Journal of Computer Science and Information Technology
ISSN: 3080-3586
DOI: https://doi.org/10.61424/jcsit.v3i2.1015
Date Published Online: August 26, 2026
Journal Homepage: https://bluemarkpublishers.com/index.php/JCSIT

JCSIT
BLUEMARK PUBLISHERS

| RESEARCH ARTICLE

Integrated Machine Learning and Smart Infrastructure Frameworks for Advanced Additive and Hybrid Manufacturing Systems

Md Rehan Uddin[1] ✉ and Sumi Ghosh[2]
[1]Bachelor's in Computer Application, at Scholars Institute of Technology and Management, Jiribam, Manipur, India
[2]Department of Banking and Finance, West Guwahati Commerce College, Guwahati, Assam, India.
Corresponding Author: Md Rehan Uddin, **E-mail**: rehanlaskar028@gmail.com

| ABSTRACT
Machine learning, digital twins, cyber-physical systems, and smart infrastructure are changing the way additive and hybrid manufacturing goes from static, process-defined to adaptive, data-driven manufacturing. The reviewed integrated architectural approach is able to link manufacturing at the physical level with the sensing, data infrastructure, physics-based modelling, surrogate modelling, artificial intelligence, and closed-loop control levels. Digital threads enable ongoing data connectivity and traceability from design to production, inspection, and maintenance phases, and digital twins maintain a dynamic representation of changing conditions in the processes. In the manufacturing sector, Edge and cloud infrastructure make it possible to capture and process data in real time and manage and analyze it at scale in a variety of factory conditions. Surrogate and physics-informed models complement high-fidelity physics-based simulations for reducing computational demands and enabling rapid prediction and optimization. Layer-to-layer and within-layer control strategies further allow the adjustment of manufacturing parameters in an adaptive way using real-time process information. The framework also introduces the possibility of hybrid manufacturing processes: Additive deposition and subtractive machining, finishing, and inspection processes are linked through continuous digital data exchange. Key needs for safe industrial deployment are identified to include safety, cyber security, regulatory compliance, data governance, and model traceability. Overall, the integrated approach offers a way to more autonomous, responsive, traceable, and efficient manufacturing systems, and puts the emphasis on the remaining need for physics-based knowledge, transparent decision making, human supervision, and validated control architectures.

| KEYWORDS

Machine learning; Digital twins; Additive manufacturing; Hybrid manufacturing; Smart infrastructure.

| ARTICLE INFORMATION

ACCEPTED: July 12, 2026 **PUBLISHED:** August 26, 2026 **DOI:** https://doi.org/10.61424/jcsit.v3i2.1015

1. Introduction
Integrated machine learning and smart infrastructure frameworks are becoming a growing reality and are increasingly shaping additive and hybrid manufacturing by providing intelligent coordination of various machine and infrastructure data, advanced modelling, real-time monitoring, and adaptive decision-making [Hossain, 2024]. In modern manufacturing environments, there are many material, thermal, mechanical, and geometric processes that are tightly coupled, for which small deviations in the operating conditions can significantly affect the product quality and process stability. Conventional manufacturing processes, which are mostly based on the knowledge of the required process parameters and off-line inspection, are increasingly supplemented with data-driven and

physics based methods that enable continuous monitoring, prediction, optimization, and control [Duflou, 2016]. These developments take place in a context of additive and hybrid manufacturing. Additive manufacturing and hybrid manufacturing are methods that can be used to produce complex geometries using the layer-wise deposition of material, while hybrid manufacturing combines subtractive and additive methods to obtain better dimensional accuracy, surface quality, and manufacturing flexibility. In this context, intelligent infrastructure will be needed to link sensing systems, computational models, manufacturing equipment, and decision support mechanisms in a single framework [Karunakaran, 2010]. To resolve these issues, models from physics and models from machine learning are integrated. Fundamental phenomena like heat transfer, melt pool behavior, phase transformation, microstructure evolution, residual stress, and mechanical response can be described using physics-based models. These methods can be complemented by machine learning models that can capture complex nonlinear relationships among large experimental and simulation datasets. Physics-informed neural networks, surrogate models, and other hybrid models will then be able to use these to enhance the accuracy of the predictions and reduce the computational cost of frequent high-fidelity simulations [Saxena, 2018]. This combination enables quicker design exploration, process optimization, and uncertainty analysis alongside an improved prediction of manufacturing results. Digital twins, cyber physical systems, and the digital thread are the infrastructure that enable the fruition of these computational capacities with physical manufacturing environments. A digital twin can continuously model the state and behavior of a manufacturing process, which is possible by combining the data obtained from sensors, the results of a simulation, historical process data, and predictive models [Pragana, 2021]. Cyber physical systems are those that enable a dynamic response from manufacturing processes to changes in process conditions by establishing a communication link between machines, sensors, computation, and control. The digital thread continues this connectivity throughout the product lifecycle by linking the design information, process parameters, product properties, inspection data, and final product performance [Lauwers, 2014]. These technologies all serve to increase traceability, real-time visibility, and coordinated decision-making. In the field of additive manufacturing, intelligent workflows are increasingly linked to the thermodynamics of the melt pool, the development of the microstructure, the crystallographic behavior, and the mechanical performance. End-to-end computational pipelines like this enable systematic investigation of relationships between the manufacturing parameters and the properties of the produced parts [Sebbe, 2022]. These pipelines can be supplemented with machine learning for the purpose of creating efficient surrogate models, determining process variables that have a significant influence on the quality, forecasting the quality outcome, and suggesting process changes.

2. Foundational Concepts and Integrated Manufacturing Architecture

The following concepts are closely linked to the advanced machine learning (ML) and smart infrastructure frameworks for intelligent, adaptive, and data-driven manufacturing. Digital twins, Cyber Physical Systems (CPS), Intelligent Manufacturing, Advanced sensing, Data Analytics, Surrogate modelling, and Closed loop control are all key components to real-time monitoring, prediction, decision making, and continuous process improvement (Table 1) [Krimpenis, 2023]. These ideas allow manufacturing systems to shift from fixed and programmed operation to responsive production systems where process conditions can be continually monitored, evaluated, and modified. Digital twins are virtual representations of physical assets, processes, and manufacturing systems that are continuously synced with their real-world counterparts by exchanging data [Merklein, 2016]. They represent the physics of process, materials, equipment states, and operating conditions throughout the product's life cycle in a digital form. A digital twin can be used for process prediction, anomaly detection, optimization, and closed-loop control through real-time monitoring, simulation, analytics, and decision-making [Hossain, 2026]. They can help enhance reliability, minimize downtime, facilitate predictive maintenance, and streamline production processes. The digital thread complements the digital twin by offering traceability and connectivity of information throughout the entire product lifecycle. It connects to the design, prototyping, production, inspection, and maintenance processes and the eventual product retirement, with information flowing from one phase to the next [Celik, 2025]. Cyber physical systems are the backbone for the communication and control that is needed to integrate digital technologies and physical manufacturing processes. CPS encompasses an integrated environment combining the togetherness of sensors, machines, and controllers, communication networks, operational technology, and enterprise information systems.

Table 1. Major components of the integrated machine learning and smart infrastructure framework

Framework component	Main technologies	Primary function in manufacturing	Expected contribution	References
Digital twin	Real-time process models, sensor data, simulation, predictive analytics	Represents and continuously monitors the physical manufacturing process	Anomaly detection, prediction, optimization, predictive maintenance, and adaptive control	[5], [9], [10], [19]
Cyber physical systems	Sensors, machines, controllers, communication networks, operational technology	Connects physical manufacturing equipment with computational and control systems	Real-time communication, monitoring, and coordinated decision making	[3], [8]
Digital thread	Product lifecycle data connectivity, traceability, design and production information	Links design, manufacturing, inspection, maintenance, and product performance data	Lifecycle traceability and continuous information exchange	[6], [11], [27], [30], [31]
Advanced sensing	Thermal cameras, optical sensors, acoustic sensors, force sensors, dimensional inspection	Captures real-time information about machine, material, and process conditions	Early detection of deviations, improved process understanding, and quality monitoring	[18], [19]
Physics-based modeling	Heat transfer, melt pool behavior, phase transformation, microstructure, and residual stress models	Describes the underlying physical behavior of manufacturing processes	Improved physical understanding and reliable process prediction	[4], [14], [15]

3. Modeling Layer

The Modeling layer provides the computational base to predict manufacturing behavior, optimize the manufacturing parameters, and support real-time decision making. Surrogate modeling is especially relevant since it offers quick estimates to high-fidelity, expensive models. Surrogate models can model complex numerical models in an efficient manner in terms of computation, allowing larger design spaces to be explored and allowing faster decision support [Chattopadhyay, 2024]. For advanced additive and hybrid manufacturing, surrogate models can be used in conjunction with physics based simulations, offering a speedy prediction tool that retains the key relationships between process parameters, material behavior, and manufacturing outcomes (Figure 1). Hierarchical surrogate modeling can be very useful to bridge the gap between high-fidelity physical testing and manufacturing control systems for multi-layer laser powder bed fusion. The high fidelity model is able to capture the detail of the process behavior, while the surrogate is able to make fast and interpretable predictions that can be used by within-layer controllers and layer-to-layer planning systems [Mahale, 2025]. The concept is that time-sensitive operational decisions can be made with a computationally lighter model, while the computationally heavier model can be used for detailed analysis. There is a high need for multilayer LPBF simulation with high-fidelity numerical frameworks, which can represent the coupled physical phenomena during material deposition [Praveena, 2022]. The final manufactured product can be affected by thermo-fluid dynamics, cooling of the melt pool, phase transitions, powder deposition, and cooling between successive layers. One practical way to represent the motion of molten material is to use a mesh-free method, like smoothed particle hydrodynamics [Jakimiuk, 2024]. A two-dimensional representation, along with some assumptions including volumetric heat input (Beer-Lambert law), laser velocity constant, incompressible molten flow, negligible gas phase and evaporation effects, and simplified spherical powder geometry, can be used in a control-oriented framework for SPH. Consequently, the manufacturing process can be stabilized between the successive layers and accommodate the short-term variability between the layers [Chénier, 2023]. The role of modeling is not limited to LPBF and can be applied to a wide variety of engineering applications.

Computational approximations of costly simulations or experiments are known as surrogate models, metamodels, emulators, or response surface models.

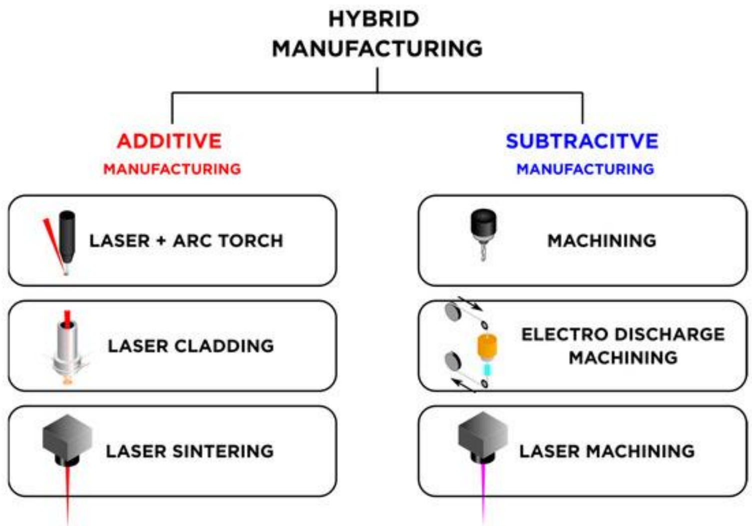

Figure 1. Schematic overview of hybrid manufacturing systems integrating additive processes [Liu, 2024]

4. Closed Loop Control and Runtime Orchestration Layer

The Closed Loop Control and Runtime Orchestration layer is the operational decision-making part of the manufacturing architecture. It's intended to link real-time sensing, the digital twin representation, predictive models, optimization algorithms, and machine control systems, enabling the adjustment of manufacturing parameters in real-time [Neumann, 2025]. Unlike fixed process programs, closed-loop systems constantly monitor the real process condition and decide how to correct the process based on the feedback. To attain this, in situ monitoring of the condition of machines, tools, materials, and workpieces is required. Residual stress mitigation and distortion control in laser powder bed fusion components for high reliability engineering applications require continuous in situ monitoring, where thermal cameras, optical sensors, acoustic sensors, force measurements, and dimensional inspection systems provide ongoing data on changing process conditions. Intelligent sensors can further perform signal acquisition, filtering, local analysis, adaptive sensitivity regulation, and communication with higher-level systems, enabling early identification of thermal and mechanical deviations that contribute to residual stress and distortion [Hossain, 2025]. Sensor fusion also integrates data from various types of sensors to improve confidence in machine sensing and decrease uncertainty in process understanding. An important coordination mechanism in this closed-loop environment is digital twins. The physical manufacturing system continually creates observations that are fed back to the digital manufacturing system. The digital twin can then be used to compare observed or predicted values with what was expected or desired, and give information to the control algorithms [Jayawardane, 2023]. If any deviation is observed, corrective actions can be computed and fed back into the physical system. This forms a loop of sensing, predicting, decision-making, and actuation. Digital twin-based systems can be applied in additive manufacturing for anomaly detection, process optimization, defect mitigation, quality assurance, and adaptive parameter control. The Closed Loop Control and Runtime Orchestration layer takes the information created by the lower layers of the architecture and converts it to physical manufacturing actions [Mechete, 2023]. Sensing is used to obtain information on the state of the process; digital twins and predictive models are used to estimate current and future process behavior; optimization algorithms process information to determine the correct response to the current process; control systems use information to change process parameters.

5. Smart Infrastructure Frameworks for Deployment

Smart infrastructure architectures for advanced manufacturing enable the architecture necessary to connect manufacturing equipment, data pipelines, analytical systems, digital twins, and AI for decision support across a distributed production setting. These are the frameworks that focus on location-independent and real-time data orchestration on premises, edge, and cloud [Jung, 2023]. This is an architecture that enables operational data collection and processing to be done near manufacturing equipment, as well as centralized analytics, long term storage, machine learning, and cross facility coordination. One of the key benefits of this is the ability to enable each organizational unit to access analytical data products based on its operational needs while maintaining a decentralized data architecture. Data can be analyzed and managed nearer to its origin without having to pass through a single repository, and made available via standard interfaces [Segovia-Guerrero, 2025]. This setup ensures greater flexibility and enables the use of data in the manufacturing, production, quality, maintenance, and management systems, depending on their specific needs. Smart infrastructure also facilitates the quick and easy conversion of streaming data. Machines, sensors, inspection systems, and enterprise platforms can provide continual information, which can be processed during production [Prasad, 2024]. The transformations, filtering, aggregation, anomaly detection, and rule-based alerts can then be applied to the flow of data. The synergy between edge and cloud computing results in a distributed design, where certain decisions can be taken at the edge of the network, while high-power computations would be carried out at a centralized location for long-term trend evaluation. This is especially appropriate for additive and hybrid production, where certain actions must be performed in milliseconds, while others are based on analysis of huge historical databases [Du, 2016].

6. Additive and Hybrid Manufacturing Workflows

Additive and hybrid manufacturing workflows involve the combination of coordinated material deposition, machine processing, finishing, inspection, and process optimization in the production process. Hybrid manufacturing is the integration of additive and subtractive processes to take advantage of their benefits (Figure 2) [Loyda, 2023]. Additive operation may be utilized to produce material quickly or to replace a damaged area, and then subtractive operation can be used to attain dimensional accuracy, surface quality, and necessary geometric tolerances. Further additive deposition can then be done if needed, and a manufacturing sequence is formed iteratively. The process planning step and the identification of the areas to be deposited, machined, or finished are crucial steps in a typical hybrid manufacturing process [Akhtaruzzaman, 2025]. The necessary order of operations is based on the geometry, material properties, tolerances, surface quality, and production goals of the components. CAD and CAM systems are used to create deposition and machining toolpaths. This can be additive deposition, alternating additive and subtractive operations, multiple operations, and/or inspection and/or finishing. The synergistic operation is impossible without digital integration. A digital thread allows for the linkage of design information, machine operation data, thermal histories, toolpath information, inspection measurements, and outcomes of the process [Soe, 2024]. This helps in making decisions at the next stage of the manufacturing process based on what has been produced at the previous stage. For machine operation data, it can be correlated with spatial information from toolpaths and thermal information from the deposition process. The results of the inspection can then be linked to the location and process conditions to provide a complete report of the influence of the manufacturing conditions on a finished part [Zhu, 2013]. Important elements of this digital integration include open machine connectivity standards and CAD/CAM derived toolpath information. Information about the machine could be fed into a machine monitoring platform, and a toolpath trajectory could be used to give the spatial context that allows the process information to be correlated with a part of the component. Integrating thermal imaging, geometric inspection, machine state information, and toolpath coordinates with multi-material and functionally graded additive manufacturing enables a more comprehensive understanding of process behavior and supports the development of next-generation mechanical and thermal engineering components with tailored properties and improved manufacturing performance [Khan, 2026]. This integrated data can be used for process monitoring, model development, defect analysis, and adaptive control.

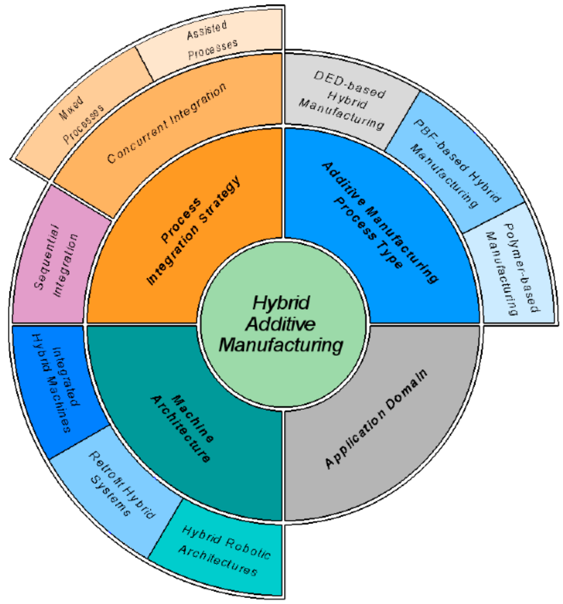

Figure 2. Recent Advances and Challenges in Hybrid Additive Manufacturing [Tosi, 2022]

7. Digital Thread and Data Continuity

A digital thread offers real-time connectivity and traceability of information across the product lifecycle, while a digital twin offers a dynamic digital model of a physical asset, process, or system to simulate, monitor, and analyse. The concepts are very interdependent, as the digital thread provides a continuous stream of information needed to keep a digital twin in sync with its physical twin [Flynn, 2026]. The integrated framework is not limited to specific product development or production aspects, but it allows linking information together from the design, production, inspection, maintenance, and product use parts and continuously updating them. The digital thread, in the context of additive and hybrid manufacturing, can be a far-reaching data fabric that links design models, material data, machine parameters, sensor data, process data, inspection data, and maintenance data. Process planning can be based on design specifications; production data can be used to assess the quality of production, inspection results can be linked to specific conditions of production, and maintenance information can be fed into future production decisions to enhance the quality of future production [Lalegani, 2022]. This lifecycle connectivity leads to traceable and adaptive manufacturing. One of the key challenges in digital threads is the need to capture and preserve the dynamic nature of complex manufacturing systems. Physical changes in the production process can be reflected in the digital representation as digital data is exchanged continuously. This way, the digital twin can capture changes in machine condition, material behaviour, thermal history, geometric development, and the quality of the product [Jiménez, 2021]. The digital thread is then the information infrastructure that allows modeling, simulation, monitoring, optimization and control to stay connected throughout the manufacturing lifecycle. For adaptive control, a well-managed digital thread is also crucial. In situ monitoring can provide high-resolution data on the process dynamics, such as thermal behaviour, melt pool characteristics, dimensional changes, tool condition, and surface quality. Such observations can be used to provide information for analytical and ML models and to be used to generate suitable control actions.

8. Safety, Regulatory Compliance, and Governance Framework

The application of integrated machine learning and smart infrastructure for advanced additive and hybrid manufacturing should cover safety, regulatory compliance, cybersecurity, and governance throughout the manufacturing process [Rabalo, 2025]. With the growing interconnection of manufacturing systems via sensors, digital twins, cloud platforms, ML models, and automated control systems, safeguarding and ensuring the integrity of both physical and digital assets is crucial. A manufacturing infrastructure that is trusted is built on the principles of confidentiality, data integrity, system availability, and the ability to resist unauthorized access or disruption. Special attention must be paid to safety and governance in the event that AI based systems automatically control the manufacturing parameters (Table 2) [Freitas, 2025]. The decisions resulting from the application of ML models could impact the laser power, deposition conditions, machining parameters, thermal behavior, material properties, and final quality of the components. This means that intelligent systems must be designed in a manner that the decisions made by the intelligent system are confined to certain operational and safety limits. The architecture needs to incorporate facilities and tools to validate, monitor, intervene as needed, and respond in the event of emergencies before any autonomous decisions can impact the physical equipment [Nau, 2011]. Manufacturing systems are increasingly becoming connected, and cybersecurity turns into a basic safety need. Digital twins, edge devices, cloud systems, industrial controllers, and enterprise systems establish a number of communication channels, which could be targeted without proper protection.

Table 2. Applications of intelligent additive and hybrid manufacturing

Application area	Intelligent approach	Potential benefits	Major challenges	References
Process monitoring	In situ sensing, sensor fusion, digital twins, ML	Continuous visibility of process conditions and early identification of abnormalities	Heterogeneous sensor data, noise, synchronization, and data quality	[18], [19], [43]
Process optimization	ML, surrogate models, physics based models	Faster exploration of process parameters and improved manufacturing performance	Computational cost, model accuracy, and limited generalizability	[12], [14], [36], [39]
Defect detection and mitigation	Digital twins, imaging, thermal monitoring, ML	Detection of defects during production and potential corrective action	Model reliability and validation under changing operating conditions	[10], [19], [20], [48]
Adaptive parameter control	Closed loop control, real time sensing, predictive models	Dynamic adjustment of manufacturing parameters and improved process stability	Safety constraints, latency, validation, and reliable control architectures	[17], [20], [34], [35]
Hybrid additive and subtractive manufacturing	Digital thread, CAD/CAM, toolpath data, inspection data	Coordination of deposition, machining, finishing, and inspection	Interoperability and integration of heterogeneous manufacturing systems	[25], [26], [27], [29]

9. Limitations and Open Problems

While knowledge guided surrogate modeling has great potential for advanced manufacturing, there are a number of limitations. The RBF based generative surrogate modeling requires the parameters of the RBF model, such as number of RBF centers, RBF scaling factors, and penalty weights, to be properly selected [Schuh, 2009]. Tuning can lead to better prediction performance but can also complicate implementation and affect usability for engineers with no modeling background. The ability of these approaches to incorporate domain knowledge is also currently limited by the types of physical information that can be represented. Other aspects of engineering knowledge, such as monotonicity, positivity, bounds, smoothness, and related constraints, can be integrated relatively naturally, while other engineering knowledge may need further model structures [Williams, 2016]. Representing periodic, oscillatory, transient, or highly nonlinear relationships may be more challenging. Establishing flexible methods for embedding a range of physical knowledge is a research field worthy of further investigation. The quality of domain knowledge may also affect the performance of surrogate models. Even if the data that went into the model are accurate, they may be incomplete or incorrect given the engineering assumptions that were made in a model [Kapil, 2022]. The influence of uncertain, noisy, or conflicting domain knowledge is thus left to be explored further. A strong technique is required to distinguish between physical constraints that are likely to be true and assumptions that may not be valid under a variety of operating conditions. Another significant restriction is generalizability. Typically, knowledge guided surrogate models are validated with particular benchmark problems or relatively constrained engineering scenarios [Rokkala, 2026]. Uncontrolled process parameters (high dimensional process space, nonlinear interactions, changing material properties, thermal history, machine specific properties, and limited experimental data sets) may influence their performance in complex additive and hybrid manufacturing environments. Additional validation on other machines, materials, geometry, and manufacturing process would then be needed.

10. Discussion

The advent of machine learning, digital twins, cyber physical systems, advanced sensing, and smart infrastructure is transforming the operating bedrock of additive and hybrid manufacturing. The overarching system presented in this study suggests that intelligent manufacturing is not just the integration of AI into the current manufacturing equipment. Instead, it is an architecture that is integrated where physical processes, digital models, data infrastructure, computational methods, and control systems continuously feed into each other [Stahmann, 2025]. Thus, a static process model is no longer sufficient to guarantee stable production process performance under varying production conditions. Digital transformation is enabled by digital twins and digital threads. The integration is especially relevant in the field of additive (AM) and hybrid manufacturing as there are many interactions between thermal conditions, material properties, machine states, geometric changes, and environmental factors that affect process behavior [Hossain, 2025]. Envisioning the state of a process or asset through a digital twin, the digital thread provides continuity and traceability of information throughout the product lifecycle. Their integration enables information to be held together from design, process planning, manufacturing, inspection, maintenance, and quality assessment. This is especially useful for additive and hybrid manufacturing in which decisions made during material deposition may affect subsequent machining, finishing, inspection, and finally component performance [Nagamatsu, 2025]. Continuous synchronization also makes it possible to include historical information in current decisions and turn a manufacturing system into one in which past manufacturing conditions can be used to make decisions in the present. In relation to Sensing and Infrastructure, the need for intelligent decision making is largely based on the quality of the data. Heterogeneous information from thermal cameras, optical systems, machine controllers, inspection devices, material databases, and enterprise systems are generated in additive and hybrid processes. The data vary in format, frequency, resolution, and reliability [Yue, 2024]. However, intelligent manufacturing cannot be achieved by simply gathering data. The data has to be filtered, understood in a specific context, synchronized, validated, and processed into meaningful information for a process. In addition to initial processing near the machine, there are two other aspects that could benefit from cloud and centralized infrastructure: historical analysis, model training, and cross facility optimization [Sun, 2019]. This division provides a practical architecture whereby latency-critical decisions are made at the local level and computationally demanding analysis is done at higher levels of the architecture. The capabilities must be deployed at industrial scale, which requires smart infrastructure. Completely replacing the infrastructure is not feasible in manufacturing facilities because they are likely to have a mix of modern digital equipment and legacy machines. Digital integration can happen gradually through gatewaying with the edge, industrial communication protocols, on premises data processing, and cloud platforms [Xu, 2020]. This makes it important to connect different equipment by using, for example, OPC UA, MQTT, Modbus TCP, Profinet, and EtherNet/IP. Latency, availability, cybersecurity, and scalability are also important factors in the deployment architecture. Local processing to meet critical process control requirements can be solved by cloud infrastructure, while long term optimization and cross plant analytics can be done locally [Baufeld, 2023]. For intelligent manufacturing, the combination of additive and subtractive processes brings up further possibilities. Rapid material deposition can be coupled with precision machining and finishing in hybrid manufacturing. The importance of digital continuity increases as the quality that is created at one stage impacts on the needs of the following stages. The digital thread can connect toolpath information, thermal measurements, machine states, deposition conditions, and machining data with inspection results. These can then be used to form relationships between the fabrication conditions and the resulting surface quality, dimensions, or tool wear, which can then be identified by ML models [Svetlizky, 2021]. This provides a chance to coordinate additive deposition and subtractive finishing processes as one together, rather than separately. Another important consideration for this integration is in situ monitoring. Monitoring methods, such as high speed imaging, infrared thermography, acoustic sensing methods, and others, are used to obtain process information during production. These measurements can be used to predict defects, estimate tool wear, characterize the melt pool, and characterize quality through ML models [Osipovich, 2023]. Monitoring becomes a part of manufacturing when coupled with closed loop control, and not just a passive inspection tool. This shift can reduce reliance on postproduction inspection and offer the opportunity to address defects as they develop. Cybersecurity is no exception to the rule that it can't be separated from manufacturing safety. As industrial equipment, edge systems, cloud platforms, and enterprise applications become more connected, there are more points of exposure. The architecture should thus include encryption, authentication, role-based access, network segmentation, audit logging, secure communication, and incident response procedures [Hossain, 2021]. Smart manufacturing frameworks for real time monitoring, predictive maintenance, and quality control rely on interconnected sensors and automated controllers. Security failures can therefore produce physical effects, making operational safety as important as information security. High volume sensor streams also require substantial computational capacity for real time analysis. Edge computing and distributed processing can reduce latency and support timely detection of faults and abnormal conditions. However, further validation, scalability testing, and safety assessment are required before such frameworks can be widely adopted in advanced mechanical production systems [Sommer, 2021]. Further, performance in physics-informed or knowledge-guided models may depend heavily on the quality of the domain knowledge. For reliable transfer of models between manufacturing platforms, there is a need for standardization and interoperability. The integrated framework showcases how intelligent additive and hybrid manufacturing relies on synergies between different layers rather than on individual AI applications.

11. Conclusion

Integrated machine learning and smart infrastructure provide a comprehensive foundation for intelligent additive and hybrid manufacturing. Digital twins and digital threads enable continuous data connectivity, while advanced sensing, edge computing, surrogate modeling, and physics informed learning support accurate prediction and adaptive decision making. Closed loop control allows manufacturing parameters to respond dynamically to changing process conditions, improving quality, stability, and efficiency. Smart infrastructure further enables scalable deployment across heterogeneous equipment and distributed environments. However, cybersecurity, data quality, interoperability, regulatory compliance, model reliability, and certification remain important challenges. Future development should prioritize validated, explainable, secure, and interoperable frameworks that combine physical knowledge with data-driven intelligence.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers

Artificial Intelligence (AI) Use Disclosure: The authors declare that no artificial intelligence tools were used in the preparation of this manuscript.

Author Contributions

M.R.U. conceptualized and designed the study, developed the methodology, conducted the data collection and analysis, interpreted the results, and drafted the original manuscript. S.G. contributed to the study design, data interpretation, critical revision of the manuscript, and overall supervision. Both authors reviewed and approved the final version of the manuscript.

References

[1] Akhtaruzzaman M., Barman S. C., Hossain M. A., Ahmad M., and Ali R. A., (2025) Cloud enabled AI smart energy infrastructure for industrial and utility applications, in *2025 8th Int. Conf. Energy Conserv. Efficiency (ICECE)*, Lahore, Pakistan, 2025, pp. 1–6, doi: 10.1109/ICECE69114.2025.11272935.

[2] Baufeld B., (2023) Wire electron beam additive manufacturing of copper, *J. Phys. Conf. Ser.*, vol. 2443, no. 1, p. 012001, 2023, doi: 10.1088/1742-6596/2443/1/012001.

[3] Celik H. K., Elham A., Erbil M. A., Rennie A. E. W., and Akinci I., (2025) A decade of design for additive manufacturing research: A bibliometric analysis (2014-2024), *Rapid Prototyp. J.*, 2025, ahead-of-print, doi: 10.1108/RPJ-02-2025-0086.

[4] Chattopadhyay S., Mahapatra S. D., and Mandal N. K., (2024) Advancements and challenges in additive manufacturing: A comprehensive review, *Eng. Res. Express*, vol. 6, no. 1, p. 012505, 2024, doi: 10.1088/2631-8695/ad30b1.

[5] Chénier F., Parent G., Leblanc M., Bélaise C., and Andrieux M., (2023) Using a quantitative assessment of propulsion biomechanics in wheelchair racing to guide the design of personalized gloves: A case study, *arXiv*, 2023, doi: 10.1080/10255842.2024.2311324.

[6] Du W., Bai Q., and Zhang B., (2016) A novel method for additive/subtractive hybrid manufacturing of metallic parts, *Procedia Manuf.*, vol. 5, pp. 1018–1030, 2016, doi: 10.1016/j.promfg.2016.08.067.

[7] Duflou J. and Kellens K., (2016) Cleaner production, in *CIRP Encyclopedia of Production Engineering*, Berlin/Heidelberg, Germany: Springer, 2016, pp. 1–4, doi: 10.1007/978-3-642-35950-7_6635-3.

[8] Flynn J. M., Shokrani A., Newman S. T., and Dhokia V., (2016) Hybrid additive and subtractive machine tools-Research and industrial developments, *Int. J. Mach. Tools Manuf.*, vol. 101, pp. 79–101, 2016, doi: 10.1016/j.ijmachtools.2015.11.007.

[9] Freitas B. *et al.*, (2025) A review of hybrid manufacturing: Integrating subtractive and additive manufacturing, *Materials*, vol. 18, no. 18, p. 4249, 2025, doi: 10.3390/ma18184249.

[10] Hossain M. A. and Bhuiyan M. A. A., (2025) Digital twin-based process optimization and defect prediction in metal additive manufacturing for critical mechanical components, *Brit. J. Multidiscip. Stud.*, vol. 3, no. 2, pp. 57–72, 2025, doi: 10.32996/bjmss.2025.3.2.5.

[11] Hossain M. A., (2025) Residual stress mitigation and distortion control in laser powder bed fusion components for high-reliability engineering applications, *Amer. J. Adv. Tech. Eng. Sol.*, vol. 1, no. 2, pp. 173–215, 2025, doi: 10.63125/1b3nyj37.

[12] Hossain M. A., Barman S. C., and Islam S. M. T., (2026) Additive manufacturing of lightweight, fire-resistant alloys for automotive and aerospace applications, *J. Mech. Civil Ind. Eng.*, vol. 7, no. 3, pp. 06–16, 2026, doi: 10.32996/jmcie.2026.7.3.2.

[13] Hossain M. A., Bhuiyan M. A. A., Rahman A., and Hasan D. W., (2024) Integration of artificial intelligence for real-time monitoring and process control in metal additive manufacturing systems, *J. Mech. Civil Ind. Eng.*, vol. 5, no. 3, pp. 08–28, 2024, doi: 10.32996/jmcie.2024.5.3.2.

[14] Hossain M. A., Pi W., Islam S. M. T., and Lide M. I., (2021) Smart manufacturing framework for real-time process monitoring, predictive maintenance, and quality control in advanced mechanical production systems, *J. Mech. Civil Ind. Eng.*, vol. 2, no. 1, pp. 11–24, 2021, doi: 10.32996/jmcie.2021.2.1.3.

[15] Jakimiuk A., Skwira A., Wróbel Z., and Wróbel Z., (2024) 3D-printed patient-specific implants made of polylactide (PLDLLA) and tricalcium phosphate TCP) for corrective osteotomies of the distal radius, *3D Print. Med.*, vol. 10, p. 42, 2024, doi: 10.1186/s41205-024-00240-z.

[16] Jayawardane H., Davies I. J., Gamage J. R., John M., and Biswas W. K., (2023) Sustainability perspectives-A review of additive and subtractive manufacturing, *Sustain. Manuf. Serv. Econ.*, vol. 2, p. 100015, 2023, doi: 10.1016/j.smse.2023.100015.

[17] Jiménez A. *et al.*, (2021) Powder-based laser hybrid additive manufacturing of metals: A review, *Int. J. Adv. Manuf. Technol.*, vol. 114, pp. 63–96, 2021, doi: 10.1007/s00170-021-06855-4.

[18] Jung S., Kara L. B., Nie Z., Simpson T. W., and Whitefoot K. S., (2023) Is additive manufacturing an environmentally and economically preferred alternative for mass production?, *Environ. Sci. Technol.*, vol. 57, no. 17, pp. 6373–6386, 2023, doi: 10.1021/acs.est.2c04927.

[19] Kapil S., Rajput A. S., and Sarma R., (2022) Hybridization in wire arc additive manufacturing, *Front. Mech. Eng.*, vol. 8, p. 981846, 2022, doi: 10.3389/fmech.2022.981846.

[20] Karunakaran K. P., Suryakumar S., Pushpa V., and Akula S., (2010) Low cost integration of additive and subtractive processes for hybrid layered manufacturing, *Robot. Comput.-Integr. Manuf.*, vol. 26, no. 5, pp. 490–499, 2010, doi: 10.1016/j.rcim.2010.03.008.

[21] Khan U. *et al.*, (2026) A comprehensive survey on deep learning-based predictive maintenance, *ACM Trans. Embed. Comput. Syst.*, vol. 25, no. 1, pp. 1–43, 2026, doi: 10.1145/3732287.

[22] Krimpenis A. A. and Iordanidis D. M., (2023) Design and analysis of a desktop multi-axis hybrid milling-filament extrusion CNC machine tool for non-metallic materials, *Machines*, vol. 11, no. 6, p. 637, 2023, doi: 10.3390/machines11060637.

[23] Lalegani D M. *et al.*, (2022) A review on additive/subtractive hybrid manufacturing of directed energy deposition (DED) process, *Adv. Powder Mater.*, vol. 1, no. 2, p. 100054, 2022, doi: 10.1016/j.apmate.2022.100054.

[24] Lauwers B., Klocke F., Klink A., Tekkaya A. E., Neugebauer R., and Mcintosh D., (2014) Hybrid processes in manufacturing, *CIRP Ann.-Manuf. Technol.*, vol. 63, no. 2, pp. 561–583, 2014, doi: 10.1016/j.cirp.2014.05.003.

[25] Liu Y. *et al.*, (2024) Study on the surface quality of overhanging holes fabricated by additive/subtractive hybrid manufacturing for Ti6Al4V alloy, *Metals*, vol. 14, no. 9, p. 979, 2024, doi: 10.3390/met14090979.

[26] Loyda A., Arizmendi M., Ruiz de Galarreta S., Rodriguez-Florez N., and Jimenez A., (2023) Meeting high precision requirements of additively manufactured components through hybrid manufacturing, *CIRP J. Manuf. Sci. Technol.*, vol. 40, pp. 199–212, 2023, doi: 10.1016/j.cirpj.2022.11.011.

[27] Mahale Y., Kolhar S., and More A. S., (2025) Enhancing predictive maintenance in automotive industry: Addressing class imbalance using advanced machine learning techniques, *Discov. Appl. Sci.*, vol. 7, no. 3, p. 340, 2025, doi: 10.1007/s42452-025-06827-3.

[28] Mechete A., Tarlochan F., and Kucukvar M., (2023) A review of conventional versus additive manufacturing for metals: Life-cycle environmental and economic analysis, *Sustainability*, vol. 15, no. 16, p. 12299, 2023, doi: 10.3390/su151612299.

[29] Merklein M., Junker D., Schaub A., and Neubauer F., (2016) Hybrid additive manufacturing technologies-An analysis regarding potentials and applications, *Phys. Procedia*, vol. 83, pp. 549–559, 2016, doi: 10.1016/j.phpro.2016.08.057.

[30] Nagamatsu H., Sasahara H., Mitsutake Y., and Hamamoto T., (2020) Development of a cooperative system for wire and arc additive manufacturing and machining, *Addit. Manuf.*, vol. 31, p. 100896, 2020, doi: 10.1016/j.addma.2019.100896.

[31] Nau B., Roderburg A., and Klocke F., (2011) Ramp-up of hybrid manufacturing technologies, *CIRP J. Manuf. Sci. Technol.*, vol. 4, no. 3, pp. 313–316, 2011, doi: 10.1016/j.cirpj.2011.04.003.

[32] Neumann G. *et al.*, (2025) A data-based certification approach for additively manufactured metal aircraft components, *Prog. Addit. Manuf.*, vol. 10, pp. 4061–4071, 2025, doi: 10.1007/s40964-025-01107-3.

[33] Osipovich K. *et al.*, (2023) Wire-feed electron beam additive manufacturing: A review, *Metals*, vol. 13, no. 2, p. 279, 2023, doi: 10.3390/met13020279.

[34] Pragana J. P. M., Sampaio R. F. V., Bragança I. M. F., Silva C. M. A., and Martins P. A. F., (2021) Hybrid metal additive manufacturing: A state-of-the-art review, *Adv. Ind. Manuf. Eng.*, vol. 2, p. 100032, 2021, doi: 10.1016/j.aime.2021.100032.

[35] Prasad G. *et al.*, (2024) Advancing sustainable practices in additive manufacturing: A comprehensive review on material waste recyclability, *Sustainability*, vol. 16, no. 23, p. 10246, 2024, doi: 10.3390/su162310246.

[36] Praveena B. A. *et al.*, (2022) A comprehensive review of emerging additive manufacturing (3D printing technology): Methods, materials, applications, challenges, trends and future potential, *Mater. Today Proc.*, vol. 52, pp. 1309–1313, 2022, doi: 10.1016/j.matpr.2021.11.059.

[37] Rabalo M. Á., García A., and Rubio E. M., (2025) Emerging trends in hybrid additive and subtractive manufacturing, *Appl. Sci.*, vol. 15, no. 11, p. 6102, 2025, doi: 10.3390/app15116102.

[38] Rokkala U. *et al.*, (2026) Advancements and applications of wire arc additive manufacturing with future perspectives, in *Engineering Advanced Materials for Manufacturing, Energy, and Smart Systems*, D. Balakrishnan, R. Buradagunta, and W. Fernando, Eds., Hershey, PA, USA: IGI Global Scientific Publishing, 2026, pp. 195–212, doi: 10.4018/979-8-3373-9454-1.ch006.

[39] Saxena K. K., Bellotti M., Qian J., Reynaerts D., Lauwers B., and Luo X., (2018) Chapter 2-Overview of hybrid machining processes, in *Hybrid Machining*, London, UK: Academic Press, 2018, pp. 21–41, doi: 10.1016/B978-0-12-813059-9.00002-6.

[40] Schuh G., Kreysa J., and Orilski S., (2009) Roadmap 'Hybride Produktion', *Z. Wirtsch. Fabr.*, vol. 104, no. 5, pp. 385–391, 2009, doi: 10.3139/104.110072.

[41] Sebbe N. P. V., Fernandes F., Sousa V. F. C., and Silva F. J. G., (2022) Hybrid manufacturing processes used in the production of complex parts: A comprehensive review, *Metals*, vol. 12, no. 11, p. 1874, 2022, doi: 10.3390/met12111874.

[42] Segovia-Guerrero L., Baladés N., Gallardo-Galán J. J., Gil-Mena A. J., and Sale D. L., (2025) Additive vs. subtractive manufacturing: A comparative life cycle and cost analyses of steel mill spare parts, *J. Manuf. Mater. Process.*, vol. 9, no. 4, p. 138, 2025, doi: 10.3390/jmmp9040138.

[43] Soe A. N. *et al.*, (2024) Effect of post-processing treatments on surface roughness and mechanical properties of laser powder bed fusion of Ti-6Al-4V, *J. Mater. Res. Technol.*, vol. 32, pp. 3788–3803, 2024, doi: 10.1016/j.jmrt.2024.08.197.

[44] Sommer D., Götzendorfer B., Esen C., and Hellmann R., (2021) Design rules for hybrid additive manufacturing combining selective laser melting and micromilling, *Materials*, vol. 14, no. 19, p. 5753, 2021, doi: 10.3390/ma14195753.

[45] Stahmann P., Nebel M., and Janiesch C., (2025) AI-based real-time anomaly detection in industrial engineering: A structured literature review, taxonomy, and research agenda, *Comput. Ind. Eng.*, vol. 207, p. 111236, 2025, doi: 10.1016/j.cie.2025.111236.

[46] Sun G. F. *et al.*, (2019) Laser metal deposition as repair technology for 316L stainless steel: Influence of feeding powder compositions on microstructure and mechanical properties, *Opt. Laser Technol.*, vol. 109, pp. 71–83, 2019, doi: 10.1016/j.optlastec.2018.07.051.

[47] Svetlizky D. *et al.*, (2021) Directed energy deposition (DED) additive manufacturing: Physical characteristics, defects, challenges and applications, *Mater. Today*, vol. 49, pp. 271–295, 2021, doi: 10.1016/j.mattod.2021.03.020.

[48] Tosi R., Muzangaza E., Tan X. P., Wimpenny D., and Attallah M. M., (2022) Hybrid electron beam powder bed fusion additive manufacturing of Ti-6Al-4V: Processing, microstructure, and mechanical properties, *Metall. Mater. Trans. A*, vol. 53, no. 3, pp. 927–941, 2022, doi: 10.1007/s11661-021-06565-2.

[49] Williams S. W., Martina F., Addison A. C., Ding J., Pardal G., and Colegrove P., (2016) Wire + Arc Additive Manufacturing, *Mater. Sci. Technol.*, vol. 32, no. 7, pp. 641–647, 2016, doi: 10.1179/1743284715Y.0000000073.

[50] Xu Z., Ouyang W., Jia S., Jiao J., Zhang M., and Zhang W., (2020) Cracks repairing by using laser additive and subtractive hybrid manufacturing technology, *J. Manuf. Sci. Eng.*, vol. 142, no. 3, p. 031006, 2020, doi: 10.1115/1.4046161.

[51] Yue W., Zhang Y., Zheng Z., and Lai Y., (2024) Hybrid laser additive manufacturing of metals: A review, *Coatings*, vol. 14, no. 3, p. 315, 2024, doi: 10.3390/coatings14030315.

[52] Zhu Z., Dhokia V. G., Nassehi A., and Newman S. T., (2013) A review of hybrid manufacturing processes-state of the art and future perspectives, *Int. J. Comput. Integr. Manuf.*, vol. 26, no. 7, pp. 596–615, 2013, doi: 10.1080/0951192X.2012.749530.