Journal of Business and Management Studies
ISSN: 2709-0876
DOI: 10.32996/jbms
Journal Homepage: www.al-kindipublisher.com/index.php/jbms

JBMS

AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

AI-Augmented Predictive Quality Control in Additive Manufacturing Supply Chains

[1]Raghuram Katakam, [2]Srinivas Reddy Kosna and [3]Angshuman Rudra

[1]*Independent Researcher, Atlanta, GA, USA*
[2]*Senior Engineering Architect, Cisco, USA*
[3]*Cornell University, Ithaca, NY, USA*
Corresponding Author: Raghuram Katakam, **Email**: raghu.pro2007@gmail.com

| ABSTRACT

Additive manufacturing (AM) has transformed the present-day supply chains with on-demand manufacturing, adaptive design, and digital inventory management. The distributed and heterogeneous nature of AM networks, however, induces inherent problems with stable product quality across distributed networks. Reactive and inspection-based quality control practices common with traditional quality control prove insufficient to handle variability in processes, material variability, and machine variability characteristic of AM networks. This paper proposes a conceptual framework of AI-augmented predictive quality control (PQC) applicable to additive manufacturing supply chains. The framework uncovers multi-faceted components: in-situ monitoring-based real-time data capture, AI-based analytics for defect prediction and anomaly recognition, decision support systems for adaptive intervention, and closed-loop continuous feedback facilities aided with digital twins. With the help of machine learning, deep learning, and reinforcement learning-based strategies, predictive frameworks are able to forecast defects, reduce scrap to a minimum, and transform supply chains with increased resiliency. The paper also elaborates on the theoretical benefit of AI-augmented PQC, including improved traceability, economy of costs, and increased congruity with just-in-time logistics. Data heterogeneity, scalability, cybersecurity, and workers' adaptability are also paramount challenges discussed in the paper. The future research directions are also enumerated in terms of hybrid AI-physics models, standardizable datasets, integration with blockchain, and human-AI teaming. This research enlists the transformative potential of AI-augmented PQC in making AM supply chains more reliable and viable.

| KEYWORDS

Additive manufacturing, supply-chain, quality control, AI, blockchain

| ARTICLE INFORMATION

ACCEPTED: 15 October 2024 **PUBLISHED:** 02 November 2025 **DOI:** 10.32996/jbms.2025.7.7.1

1. Introduction

Additive manufacturing (AM) has been a transformative technology of value chains around the globe with great promise to realize on-demand manufacturing, flexible design, and mass customization. Compared to conventional manufacturing, AM does not require significant reliance on high inventory levels or fixed locations; AM enables distributed and digital-based value chains wherein components can be produced closer to the location of consumption. Though the attributes offer significant operational advantages, they present quality homogenization problems across heterogeneous locations of production, machines, and material [1].

AM value chains continue to suffer from poor quality assurance. Failures such as porosity, warpage, and residual stress are frequent defects found in layer-wise fabrication, and quality differences tend to transfer over to downstream shipping and customer complaints. Traditional quality control (QC), inspect-based and largely reactive, doesn't measure up to keeping up with AM processes' velocity and variability. This disconnect makes the rising visibility of predictive quality control (PQC) more apparent, as it strives to predict defects and ensure reliability prior to failures occurring [2].

Artificial Intelligence (AI) provides a promising avenue to augment PQC in AM supply chains. Utilizing high-level machine learning, deep learning, and real-time data analytics, AI is capable of managing high-dimensional sensor streams, predicting quality deviations, and supporting adaptive decision-making. This paper introduces a conceptual framework of AI-augmented PQC in AM supply chains based on their theoretical foundations, possible benefits, limitations, and future research scopes. Through it, it places AI's contribution to the creation of resilient, high-quality, and sustainable manufacturing networks in spotlight [3].

2. Literature Foundations

2.1 Additive Manufacturing Supply Chains

Additive manufacturing has shifted supply chains from inventory-based, centrally focused ones to distributed and digital networks. Parts can be designed in one location and transmitted electronically to be manufactured on an as-required basis in a second location, with minimal transport needs and lead time. Although having these advantages, AM also introduces new forms of vulnerability. Layer-by-layer manufacturing typically creates non-uniform microstructure, anisotropy, and porosity, so it is difficult to maintain stable quality through more than a single location of manufacturing. These challenges generate confusion among supply chain managers who must compromise on cost efficiency, reliability, and product functionality [4].

2.2 Traditional Quality Control Approaches

Classical manufacturing has relied on inspection-based quality assurance and statistical quality control. They focus on detection of nonconformity during or after manufacturing, but prevention is lacking. For AM, such reactive method doesn't work because feed material quality, alignment of the machine, and operating environment show strong variability. Much material, time, and money could be wasted before nonconformity is detected. Moreover, traditional methods do not adequately encompass the dynamic interactions of manufacturing processes and logistics through a supply chain, with the result that quality assurance suffers gaps [5].

2.3 Emergence of AI in Quality Assurance

Recent AI advancements have provided renewed promises to predictive quality management. Near-real-time processing of sensor data, defect pattern recognition, and predictive outputs from machine learning and deep learning algorithms are possible. AI has been applied in predictive maintenance, anomaly detection, and process optimization with measurably improved efficiency and economic savings in general manufacturing. Implementations in additive manufacturing supply chains are immature and fragmented. Research presently conducted indicates potential but does not provide an integrated framework involving AI-based quality prediction with supply chain management. This void provides the foundation for examining AI-augmented predictive quality control [6][7].

3. Conceptual Framework: AI-Augmented Predictive Quality Control

Predictive Quality Control (PQC) refers to the advance detection and prevention of quality issues before their emergence in finished goods. For additive manufacturing (AM) value chains, where variability is inherent and decentralized manufacturing is the order of the day, a PQC system must go beyond inspection and integrate intelligence across the design, manufacturing, and logistics chain. In response to these imperatives, the present paper proposes an AI-powered PQC framework comprising four interconnected layers:

3.1 Data Acquisition Layer

Central to the framework is integrated data acquisition. For AM, such data comprise in-situ monitoring of build processes (thermography, acoustic emission, and laser scanning), machine settings, material characteristics, and environmental conditions. From the front of the supply chain, procurement data, supplier quality, and logistics data also come into play. As a collective set, these multi-source feeds yield a comprehensive quality dataset.

3.2 AI Analytics Layer

Data gathered here is then filtered through AI-capable models capable of extracting predictive information. Machine learning assigns likely defect categorizations, deep learning identifies complex spatiotemporal patterns from sensor feeds, and reinforcement learning helps adaptive optimization of parameters during procedures. This level transforms raw data into actionable intelligence.

3.3 Decision Support Layer

AI analytics recommendations are incorporated in decision-making processes. Operators, engineers, and logistics directors receive prescriptive recommendations: changing laser power during fabrication, alerting to a questionable lot from a vendor, or changing logistics so delivery schedules are maintained. Proactive actions reducing the likelihood of failure outnumber ex post corrections.

3.4 Feedback and Continuous Learning Layer

Ultimately, the framework is also fortified with learning loops continuously. AM manufacturing process and supply chain node digital twins are synthetic testbeds through which predictions are virtually tested and refined. Results of production feedback sharpens AI-based models so the framework accommodates with different conditions, changes in material, and technologies [8].

This multi-layer framework highlights the potential of AI to interface variability in AM's micro-level processes with macro-level AM networks while facilitating strategic quality management as a catalyst of sustainable and resilient networks.

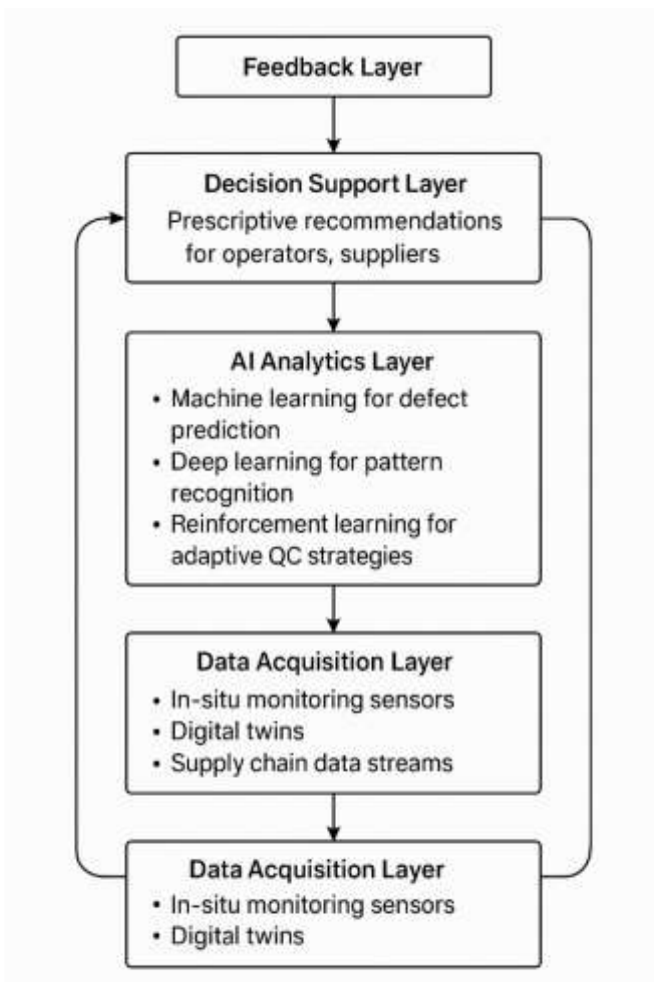

Fig 1: Conceptual Framework for AI-Augmented Predictive Quality Control

4. AI Methods for Predictive Quality in Additive Manufacturing

Artificial Intelligence provides diversified methods which could be tailored to accommodate the variability and multiplicity of additive manufacturing (AM) supply chains. These have varying strengths of predictive quality control (PQC), considering the type of data taken into account and stage of decision-making.

4.1 Machine Learning Models

Supervised machine learning algorithms, such as support vector machines and decision trees, are more suitable to defect type classification with given labeled data sets. For example, surface roughness or porosity levels might be predicted from historical process parameters. Unsupervised algorithms, such as clustering or principal component analysis, discover hidden structures or outliers without prior knowledge of labels and are a value in discovering unknown defect modes from real-time sensor data streams.

4.2 Deep Learning Architectures

Predictive capability is also extended by deep learning through the retention of nonlinear interactions in high-dimensional data. Convolutional Neural Networks (CNNs) are broadly transferable to the investigation of images of the microstructure or quality of deposited layer. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are, in turn, transferable to time-series data from temperature probes, melt-pool monitoring, or sound emission data. These networks have the capability of anticipating defect formation with respect to temporal dependence during build processes.

4.3 Reinforcement Learning

Reinforcement learning (RL) offers adaptive solutions with algorithms learning optimum actions through AM environment interactions. For instance, an agent's build parameters, i.e., laser power or feed rate, can be dynamically established with quality feedback to minimize defect probability. At the level above the machine, RL offers potential optimization of supply chain decisions with a tradeoff of cost, quality, and delivery performance during ambiguity.

4.4 Digital Twins Integration

Digital twins allow computerized replicas of AM processes and supply chain nodes such that predictive verification and simulation are feasible. AI models with digital twins are able to ask “what-if” questions, such as what final part performance results from powder quality or machine calibration variations. This experimentation virtually reduces reliance on costly trial-and-error, while raising confidence with predictive outcomes.

By combining these methodologies, AM chains achieve multi-layered predictive capability. Defect classification is done through machine learning, deep learning extracts underlying patterns, reinforcement learning offers adaptive control, and digital twins validate scenarios across the entire supply chain environment. As a comprehensive set of tools, these put AI center stage in predictive quality monitoring in AM.

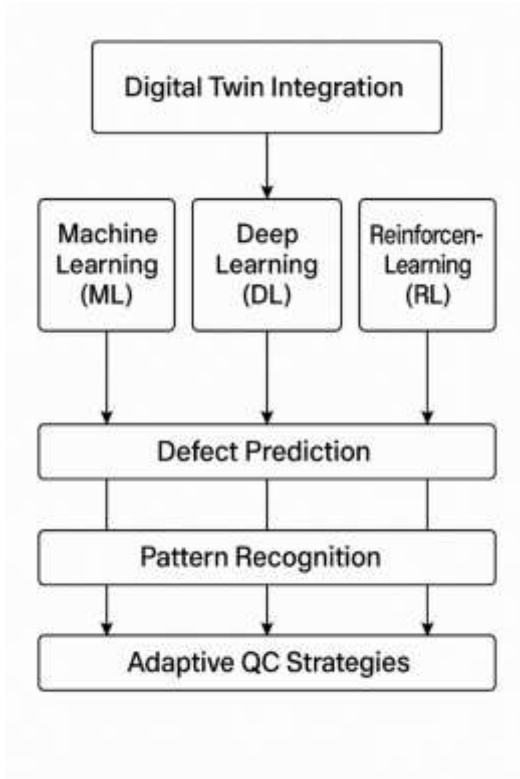

Fig 2: AI Methods for Predictive Quality in AM

5. Theoretical Benefits in Supply Chain Context

Addition of AI-augmented predictive quality control (PQC) to additive manufacturing (AM) supply chains offers transformative benefits far beyond defect detection. At its core, PQC makes quality assurance an active enabler of operational resiliency, economic efficiency, and customer assurance.

5.1 Augmented Defect Detection and early correction

With the use of analytics in real-time, defects are foreseen prior to causing damage to finished products. This predictive function decreases the rate of scrap and incidents of costly rework. In AM distributed networks, early warning prevents damaged components from propagating through downstream supply chain stages.

5.2 Cost Minimization and Resource Effectiveness

Waste reduction directly implies minimizing material waste, which is paramount in AM because feedstocks such as metallic powders are potentially expensive. Predictive modeling also minimizes unplanned downtime through regular quality of processes and consequently lowers operational costs.

5.3 Supplier Reliability and Risk Mitigation

AI-based supplier input monitoring automatically identifies potential issues like powder batch quality or machine calibration history. This encourages earlier responsibility from the supplier and allows proactive actions so quality remains consistent across geographically dispersed locations of manufacturing.

5.4 Just-in-Time Logistics Alignments

Typical just-in-time delivery chains in AMs also take advantage of predictive QC such that components are delivered without causing timetable delays from post-production inspection or rework. This synchronization smoothens out manufacturing and logistics coordination with short lead time and improved customer satisfaction.

5.5 Traceability and Compliance

By combining predictive QC with electronic records, businesses gain robust quality decision traceability. This makes it easier to comply with customer needs and sectoral regulatory demands as well as audit trails to support transparency.

These benefits collectively illuminate the means through which AI-enabled PQC transforms quality control from an expert technical function to a strategic instrument strengthening the entire AM value chain.

6. Challenges and Limitations

While AI-augmented predictive quality control (PQC) holds immense potential for additive manufacturing (AM) supply chains, there are adoption-related challenges involving both technical constraints and organizational needs to be identified to ensure widespread application.

6.1 Data Availability and Quality

Data-intensive AI-based PQC needs vast, heterogeneous, and uniform data sets. Data from the sensor for AM vary with machine setup, build chamber, and material batch. Such heterogeneity makes standardizing input data to achieve strong predictive modeling harder. In addition, labelled defect data scarcity limits the level of precision possible via supervised learning-based methods.

6.2 Model Generalization

Models from just a single AM process or material may not transfer across others. A titanium alloy fine-tuned model, for example, may not function when applied to polymers or composites. This non-transferability makes implementation more challenging due to continuous retraining and calibration needs.

6.3 Computational Cost and Scalability

Simulations of digital twins and deep learning are computationally intensive. Deploying them across global AM supply chains leads to high infrastructure costs, particularly among small and medium-sized enterprises (SMEs).

6.4 Cybersecurity and Data Privacy

Being constructed upon networks of digital platforms, PQC frameworks are vulnerable to cyber threats. Improper utilization of quality information or predictive algorithms may compromise product safety in addition to intellectual property.

6.5 Human and Organizational Factors

Finally, workforce adaptations are difficult. Over-reliance on AI may undermine human expertise, while insufficient faith in AI counsel may deter adoption. Aligning human–AI collaborations is a necessary imperative.

Overcoming these challenges is critical to achieving the full potential of predictive quality control in AM supply chains.

7. Future Research Directions

The creation of AI-augmented predictive quality control (PQC) in additive manufacturing (AM) value chains will involve targeted research capable of overcoming technical gaps alongside organizational challenges. Some of the principal direction's forthcoming as promising future research lines include:

7.1 Standardized Datasets for AM Quality

One significant challenge preventing AI implementation is the absence of large, high-grade, and standard data sets. Future work needs to emphasize the development of open-access data repositories of AM processes and defects so that model benchmarks and cross-industry sharing are possible [9].

7.2 Hybrid AI-Physics

Data-only approaches could be non-robust when they are applied to new material or machine data. Incorporation of AI with physics-based simulation forms hybrid models in order to elevate predictive ability and generalization. This blending also offers better interpretability so AI results are more reliable for operators [10].

7.3 Traceable Quality Records with Blockchain

Integrating PQC with blockchain is capable of attaining tamper-proof quality histories on decentralized supply chains. This, in addition to improved traceability and compliance, would also raise the trust level of customers, regulators, and supply chain partners [11].

7.4 Human-AI Collaboration in Industry 5.0

Future supply chains must find a balance between human expertise and automation. Studies should investigate ways predictive AI technologies can augment decision-making and operational intuition of the operator, developing collaborative systems instead of pure black boxes [12].

7.5 Interdisciplinary

Development will also require integration across materials science, computer science, and supply chain management disciplines. Future research needs to focus more on cross-domain integration so that predictive QC frameworks consider technical, operational, and strategic aspects together [13].

By pursuing these paths, future studies can reinforce the pillars of AI-facilitated PQC so AM supply chains can become more efficient, resilient, and sustainable.

8. Conclusion

Additive manufacturing has changed the operation of supply chains with unprecedented responsiveness and flexibility. But stable product quality across distributed AM networks remains the ultimate challenge. Standard quality control measures, because they are largely reactive, fail to handle the variability present in the AM processes. This paper has described a conceptual framework of AI-augmented predictive quality control (PQC) as a multi-layered proactive measure integrating data acquisition, AI-driven analytics, decision support, and closed-loops of continuous feedback.

The paper elaborated on how predictive capabilities are reinforced through machine learning, deep learning, reinforcement learning, and digital twins, while extending benefits across the full length of the supply chain, with reduced scrap, improved traceability, and integration with just-in-time logistics. Difficult challenges were also pinpointed as data heterogeneity, model generalizability, cybersecurity, and worker adaptation.

Standardized data sets, physics-based AI-hybrid frameworks, enabling of traceability through blockchain, and human-AI collaboration on Industry 5.0 foundations should all be addressed in future research. Individually and collectively, these technologies will redefine predictive QC as a strategic enabler of strong, sustainable, and high-performance additive manufacturing value chains.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.

References

[1] G. Prashar, H. Vasudev, and D. Bhuddhi, "Additive manufacturing: expanding 3D printing horizon in industry 4.0," *International Journal on Interactive Design and Manufacturing*, vol. 17, no. 5, 2023, doi: 10.1007/s12008-022-00956-4.
[2] T. Herzog, M. Brandt, A. Trinchi, A. Sola, and A. Molotnikov, "Process monitoring and machine learning for defect detection in laser-based metal additive manufacturing," 2024. doi: 10.1007/s10845-023-02119-y.
[3] S. J. Plathottam, A. Rzonca, R. Lakhnori, and C. O. Iloeje, "A review of artificial intelligence applications in manufacturing operations," 2023. doi: 10.1002/amp2.10159.
[4] S. C. Ligon, R. Liska, J. Stampfl, M. Gurr, and R. Mülhaupt, "Polymers for 3D Printing and Customized Additive Manufacturing," 2017. doi: 10.1021/acs.chemrev.7b00074.
[5] B. M. Colosimo, Q. Huang, T. Dasgupta, and F. Tsung, "Opportunities and challenges of quality engineering for additive manufacturing," *Journal of Quality Technology*, vol. 50, no. 3, 2018, doi: 10.1080/00224065.2018.1487726.
[6] Akash Kadam, Diwakar Reddy Peddinti, & Aditya Gupta. (2025). The Evolution of Smart Factories: Integrating IOT and Machine Learning in Supply Chain and Manufacturing. Journal of Computer Science and Technology Studies, 7(5), 251-261. https://doi.org/10.32996/jcsts.2025.7.5.32
[7] K. Siau and W. Wang, "Artificial intelligence (AI) Ethics: Ethics of AI and ethical AI," 2020. doi: 10.4018/JDM.2020040105.
[8] Kadam, A.A. & Pitkar, H. 2025, "Blockchain-Enabled Lean Automation and Risk Mitigation in Supply Chain 4.0 A Systematic Review and Future Directions", Journal of Economics, Finance, and Accounting Studies, vol. 7, no. 3, pp. 64-81.

[9] W. L. Ng, G. L. Goh, G. D. Goh, J. S. J. Ten, and W. Y. Yeong, "Progress and Opportunities for Machine Learning in Materials and Processes of Additive Manufacturing," 2024. doi: 10.1002/adma.202310006.

[10] S. Kasilingam, R. Yang, S. K. Singh, M. A. Farahani, R. Rai, and T. Wuest, "Physics-based and data-driven hybrid modeling in manufacturing: a review," *Prod Manuf Res*, vol. 12, no. 1, 2024, doi: 10.1080/21693277.2024.2305358.

[11] P. Azevedo, J. Gomes, and M. Romão, "Supply chain traceability using blockchain," *Operations Management Research*, vol. 16, no. 3, 2023, doi: 10.1007/s12063-023-00359-y.

[12] I. Jackson, D. Ivanov, A. Dolgui, and J. Namdar, "Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation," *Int J Prod Res*, vol. 62, no. 17, 2024, doi: 10.1080/00207543.2024.2309309.

[13] P. Helo and Y. Hao, "Artificial intelligence in operations management and supply chain management: an exploratory case study," *Production Planning and Control*, vol. 33, no. 16, 2022, doi: 10.1080/09537287.2021.1882690.