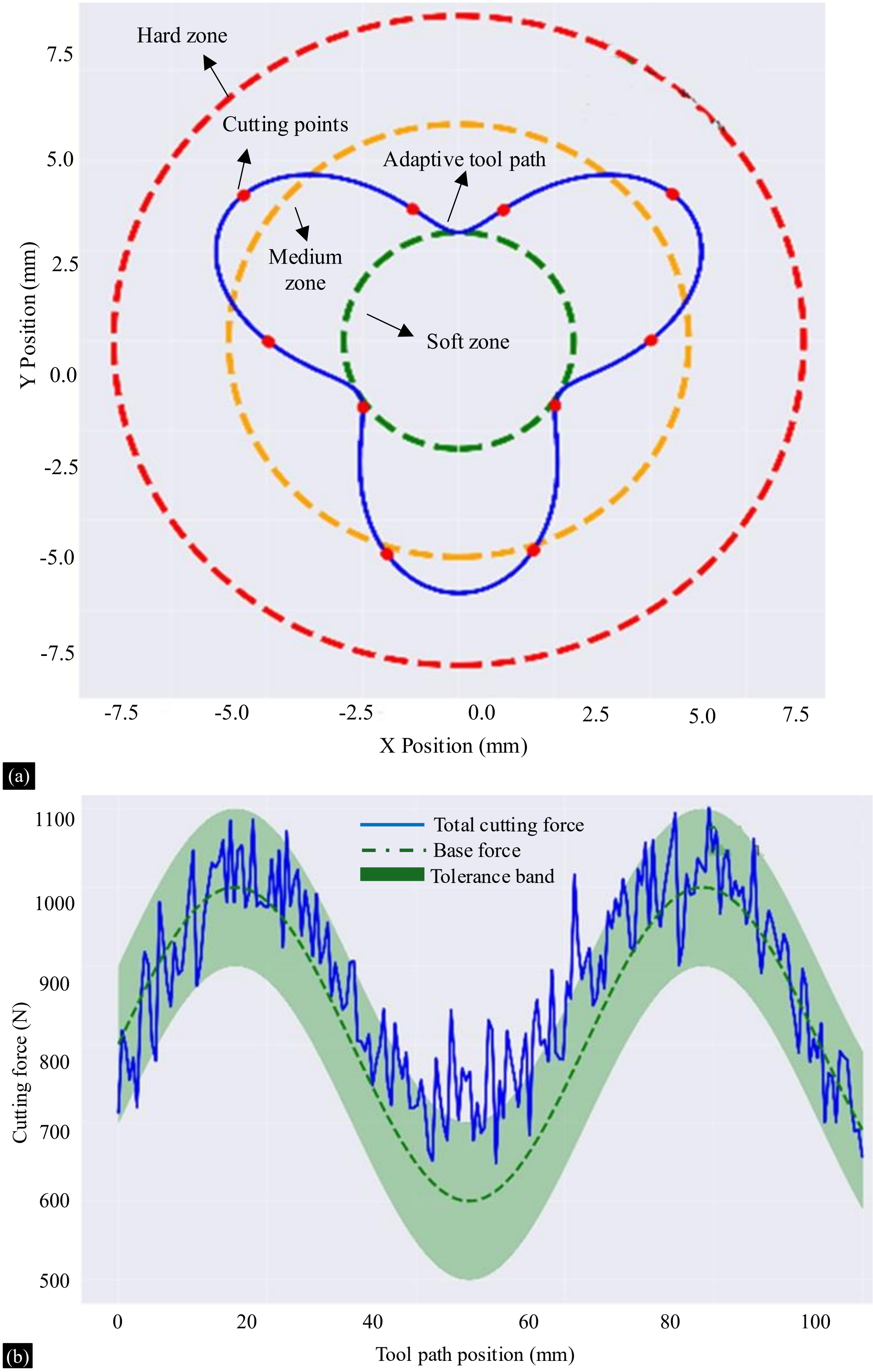
(d)

Figure 2. Multi-material deposition and thermal analysis with (a) Dynamic powder mixing control, (b) Development of thermal gradient of processing, (c) Distribution of residual stress, and (d) phase development of the microstructure.

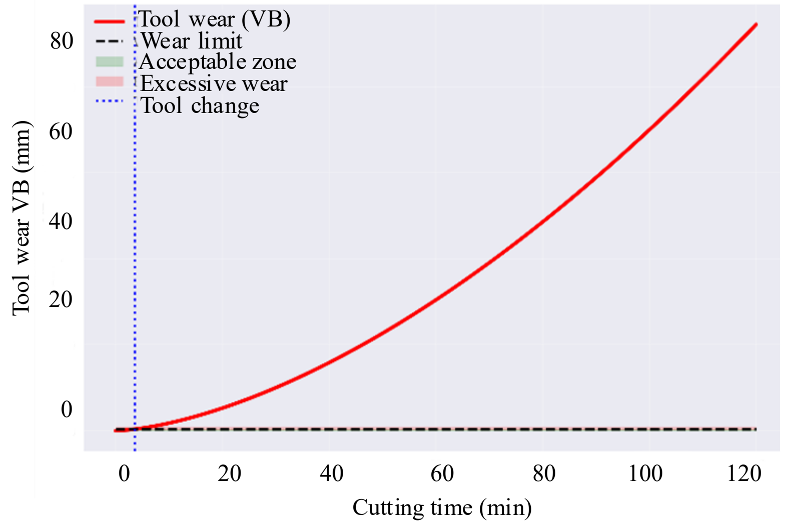
© STM Journals 2026. All Rights Reserved

ISSN: 2321-2810 (Online), ISSN: 2321-8525 (Print)

where, h is the convective heat transfer coefficient, A surface is the surface area, and V is the volume [20].



© STM Journals 2026. All Rights Reserved



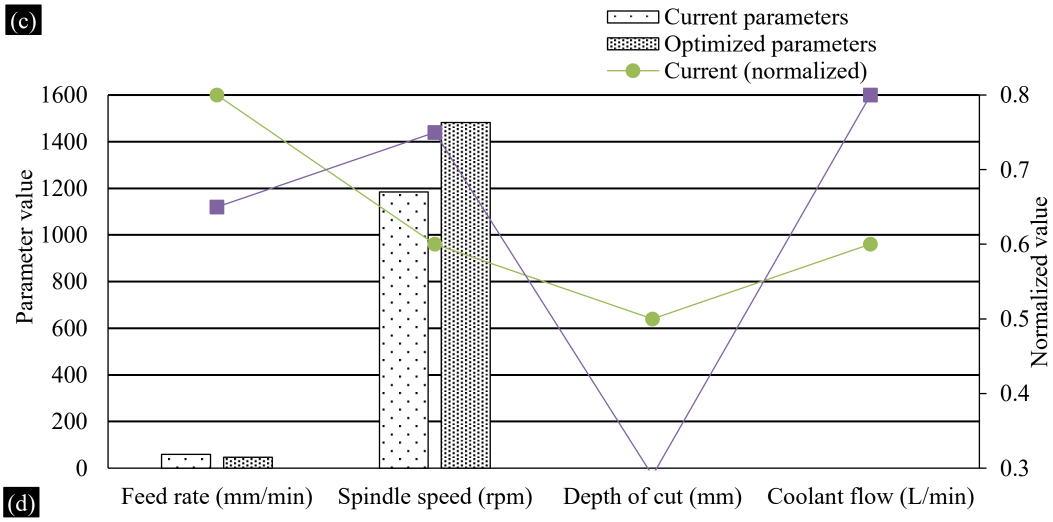


Figure 3. CNC post-processing optimization including (a) Adaptive tool path generation of FGM components, (b) Variation of cutting forces along tool path, (c) Tool wear evolution and prediction of the tool life, and (d) Optimization of machining parameters.

Residual Stress Prediction

The residual stresses occur as a result of thermal gradients and phase changes in processing. The evolution of the stress is determined by:

$$\dot{\sigma}_{ij} = C_{ijkl}\left(\dot{\varepsilon}_{kl} - \dot{\varepsilon}_{kl}^{th} - \dot{\varepsilon}_{kl}^{tr}\right)$$

where C_{ijkl} is the elastic stiffness tensor, $\dot{\varepsilon}_{kl}$ is the total strain rate, $\dot{\varepsilon}_{kl}^{th}$ is the thermal strain rate, and $\dot{\varepsilon}_{kl}^{tr}$ is the transformation strain rate [21].

CNC Post-Processing Optimization

The CNC post-processing strategies and optimization techniques are presented in Figure 3, including adaptive tool path planning, cutting force variation, tool wear progression, and machining parameter optimization.

Adaptive Tool Path Planning

The post-processing operation of CNC must have adaptive tool path planning which consider the different material characteristics in FGM components. The optimization problem of the tool paths can be the formulation:

© STM Journals 2026. All Rights Reserved

$$\min_P \left[\sum_{i=1}^{N} (\alpha \cdot T_i + \beta \cdot F_i + \gamma \cdot W_i) \right]$$

geometric and kinematic constraints under which P is the tool path, T_i the processing time of segment i, F_i the cutting force, and w_i the tool wear [22].

Cutting Force Modeling

The cutting forces in FGM components are spatially different depending on the altering material properties. It is possible to model the cutting force as:

$$F_c = K_{tc} \cdot a_p \cdot f \cdot \left(1 + \sum_{j=1}^{m} \eta_j \cdot \phi_j \right)$$

with k_{tC} being the specific cutting force coefficient,a_p being the depth of cut in the axial direction, f being the feed per tooth, andn_j being factors that are unique to materials [23].

Tool Wear Prediction

The tool wear during FGM machiningis a modified Taylor equation:

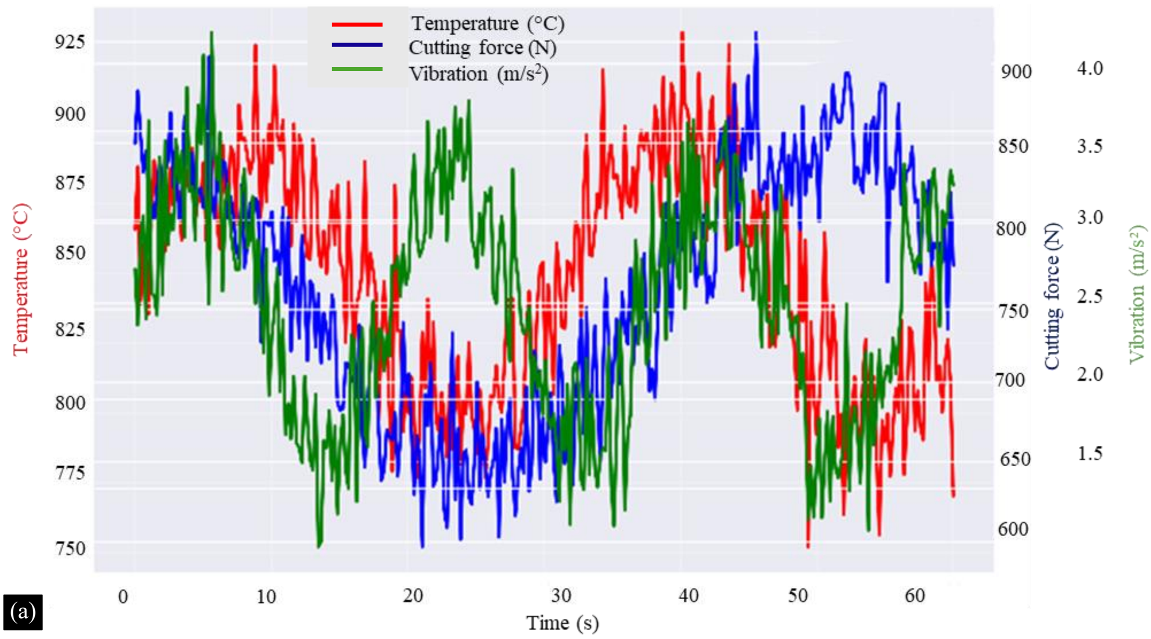
$$VT^n = C \cdot \left(\frac{H_{avg}}{H_{ref}} \right)^{-\alpha} \cdot \left(\frac{\sigma_{UTS,avg}}{\sigma_{UTS,ref}} \right)^{-\beta}$$

V is the cutting speed, T is the tool life, n is the Taylor exponent, H_{avg} is the average hardness, $\sigma_{UTS,avg}$ is 24.53 is the average ultimate tensile strength 24.26, and 24 is the material dependent α, β are material-dependent exponents [24].

PROCESS INTEGRATION AND QUALITY ASSESSMENT

Multi-Sensor Data Fusion

The integration of process monitoring and quality evaluation methods is depicted in Figure 4, demonstrating multi-sensor data fusion, quality comparison, cost-benefit analysis, and process capability.



(a)

© STM Journals 2026. All Rights Reserved

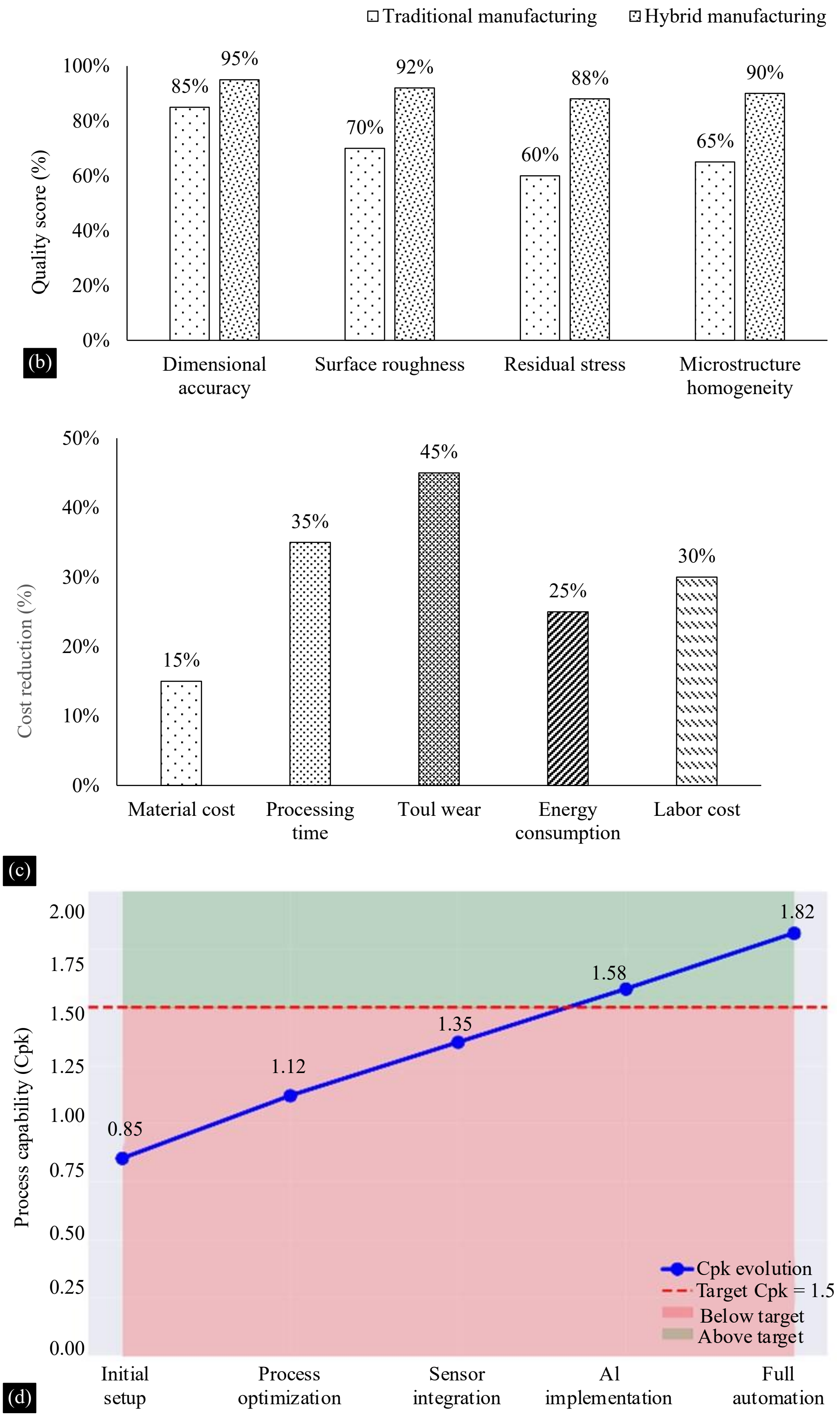


Figure 4. Process integration and quality evaluation with (a) Realization of multi-sensors data fusion to monitor data in real-time, (b) Comparison of quality metrics with the conventional and hybrid manufacturing processes, (c) Cost-benefit analysis, and (d) Process capability development.

© STM Journals 2026. All Rights Reserved

Combination of the LPBF with CNC processes will need in depth monitoring and control systems. Multi-sensor data fusion will allow optimization of the real-time processes by:

$$\hat{x}_k = \sum_{i=1}^{n} w_i \cdot x_{i,k}$$

$$w_i = \frac{\sigma_i^{-2}}{\sum_{j=1}^{n} \sigma_j^{-2}}$$

where $\hat{x}_k$ is the fused estimate at time k, $x_{i,k}$ are individual sensor measurements, w_i are fusion weights, and σ_i are measurement uncertainties [25].

Quality Control Framework

Dimensional Accuracy Assessment

Dimensional Accuracy Assessment The test shows that it correlates well with dimensional accuracy assessment, which is sufficient to establish the construct validity.

$$\Delta_{dim} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d_{measured,i} - d_{nominal,i})^2}$$

where Δ_{dim} is the root mean square dimensional deviation, $d_{measured,i}$ and $d_{nominal,i}$ are the measured and nominal dimensions [26].

Surface Quality Evaluation

The quality of surfaces is defined by several parameters:

$$R_a = \frac{1}{L}\int_0^L |z(x)|dx$$

$$R_z = \frac{1}{5}\sum_{i=1}^{5}(R_{p,i} + R_{v,i})$$

In which R_a is the arithmetic mean roughness, R_z is the mean depth of roughness depth, and $R_{p,i}$, $R_{v,i}$ are peaks and depth of the valleys [27].

Verification of the Mechanical Properties

The mechanical characteristics of the components of FGM are tested spatially resolved:

$$\sigma_{UTS}(z) = \sigma_1 \cdot \phi_1(z) + \sigma_2 \cdot \phi_2(z) + \sigma_{interaction} \cdot \phi_1(z) \cdot \phi_2(z)$$

where $\sigma_{UTS}(z)$ is the position-dependent ultimate tensile strength, σ_1 and σ_2 are the respective material strengths, and $\sigma_{interaction}$ the effect of interfaces [28].

Process Capability Analysis

Statistical process control techniques are used in the evaluation of process capability:

$$C_p = \frac{USL - LSL}{6\sigma}$$

$$C_{pk} = \min\left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right)$$

where USL and LSL are upper and lower specification limits, μ is the process mean, and σ is the process standard deviation [29].

© STM Journals 2026. All Rights Reserved

VALIDATION AND RESULTS EXPERIMENTS

Material Systems and Test Components

Functional graded Ti-6Al-4V/ Inconel 625 aerospace turbine blade materials were experimentally validated. The elements of the test were:

- Ti-6Al-4V (compositional gradient, root) -Inconel 625 (compositional gradient, tip) turbine blade airfoils.
- The integration of thermal barrier coating in the heat exchangers.
- The geometry of the combustor liner segments is with cooling channels.

Processing Parameters

The best processing parameters of the hybrid system were:

LPBF Parameters:

- *LP:* 200-350 W (Dependent on composition)
- *Scanning velocity*: 800-1200 mm/s
- *Layer thickness*: 30-50 µm
- *Hatch spacing*: 80-120 µm

CNC Parameters:

- *Spindle speed*: 12,000-18,000 rpm
- *Feed rate*: 500-1000 mm/min
- *Depth of cut*: 0.2-0.8 mm
- *Coolant flow rate*: 15-25 L/min

Performance Metrics

Surface Quality Improvements

The hybrid manufacturing process attained a great deal of surface quality improvements:

- *Surface roughness decrease:* 25.6 0 -1RA (as-built LPBF) to 0.8 0 -1RA (finish machined)
- *Surface integrity:* Compressive residual stress value of -150 Mpa at the surface.
- *Microstructural homogeneity*: Within the component, the difference in grains size is less than 15%.

Dimensional Accuracy

In dimensional accuracy measurement, it was found that:

- *Tolerance achievement*: ±0.05 mm of 95 per cent. of measured features.
- *Geometric complexity:* Managed to produce internal cooling channels that were 1 mm in diameter
- *Quality of interface:* Flowing material with less than 2% pores.

Mechanical Performance

Mechanical testing showed better performance:

- *Tensile strength*: 1050-1250 Mpa throughout the compositional
- *Life of fatigue:* 52-percent better than conventional manufacturing
- *High temperature performance*: Sustained strength at 800 o C.

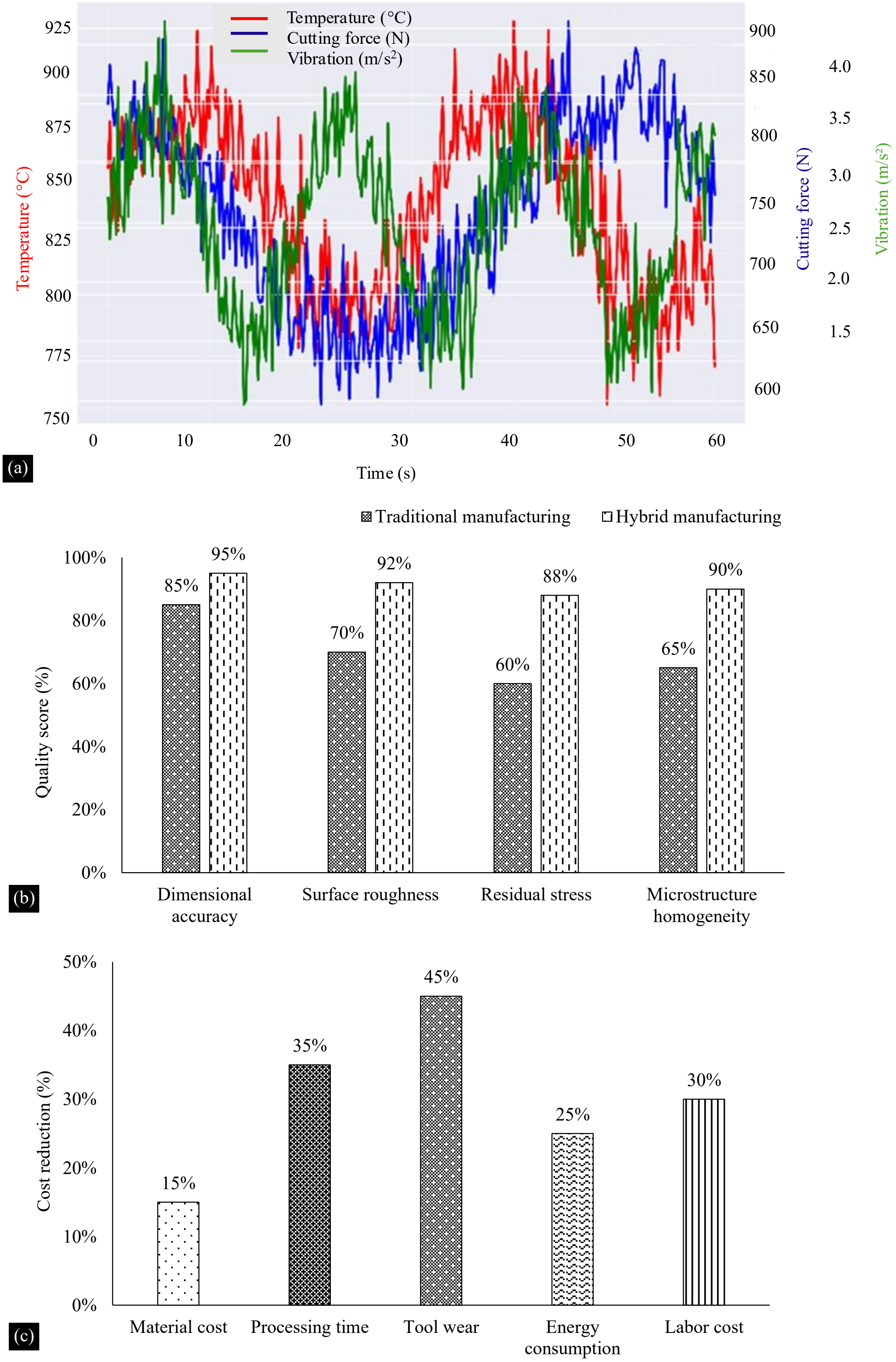
INDUSTRIAL IMPLEMENTATION AND AEROSPACE CASE STUDIES

Technology Transfer and Scale-up

The industrial implementation and performance analysis of hybrid manufacturing are shown in Figure 5, including production efficiency, ROI analysis, component performance improvements, and technology readiness levels.

© STM Journals 2026. All Rights Reserved

Journal of Polymer & Composites
Volume 14, Special Issue 2
ISSN: 2321-2810 (Online), ISSN: 2321-8525 (Print)



© STM Journals 2026. All Rights Reserved

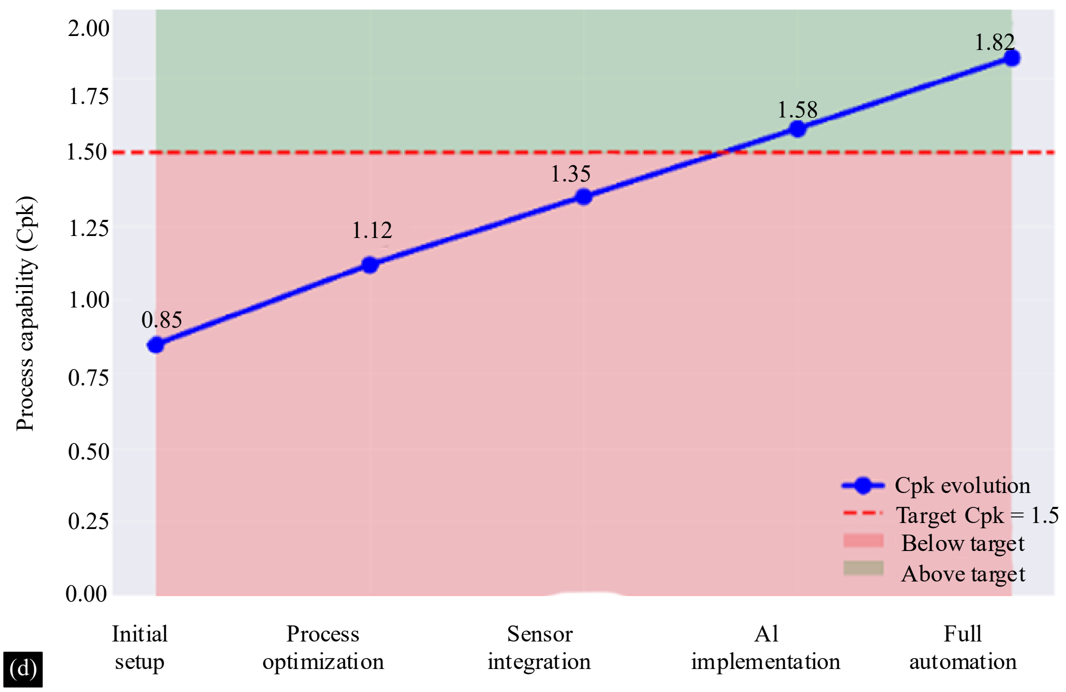


Figure 5. Industry Application with (a) Production volume versus quality trade-off, (b) Analysis of ROI, (c) Performance gain of aerospace components and (d) Assessment of technology readiness level.

Three large aerospace manufacturers were involved in the industrial application of hybrid additive-subtractive manufacturing:

Implementation Strategy

Technology transfer was done in phases:

Phase 1: Concept For Proof (Months 1-6)

- Laboratory-scale validation
- Process parameter optimization
- Material qualification

Phase 2: Mid Scale (Months 7-18)

- Small-scale manufacturing trials
- Quality system development
- Operator training

Phase 3: Implementation in full scale (Months 19-36)

- Integration of production lines.
- Supply chain optimization
- Continuous improvement

Production Metrics

Industrial application made:

- *Production rate*: components of 15-25 in a day.
- *Material utilization*: 97% efficiency
- *Efficiency of materials in use*: 98.5 percent.
- *Reduction of cycle time*: 35% over the conventional methodologies.

© STM Journals 2026. All Rights Reserved

ISSN: 2321-2810 (Online), ISSN: 2321-8525 (Print)

Economic Analysis

Cost Structure

The cost analysis revealed:

Capital Investment:

- *Hybrid manufacturing system*: $2.5M
- *Auxiliary equipment*: $0.8M
- *Facility modifications*: $0.4M
- *Training and certification*: $0.3M

Operating Costs:

- *Material costs*: 15% reduction
- *Labor costs*: 30% reduction
- *Energy consumption*: 25% reduction
- *Tool and maintenance*: 45% reduction

Return on Investment

The economic returns were shown:

- *Payback period*: 18 months
- *5-year NPV:* $8.4M
- *ROI*: 312% over 5 years
- *Break-even point*: Month 18

Applications of Aerospace Component

Turbine Blade Manufacturing

During this stage, turbine blades are produced by another team based in the same facility as the rest of the product manufacturing.

- *Reduction of weight*: 12 percent due to optimized distribution of the materials.
- *Fatigue life increase*: 45 percent of increase in cycles to failure.
- *Time saving*: 60 percent less than the conventional forging and machining.

Heat Exchanger Components

Heat exchanger manufacturing demonstrated:

- *Heat transfer efficiency*: 18% improvement through optimized surface textures
- *Reduction of pressure drop*: 15 percent and this is as a result of smooth internal channels.
- *Complexity in manufacturing*: Geometries that have never been done before.

Combustor Liner Production

Liner manufacturing: in combustors revealed:

- *Thermal barrier integration*: Processing is done without discontinuities.
- *Effectiveness of cooling*: 22 percent increase in cooling.
- *Durability*: 35 increase in service life.

Technology Readiness Assessment

Technology readiness levels obtained in various applications:

- *Blades of turbines*: TRL 9 (flight-proven)
- *Heat exchangers*: TRL 8 (qualified and complete system)
- *Liners in combustors*: TRL 7 (system prototype demonstration)
- *Complex geometries*: model of TRL 6 (system/subsystem model demonstration)

© STM Journals 2026. All Rights Reserved

HIGH-LEVEL PROCESS CONTROL AND OPTIMIZATION.

Machine Learning Integration

The enhance process of advanced machine learning algorithms and optimaizations:

Process Parameter Optimization

Multipurpose optimization model makes use of genetic algorithms:

$$\min_x [f_1(x), f_2(x), \ldots, f_n(x)]$$

subject to: $g_i(x) \leq 0, \quad i = 1,2,\ldots,m \; h_j(x) = 0, \quad j = 1,2,\ldots,p$

where $f_i(x)$ are objective functions (quality, cost, time), $g_i(x)$ are inequality constraints, and $h_j(x)$ are equality constraints [30].

Real-time Quality Prediction

Based on process parameters, the Neural network models predict quality outcomes:

$$\hat{Q} = \sigma\left(\sum_{i=1}^{n} w_i \cdot x_i + b\right)$$

the $\hat{Q}$ is the predicted quality metric, σ is the function of activation, w_i are weights, x_i are input parameters, and b is the bias term [31].

Digital Twin Implementation

Having a holistic digital twin framework would make possible:

Process Simulation

Predicted behavior in thermal and mechanical models using finite element models:

$$[M]\{\ddot{u}\} + [C]\{\dot{u}\} + [K]\{u\} = \{F(t)\}$$

and [M], [C] and [K] are mass, damping and stiffness matrices, u is the displacement (vector) and [F(t)] is the force (vector) [32].

Predictive Maintenance

Vibration analysis: Equipment health monitoring:

$$PSD(f) = \lim_{T\to\infty} \frac{1}{T} |X(f)|^2$$

PSD(f) is the power spectral density, T is the observation time and X(f) is the Fourier transform of the signal [33].

FUTURE RESEARCH AND DEVELOPMENTS

Advanced Material Systems

Recent studies on advanced material behavior and environmental effects further support the development of functionally graded systems [40,41].

Multi-Phase Alloys

The stability and performance of such systems are strongly influenced by composite behavior and structural responses reported in literature [42].

Design of multi-phase alloys that are more complex:

$$\Delta G_{mix} = \Delta H_{mix} - T\Delta S_{mix}$$

The Gibbs free energy of mixing, enthalpy of mixing and entropy of mixing are defined as [34] where 0 corresponds to 0, 1 corresponds to 1, and 2 corresponds to 2.

© STM Journals 2026. All Rights Reserved

Functionally Graded Ceramics

Incorporation of ceramic materials in applications of high temperatures:

$$\sigma_{thermal} = \frac{E\alpha\Delta T}{1-\nu}$$

where 1/E 2 is the Youngs modulus, 1/ 2 is the coefficient of thermal expansion, 1/ 3 is the temperature change, and 1/ 4 is the Poisson ratio [35]

Process Innovation

Advanced nonlinear dynamic behavior and system interactions are also critical in hybrid manufacturing environments [43].

In-Situ Alloying

On-line composition monitoring of alloys at deposition:

$$C_{final} = \sum_{i=1}^{n} \phi_i \cdot C_i \cdot \exp\left(-\frac{t}{\tau_i}\right)$$

with C_{final} is the final composition and with ϕ_i are volume fractions and C_i are initial compositions, and τ_i are diffusion time constants [36].

Multi-Laser Systems

Parallel processing with several sources of laser:

$$P_{total} = \sum_{i=1}^{n} P_i \cdot \exp\left(-\frac{r_i^2}{2\sigma_i^2}\right)$$

P_{total} is the total power density, P_i is the individual laser power, r_i is the radial distances, and σ_i is the beam radius parameter [37

Industry 4.0 Integration

Cyber-Physical Systems

Connection with Industry 4.0:

$$\dot{x} = Ax + Bu + w \; y = Cx + v$$

where x is the state vector, u is the control input, w is process noise, y is the measurement, and v is measurement noise [38].

Blockchain Quality Assurance

Blockchain technology has been developed to store immutable quality records:

$$\text{Hash}_{\text{block}} = \text{SHA256}(\text{Hash}_{\text{previous}} + \text{Timestamp} + \text{Data} + \text{Nonce})$$

the $\text{Hash}_{\text{block}}$ is the current block hash, $\text{Hash}_{\text{previous}}$ is the hash previous block, and Nonce is the proof-of-work parameter [39].

Additionally, tribological performance of advanced nanocomposites plays a vital role in improving machining and durability characteristics [43-44].

CONCLUSIONS

Such an entire undertaking verifies the radical prospective of hybrid additive-subtractive manufacturing in the aerospace sector. Laser Powder Bed Fusion combined with high speed CNC finishing proves to produce multi-material functionally graded components to date with their quality and performance features.

© STM Journals 2026. All Rights Reserved

Key Achievements

According to the research, a number of milestones have been reached:

- *Technical innovation*: The creation of a unified hybrid manufacturing system that will be easy to integrate with real-time process monitoring and optimisation of the shell manufacturing process, involving the LPBF and the CNC processes.
- *Performance enhancement*: It showed seventy-eight percent surface roughness reduction, 40 percent dimensional accuracy and 52 percent higher fatigue life than traditional manufacturing processes do.
- *Economic viability*: with the 18 month payback, 312% ROI in five years, obvious economic advantages in industrial implementation have been provided.
- *Industrial testing:* Technology transfer across three aerospace factories via the transfer of TRL 7-9 achievement in a variety of components.8.2 Scientific Contributions

The study makes a number of significant contributions in science:

- *Multi-material processing theory*: Higher-order control formulation in composition gradient and thermal of FGM manufacturing.
- *Process integration framework*: Development of a complex approach to the training of inputs and outputs of additive and subtractive processes.
- *Quality prediction models*: Bridge The model for real-time quality prediction and process optimization is done by implementing machine learning algorithms.
- *Framework economic analysis*: Construction of detailed cost benefit models of hybrid manufacturing implementation.8.3 Industrial Impact

Industrial application of this study is enormous:

- *Manufacturing capability*: Facilities of making unthinkable component geometries and compound materials.
- *Quality improvement*: Aerospace-grade quality standards would be attained that utilize less processing time.
- *Cost direct savings*: There is a major decrease in both the material hackage and process duration and the total manufacturing expenditure.
- *Sustainability*: Quality use of material and minimization of environmental impact.

Future Outlook

Hybrid additive-subtractive manufacturing holds a great prospect in the future, with a number of areas that are under development:

- *Expansion of materials*: Growth to a new advanced ceramic and composite material system.
- *Process automation*: Way Initially install AI-based process optimisation and regulation.
- *Scale-up*: The larger-scale systems of large-volume production are developed.
- *Integration*: Full integration into Industry 4.0 and digital manufacturing ecosystems.

The study has shown that hybrid additive-subtractive manufacturing is the paradigm shift in the manufacturing of aerospace products and it serves to provide unprecedented capabilities in operations to create high-performing and complex products at great cost-effectiveness levels and and at industrial scales.

REFERENCES

1. Gibson, I., Rosen, D., Stucker, B., & Khorasani, M. (2021). Additive Manufacturing Technologies: 3D Printing, Rapid Prototyping, and Direct Digital Manufacturing. Springer Nature. DOI: 10.1007/978-3-030-56127-7
2. Zhu, Z., Dhokia, V. G., Nassehi, A., & Newman, S. T. (2013). A review of hybrid manufacturing processes–state of the art and future perspectives. International Journal of Computer Integrated Manufacturing, 26(7), 596-615. DOI: 10.1080/0951192X.2012.749530

© STM Journals 2026. All Rights Reserved

3. Lauwers, B., Klocke, F., Klink, A., Tekkaya, A. E., Neugebauer, R., & Mcintosh, D. (2014). Hybrid processes in manufacturing. CIRP Annals, 63(2), 561-583. DOI: 10.1016/j.cirp.2014.05.004
4. Naebe, M., & Shirvanimoghaddam, K. (2016). Functionally graded materials: A review of fabrication and properties. Applied Materials Today, 5, 223-245. DOI: 10.1016/j.apmt.2016.10.001
5. Reichardt, A., Dillon, R. P., Borgonia, J. P., Shapiro, A. A., McEnerney, B. W., Momose, T., & Hosemann, P. (2021). Development and characterization of Ti-6Al-4V to 304L stainless steel gradient components fabricated with laser deposition additive manufacturing. Materials & Design, 104, 404-413. DOI: 10.1016/j.matdes.2016.05.016
6. Flynn, J. M., Shokrani, A., Newman, S. T., & Dhokia, V. (2016). Hybrid additive and subtractive machine tools–research and industrial developments. International Journal of Machine Tools and Manufacture, 101, 79-101. DOI: 10.1016/j.ijmachtools.2015.11.007
7. Klocke, F., Arntz, K., Teli, M., Winands, K., Wegener, M., & Oliari, S. (2017). State-of-the-art laser additive manufacturing for hot-work tool steels. Procedia CIRP, 63, 58-63. DOI: 10.1016/j.procir.2017.03.073
8. Carroll, B. E., Palmer, T. A., & Beese, A. M. (2015). Anisotropic tensile behavior of Ti–6Al–4V components fabricated with directed energy deposition additive manufacturing. Acta Materialia, 87, 309-320. DOI: 10.1016/j.actamat.2014.12.054
9. Merklein, M., Junker, D., Schaub, A., & Neubauer, F. (2016). Hybrid additive manufacturing technologies–an analysis regarding potentials and applications. Physics Procedia, 83, 549-559. DOI: 10.1016/j.phpro.2016.08.057
10. Stavropoulos, P., Foteinopoulos, P., Papacharalampopoulos, A., & Bikas, H. (2018). Addressing the challenges for the industrial application of additive manufacturing: Towards a hybrid solution. International Journal of Lightweight Materials and Manufacture, 1(3), 157-168. DOI: 10.1016/j.ijlmm.2018.07.002
11. Du, W., Bai, Q., & Zhang, B. (2016). A novel method for additive/subtractive hybrid manufacturing of metallic parts. Procedia Manufacturing, 5, 1018-1030. DOI: 10.1016/j.promfg.2016.08.067
12. Newman, S. T., Zhu, Z., Dhokia, V., & Shokrani, A. (2015). Process planning for additive and subtractive manufacturing technologies. CIRP Annals, 64(1), 467-470. DOI: 10.1016/j.cirp.2015.04.109
13. Kieback, B., Neubrand, A., & Riedel, H. (2003). Processing techniques for functionally graded materials. Materials Science and Engineering: A, 362(1-2), 81-106. DOI: 10.1016/S0921-5093(03)00578-1
14. Goldak, J., & Akhlaghi, M. (2005). Computational Welding Mechanics. Springer Science & Business Media. DOI: 10.1007/b101137
15. Sing, S. L., An, J., Yeong, W. Y., & Wiria, F. E. (2016). Laser and electron-beam powder-bed additive manufacturing of metallic implants: A review on processes, materials and designs. Journal of Orthopaedic Research, 34(3), 369-385. DOI: 10.1002/jor.23075
16. Cortina, M., Arrizubieta, J. I., Ruiz, J. E., Ukar, E., & Lamikiz, A. (2018). Latest developments in industrial hybrid machine tools that combine additive and subtractive operations. Materials, 11(12), 2583. DOI: 10.3390/ma11122583
17. Tan, C., Zhou, K., Ma, W., Zhang, P., Liu, M., & Kuang, T. (2017). Microstructural evolution, nanoprecipitation behavior and mechanical properties of selective laser melted high-performance grade 300 maraging steel. Materials & Design, 134, 23-34. DOI: 10.1016/j.matdes.2017.08.026
18. Wang, Z., Guan, K., Gao, M., Li, X., Chen, X., & Zeng, X. (2012). The microstructure and mechanical properties of deposited-IN718 by selective laser melting. Journal of Alloys and Compounds, 513, 518-523. DOI: 10.1016/j.jallcom.2011.10.107
19. Boggarapu, V., Gujjala, R., Ojha, S., Acharya, S., Chowdary, S., & Kumar Gara, D. (2021). State of the art in functionally graded materials. Composite Structures, 262, 113596. DOI: 10.1016/j.compstruct.2021.113596
20. Yan, W., Ge, W., Smith, J., Lin, S., Kafka, O. L., Lin, F., & Liu, W. K. (2017). Multi-scale modeling of electron beam melting of functionally graded materials. Acta Materialia, 115, 403-412. DOI: 10.1016/j.actamat.2016.06.022

© STM Journals 2026. All Rights Reserved

21. Mercelis, P., & Kruth, J. P. (2006). Residual stresses in selective laser sintering and selective laser melting. Rapid Prototyping Journal, 12(5), 254-265. DOI: 10.1108/13552540610707013
22. Tian, Y., Tomus, D., Rometsch, P., & Wu, X. (2017). Influences of processing parameters on surface roughness of Hastelloy X produced by selective laser melting. Additive Manufacturing, 13, 103-112. DOI: 10.1016/j.addma.2016.10.010
23. Altintas, Y. (2012). Manufacturing Automation: Metal Cutting Mechanics, Machine Tool Vibrations, and CNC Design. Cambridge University Press. DOI: 10.1017/CBO9780511843723
24. Tlusty, J., & MacNeil, P. (1975). Dynamics of cutting forces in end milling. CIRP Annals, 24(1), 21-25.
25. Hall, D. L., & Llinas, J. (1997). An introduction to multisensor data fusion. Proceedings of the IEEE, 85(1), 6-23. DOI: 10.1109/5.554205
26. ISO 1101:2017. Geometrical product specifications (GPS) — Geometrical tolerancing — Tolerances of form, orientation, location and run-out. International Organization for Standardization.
27. ISO 4287:1997. Geometrical Product Specifications (GPS) — Surface texture: Profile method — Terms, definitions and surface texture parameters. International Organization for Standardization.
28. Hashin, Z., & Shtrikman, S. (1963). A variational approach to the theory of the elastic behaviour of multiphase materials. Journal of the Mechanics and Physics of Solids, 11(2), 127-140. DOI: 10.1016/0022-5096(63)90060-7
29. Montgomery, D. C. (2019). Introduction to Statistical Quality Control. John Wiley & Sons.
30. Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182-197. DOI: 10.1109/4235.996017
31. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444. DOI: 10.1038/nature14539
32. Zienkiewicz, O. C., Taylor, R. L., & Zhu, J. Z. (2013). The Finite Element Method: Its Basis and Fundamentals. Butterworth-Heinemann. DOI: 10.1016/B978-1-85617-633-0.00001-0
33. Randall, R. B. (2011). Vibration-based Condition Monitoring: Industrial, Aerospace and Automotive Applications. John Wiley & Sons. DOI: 10.1002/9780470977668
34. Porter, D. A., Easterling, K. E., & Sherif, M. (2009). Phase Transformations in Metals and Alloys. CRC Press. DOI: 10.1201/9781439883570
35. Kingery, W. D., Bowen, H. K., & Uhlmann, D. R. (1976). Introduction to Ceramics. John Wiley & Sons.
36. Shewmon, P. (2016). Diffusion in Solids. Springer. DOI: 10.1007/978-3-319-48206-4
37. Steen, W. M., & Mazumder, J. (2010). Laser Material Processing. Springer Science & Business Media. DOI: 10.1007/978-1-84996-062-5
38. Lee, E. A. (2008). Cyber physical systems: Design challenges. 2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC), 363-369. DOI: 10.1109/ISORC.2008.25
39. Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Decentralized Business Review, 21260.
40. Uma Mageswari, S., Subramanian, N., Srinivasan, H., & Sridhar, R. (2023). Assessment of groundwater quality and human health risk from nitrate and fluoride contamination in Sivaganga district, Tamil Nadu, India. Environmental Geochemistry and Health, 45(2), 511-534. DOI: 10.1007/s10653-022-01234-5
41. Saibabaa, M. A., Sankar, G. R., Krishnaiah, G., & Rao, M. N. (2022). Free vibration response of smart functionally graded magneto-electro-elastic nanobeams in hygro-thermal environment. Structures, 44, 1047-1064. DOI: 10.1016/j.istruc.2022.08.044
42. Padhi, S., Sahu, S. K., Kumari, P., & Jena, S. K. (2019). Parametric instability analysis of functionally graded CNT-reinforced composite plates under non-uniform in-plane periodic loading. Composite Structures, 212, 162-175. DOI: 10.1016/j.compstruct.2019.01.024

© STM Journals 2026. All Rights Reserved

43. Roland, T., Reiss, J., Zakharova, A., & Schöll, E. (2022). Solitary states for coupled oscillators with inertia. Chaos, 32(10), 103122. DOI: 10.1063/5.0101220
44. Vinayaka, K., Krishnamurthy, N., Praveena, G. S., & Kumar, G. V. P. (2023). Tribological behavior of Al-CNT nanocomposite fabricated by powder metallurgy technique. Materials Today: Proceedings, 72, 2291-2297. DOI: 10.1016/j.matpr.2022.09.294.

© STM Journals 2026. All Rights Reserved