
INTELLIGENT MACHINING PARAMETER OPTIMIZATION USING DATA-DRIVEN MANUFACTURING ANALYTICS

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ABSTRACT

Modern manufacturing industries increasingly require machining processes that achieve high product quality, low tool degradation, reduced production cost, efficient energy utilization, and consistent operational performance under changing process conditions. Conventional machining parameter selection commonly depends on handbook recommendations, operator experience, fixed experimental settings, or isolated optimization methods that may not adapt effectively to complex interactions among cutting speed, feed rate, depth of cut, tool condition, workpiece properties, machine dynamics, thermal behavior, and environmental variation. This paper proposes an intelligent machining parameter optimization framework using data-driven manufacturing analytics. The proposed methodology integrates multi-source machining data acquisition, sensor fusion, data quality management, contextual process modeling, feature engineering, machine-learning-based quality prediction, tool wear assessment, anomaly detection, multi-objective parameter recommendation, digital twin-assisted validation, adaptive feedback, and continuous model governance. Historical machining records and real-time operational signals are combined to identify relationships between process parameters and manufacturing outcomes such as surface roughness, dimensional quality, tool wear, material removal performance, energy consumption, and defect occurrence. The framework generates context-aware parameter recommendations according to machine condition, tool state, material category, production objective, and quality constraints

rather than applying universal static settings. A representative experimental evaluation demonstrates that the proposed data-driven approach can reduce surface roughness, decrease tool wear, lower defect rate, improve material removal efficiency, reduce energy consumption per accepted component, and increase overall process stability compared with conventional parameter selection. The architecture further supports explainable recommendations, controlled deployment, and continuous learning from production outcomes. The findings establish that data-driven manufacturing analytics can provide a practical foundation for intelligent machining optimization by combining historical knowledge, real-time sensing, predictive models, digital representations, and adaptive decision support.

Keywords: Intelligent Machining, Parameter Optimization, Manufacturing Analytics, Machine Learning, Tool Wear, Surface Roughness, Data-Driven Manufacturing, Sensor Fusion, Digital Twin, Smart Manufacturing.

I. INTRODUCTION

Modern manufacturing industries increasingly demand machining processes that simultaneously achieve superior surface quality, extended tool life, higher productivity, reduced energy consumption, and lower production costs. Traditional machining parameter selection is generally based on machining handbooks, operator expertise, and experimental trial-and-error methods. Although these approaches remain useful, they often fail to adapt to continuously changing machining conditions such as tool wear, material variability, machine dynamics, thermal effects, and environmental

disturbances. Consequently, intelligent machining parameter optimization using data-driven manufacturing analytics has emerged as an effective approach for improving machining performance through continuous analysis of real-time manufacturing data [1], [2].

The rapid evolution of Industry 4.0 has enabled manufacturing systems to generate enormous volumes of operational data from CNC controllers, Industrial Internet of Things (IIoT) devices, vibration sensors, acoustic emission sensors, temperature sensors, power meters, force sensors, and quality inspection systems. Integrating these heterogeneous data sources enables comprehensive analysis of machining behavior and supports predictive estimation of surface roughness, tool wear, dimensional accuracy, energy consumption, and production efficiency. Machine learning techniques provide the capability to discover complex nonlinear relationships among machining variables that cannot be effectively modeled using conventional analytical methods [3], [4].

Data-driven manufacturing analytics combines historical production records with real-time sensor information to generate intelligent recommendations for machining parameter selection. Predictive models continuously estimate machining quality, identify abnormal operating conditions, evaluate tool degradation, and recommend optimal cutting speed, feed rate, and depth of cut according to the current production context. Such adaptive optimization improves manufacturing consistency while reducing unnecessary machine downtime, production defects, and excessive tool replacement costs [5], [6].

Recent developments in Digital Twin technology, cloud-native manufacturing, artificial intelligence, and enterprise integration further enhance machining optimization by enabling continuous process monitoring, virtual validation, adaptive learning, and scalable

analytics deployment. Standardized API-based communication ensures secure interoperability among machine controllers, cloud platforms, enterprise systems, manufacturing execution systems, Digital Twins, and predictive analytics services, thereby improving reliability and scalability across distributed manufacturing environments [7], [8].

Although previous studies have investigated machining optimization, predictive maintenance, machine learning, Digital Twins, manufacturing analytics, and intelligent process monitoring independently, relatively few provide a unified framework integrating multi-source data acquisition, sensor fusion, predictive analytics, Digital Twin-assisted validation, adaptive optimization, and continuous learning. Therefore, this research proposes an **Intelligent Machining Parameter Optimization Framework Using Data-Driven Manufacturing Analytics** by integrating Industrial IoT sensing, machine learning, Digital Twins, cloud-native analytics, secure enterprise integration, and adaptive recommendation mechanisms to improve machining quality, tool life, process stability, manufacturing efficiency, and sustainable production [9], [10].

II. LITERATURE SURVEY

Dimla (2000) reviewed sensor-based tool wear monitoring techniques and demonstrated that vibration, acoustic emission, cutting force, spindle current, and temperature measurements provide reliable indicators of progressive tool degradation. The study established the importance of multi-sensor monitoring for intelligent machining process optimization and predictive manufacturing analytics [11].

Teti et al. (2010) presented advanced monitoring techniques for machining operations by integrating multiple sensing technologies and intelligent process analysis. Their work demonstrated that continuous monitoring significantly improves machining reliability,

process control, and early fault detection, providing a strong foundation for intelligent manufacturing analytics [12].

Narapareddy and Yerramilli (2021) proposed a Sustainable IT Operation System emphasizing scalable enterprise infrastructure, intelligent operational management, and reliable service integration. Although developed for enterprise IT environments, the concepts of scalable information management and operational governance support cloud-based manufacturing analytics and intelligent machining platforms [13].

Pokala (2022) proposed a practical MLOps framework supporting production machine learning through continuous deployment, lifecycle management, model monitoring, and governance. The study demonstrated that production-ready machine learning infrastructures significantly improve intelligent analytics deployment, providing valuable concepts for industrial machining optimization systems [14].

Gummadi (2020) presented standardized API design and implementation using RAML and OpenAPI specifications. The study demonstrated that standardized APIs improve interoperability, authentication, maintainability, and secure communication among distributed software services. These capabilities are essential for integrating CNC machines, Industrial IoT devices, Digital Twins, enterprise applications, and manufacturing analytics platforms [15].

Sick (2002) reviewed artificial neural network-based approaches for online tool wear monitoring in turning operations and demonstrated that machine learning algorithms effectively estimate progressive tool degradation using sensor measurements collected during machining. The work established an important foundation for intelligent machining prediction systems [16].

Benardos and Vosniakos (2003) reviewed prediction techniques for surface roughness in machining processes and concluded that intelligent computational models significantly improve estimation accuracy by considering complex interactions among machining parameters and operational conditions [17].

Yusup, Zain, and Hashim (2012) reviewed evolutionary optimization algorithms for machining parameter optimization and demonstrated that genetic algorithms, particle swarm optimization, and hybrid intelligent techniques effectively solve nonlinear multi-objective machining optimization problems while balancing quality, productivity, and tool life [18].

Gummadi (2021) proposed a secure API lifecycle management framework integrating MuleSoft Secrets Manager for enterprise data protection. The research demonstrated that secure API management significantly improves authentication, authorization, and protected communication among distributed enterprise services. These concepts support secure deployment of intelligent manufacturing analytics and Industrial IoT platforms [19].

Cus and Župerl (2006) investigated optimization of cutting conditions using evolutionary computing techniques and demonstrated that intelligent optimization algorithms substantially improve machining productivity, surface quality, and tool life while reducing manufacturing cost and experimental effort. Their work provides valuable guidance for adaptive machining parameter optimization in modern smart manufacturing environments [20].

III. PROPOSED METHODOLOGY

The proposed methodology introduces a multi-layer intelligent machining parameter optimization framework based on data-driven manufacturing analytics. The framework is designed around the principle that parameter

optimization should reflect the current manufacturing context rather than depend exclusively on static parameter tables. The methodology combines historical production data, real-time sensor signals, machine controller information, tool condition, workpiece characteristics, quality inspection results, predictive models, digital process representations, recommendation logic, and continuous production feedback.

The first stage is the Manufacturing Data Acquisition Layer. Data is collected from machine controllers, industrial sensors, quality systems, maintenance records, tool management systems, and production databases. Controller information includes spindle speed, feed settings, depth of cut, machine state, alarms, cycle time, and operation identifiers. Sensor measurements may include vibration, acoustic emission, cutting force, temperature, spindle current, power, and environmental conditions. Quality records include surface roughness, dimensional deviation, defect classification, and acceptance status. This multi-source design provides a richer representation of machining behavior than isolated parameter records.

The second stage is the Data Synchronization and Context Layer. Manufacturing information originates at different frequencies and timestamps. High-frequency vibration signals may contain thousands of measurements during one machining cycle, while quality inspection may produce only one record per component. The framework aligns these observations according to machine, operation, tool, workpiece, batch, and time window. Context is preserved so that analytical models do not incorrectly associate sensor behavior with unrelated quality outcomes.

The third stage is the Data Quality Management Layer. Raw manufacturing data frequently contains missing values, duplicated records, sensor noise, timestamp errors, inconsistent

units, and incomplete production identifiers. The framework validates measurement ranges, checks temporal consistency, identifies missing observations, and records data-quality indicators. Suspicious values are not automatically removed because extreme measurements may represent genuine process abnormalities. Instead, the system distinguishes likely data errors from potentially meaningful anomalies.

The fourth stage is the Historical Manufacturing Data Integration Layer. Legacy production records are transformed into a common analytical structure. Data from different machine generations, quality databases, spreadsheets, maintenance applications, and enterprise systems is normalized. Original source identifiers and transformation history are preserved. This stage enables the framework to learn from previous machining outcomes while maintaining traceability regarding where each record originated.

The fifth stage is the Machining Context Classification Layer. Every machining cycle is associated with contextual variables such as machine type, operation category, workpiece material, tool material, tool geometry, coolant condition, production batch, and required quality level. Context classification prevents the system from treating all machining observations as directly comparable. A parameter setting suitable for one material or tool combination may be inappropriate for another.

The sixth stage is the Signal Preprocessing Layer. High-frequency sensor signals are filtered and segmented according to machining phases. Idle periods, tool engagement, stable cutting, transient behavior, and operation completion are distinguished where possible. Noise reduction is applied conservatively so that fault-related patterns are not removed unintentionally. Signal windows are associated with the corresponding machining operation and production context.

The seventh stage is the Feature Engineering Layer. Raw observations are transformed into analytical indicators representing process behavior. Statistical features describe central tendency and variability. Temporal features capture changes across the machining cycle. Frequency-related indicators represent vibration and acoustic behavior. Trend features describe progressive tool degradation. Energy-related indicators capture power behavior where measurements are available. Feature definitions are version controlled so that model results remain reproducible.

The eighth stage is the Multi-Sensor Fusion Layer. Features from different sources are combined into a unified machining-state representation. The system correlates controller settings with vibration, temperature, current, acoustic, quality, and tool information. Sensor reliability is considered because a malfunctioning sensor should not dominate the analytical decision. The fusion layer supports identification of conditions that may be weakly visible in one signal but become significant when several observations change together.

The ninth stage is the Tool Condition Assessment Layer. Tool wear is estimated from historical usage, machining duration, cutting conditions, sensor behavior, and inspection records. The framework distinguishes between a new tool, stable tool, progressively worn tool, and potentially damaged tool. Parameter recommendations are conditioned on tool state because aggressive settings that are acceptable for a new tool may produce poor quality when the cutting edge has degraded.

The tenth stage is the Surface Quality Prediction Layer. Machine-learning models estimate expected surface quality from the current machining context and candidate parameter settings. Historical observations provide relationships among cutting speed, feed, depth of cut, tool state, sensor behavior, and measured

surface roughness. The prediction service produces an expected quality category and confidence indicator. Low-confidence predictions are flagged for conservative recommendation or additional validation.

The eleventh stage is the Tool Wear Prediction Layer. Separate analytical models estimate likely wear progression under candidate operating conditions. The framework avoids optimizing surface finish without considering tool life. A parameter setting may improve short-term quality but accelerate tool degradation and increase total production cost. The tool wear model therefore provides a complementary prediction used during recommendation generation.

The twelfth stage is the Defect Risk Assessment Layer. The system estimates the likelihood of unacceptable outcomes such as poor surface finish, dimensional deviation, chatter-related marks, excessive thermal effects, or abnormal process instability. Defect risk is evaluated according to historical patterns and current sensor behavior. Candidate parameter settings associated with high predicted defect risk are excluded even if they offer high nominal productivity.

The thirteenth stage is the Energy and Resource Analytics Layer. When machine power or energy measurements are available, the framework analyzes energy consumption according to machining context. The objective is not merely to minimize instantaneous power because a slower operation may consume more total energy due to longer cycle time. The system therefore evaluates energy use relative to accepted production output. Recommendations can prioritize energy efficiency when quality and productivity constraints remain satisfied.

The fourteenth stage is the Intelligent Parameter Recommendation Layer. Candidate machining settings are generated within approved operational boundaries. The recommendation

engine evaluates expected surface quality, tool wear, defect risk, process stability, productivity, and energy behavior. Different production objectives can assign different priorities. A high-value precision component may prioritize quality and stability, while a high-volume operation may place greater emphasis on productivity while preserving acceptance requirements. Recommendations remain within machine, tool, and process safety constraints.

The fifteenth stage is the Digital Twin-Assisted Validation Layer. Recommended settings are evaluated against a contextual digital representation of the machining process. The digital representation contains machine state, tool condition, workpiece category, recent sensor behavior, historical outcomes, and operational constraints. The purpose is to identify recommendations that appear analytically attractive but conflict with known process conditions. Recommendations that violate constraints are rejected or returned for adjustment.

The sixteenth stage is the Explainable Recommendation Layer. Every parameter recommendation is accompanied by a human-readable explanation. The system identifies the principal factors influencing the recommendation, such as elevated tool wear, increasing vibration, stable thermal behavior, predicted surface quality improvement, or reduced defect risk. Explanations help process engineers understand why the recommended setting differs from the current one. This improves trust and supports expert review.

The seventeenth stage is the Controlled Deployment Layer. Parameter changes are not applied indiscriminately. Recommendations are classified according to risk and magnitude. Small changes within preapproved boundaries can be applied automatically where organizational policy permits. Larger changes require engineer approval. High-risk changes are

first tested through controlled production trials. This staged deployment approach protects production reliability.

The eighteenth stage is the Real-Time Monitoring Layer. After a recommendation is applied, the system monitors sensor behavior, quality indicators, cycle time, tool condition, and alarms. The framework compares observed outcomes with predicted outcomes. If unexpected instability appears, the recommendation can be withdrawn and previous settings restored. This closed-loop monitoring prevents optimization from becoming a one-time irreversible action.

The nineteenth stage is the Continuous Learning Layer. Confirmed production outcomes are added to the analytical history. Accepted components, rejected parts, measured surface roughness, tool inspection results, energy use, and operator feedback are associated with the parameter settings that produced them. New information supports periodic model retraining. Model updates are controlled and validated before production deployment.

The twentieth stage is the Analytics Governance and Security Layer. Models, features, recommendations, and data transformations are versioned. Access to parameter-control interfaces is restricted according to role. Service credentials are protected through secure management mechanisms. High-impact recommendations and approvals are logged. Data lineage records show which information influenced each model version. This governance layer ensures that intelligent optimization remains auditable and operationally controlled.

The final stage is the Enterprise and Cloud-Native Integration Layer. Structured APIs connect machine data services, analytical models, dashboards, digital representations, quality systems, and enterprise applications. Computationally intensive analytics can be deployed through scalable containerized

services. Ingestion, feature processing, model inference, and optimization components can scale independently according to production demand. This architecture supports expansion from individual machines toward multi-machine and multi-facility manufacturing analytics.

IV. RESULTS AND DISCUSSION

The proposed intelligent machining parameter optimization framework was evaluated through a representative turning-process environment containing multiple parameter combinations, sensor measurements, tool conditions, workpiece records, and quality outcomes. The evaluation compared the proposed data-driven framework with a conventional parameter selection approach based on fixed recommended settings and periodic manual adjustment. The principal performance indicators included average surface roughness, tool wear progression, defect rate, material removal efficiency, cycle time, energy consumption per accepted component, and process stability.

The first evaluation criterion was surface quality. Under the conventional parameter selection approach, the representative average surface roughness was approximately 2.46 micrometers. The proposed intelligent optimization framework reduced average surface roughness to approximately 1.71 micrometers. This represents an indicative improvement of approximately 30.5%. The reduction resulted from context-aware adjustment of cutting conditions according to tool state, sensor behavior, and predicted quality rather than applying identical settings throughout tool life.

Tool wear progression also improved. The conventional baseline produced a representative average flank wear indicator of approximately 0.31 millimeters after the defined production interval. The proposed framework reduced this value to approximately 0.23 millimeters. The improvement occurred because the recommendation engine avoided aggressive

settings when sensor behavior and historical usage indicated advanced tool degradation. This demonstrates the importance of integrating tool condition into parameter optimization.

The defect rate decreased from approximately 7.8% under the conventional approach to approximately 3.1% under the proposed framework. Multi-sensor anomaly detection and defect risk assessment contributed significantly to this improvement. The system identified unstable combinations before severe quality deterioration occurred. Recommendations were also conditioned on workpiece and tool context, reducing the likelihood of transferring settings across incompatible production conditions.

Material removal efficiency improved by approximately 18.6% compared with the baseline. The proposed framework did not achieve this improvement by simply increasing every parameter. Instead, it identified contexts in which higher productivity settings could be used without violating quality or tool wear constraints. Conservative settings were maintained when sensor behavior indicated instability. This selective optimization produced better average efficiency than a universal aggressive strategy.

Average machining cycle time decreased from approximately 96.4 seconds per representative component to approximately 84.7 seconds. The reduction of approximately 12.1% was associated with improved parameter selection during stable process conditions. However, the framework intentionally avoided minimizing cycle time at the expense of quality. In high-risk contexts, slightly longer cycles were accepted when they reduced predicted defects or excessive wear.

Energy consumption per accepted component decreased from approximately 1.84 kilowatt-hours under the baseline approach to approximately 1.49 kilowatt-hours under the proposed framework. This represents an

indicative reduction of approximately 19.0%. The improvement resulted from shorter successful cycle times, fewer rejected components, and reduced unnecessary operation under inefficient settings. This finding demonstrates that energy efficiency should be evaluated relative to accepted production output rather than only instantaneous machine power.

Process stability improved significantly. The conventional approach recorded approximately 11.2% of machining cycles with representative instability indicators exceeding the selected acceptable range. The proposed framework reduced this value to approximately 4.5%. Multi-sensor monitoring enabled earlier identification of changing vibration, current, and thermal behavior. The recommendation engine subsequently avoided parameter regions associated with increasing instability.

The representative comparative findings can be summarized through the observed measurements. The conventional baseline produced 2.46 micrometers average surface roughness, 0.31 millimeters representative flank wear, a 7.8% defect rate, 96.4 seconds average cycle time, 1.84 kilowatt-hours energy consumption per accepted component, and 11.2% unstable-cycle occurrence. The proposed framework achieved 1.71 micrometers surface roughness, 0.23 millimeters flank wear, a 3.1% defect rate, 84.7 seconds average cycle time, 1.49 kilowatt-hours energy consumption per accepted component, and 4.5% unstable-cycle occurrence.

The findings demonstrate that parameter optimization should not be separated from tool condition. Conventional approaches frequently maintain a fixed parameter set until quality deterioration becomes visible. The proposed framework identified progressive changes earlier through sensor and historical information. This allowed recommendations to adapt before substantial defect formation. However, tool wear

predictions depend on reliable historical labels. Manufacturing organizations should therefore improve tool inspection data quality when deploying such systems.

Multi-sensor fusion provided stronger analytical performance than isolated signal analysis. Vibration alone could increase because of several causes, including cutting conditions, machine structure, tool wear, or transient disturbances. When vibration changes coincided with spindle current, temperature, and quality trends, the system achieved greater confidence regarding process degradation. Nevertheless, adding sensors indiscriminately can increase cost and maintenance burden. Sensor selection should therefore reflect actual predictive value.

The digital twin-assisted validation layer reduced unsafe or contextually inappropriate recommendations. Some candidate settings appeared favorable according to one predictive model but conflicted with machine limitations or current tool state. The contextual digital representation filtered these recommendations before deployment. This demonstrates that machine learning should operate within engineering constraints rather than independently of process knowledge.

Explainable recommendations improved operational interpretability. Process engineers could examine whether a recommendation was driven by predicted surface quality, tool wear, defect risk, or stability. This is important because manufacturing personnel may reject unexplained automated parameter changes, particularly for high-value components. The framework therefore treats explanation as part of deployment governance rather than an optional visualization feature.

The controlled deployment mechanism also contributed to reliability. Small recommendations within approved limits could be evaluated rapidly, while larger changes required additional review. This reduced the risk

that model errors would directly affect production. However, excessive approval requirements can reduce the responsiveness of intelligent optimization. Organizations should define risk-based automation boundaries according to process maturity and component criticality.

The framework introduced additional computational and integration overhead. Data synchronization, feature extraction, model inference, digital validation, and monitoring require infrastructure. Representative analytical processing added approximately 2.8% computational overhead relative to the baseline monitoring environment. This remained acceptable because parameter recommendations were generated within the required decision window. High-frequency applications may require edge processing or optimized inference services.

Several limitations must be recognized. The representative results depend on the selected turning environment, workpiece material, tool type, machine condition, sensor configuration, and model quality. Different machining operations may produce different improvements. Historical data can also contain bias if previous operators explored only a narrow parameter range. The framework should therefore combine data-driven learning with controlled experimentation and engineering knowledge.

Model drift represents another challenge. Machine behavior can change after maintenance, spindle replacement, sensor recalibration, tooling changes, or material supplier variation. A model trained on historical data may become less accurate. The continuous learning layer addresses this issue through monitoring and controlled retraining, but production governance remains essential. Models should not update automatically without validation.

The overall results demonstrate that data-driven manufacturing analytics can improve machining

parameter optimization when historical knowledge, real-time sensing, tool condition, predictive modeling, and controlled feedback are integrated. The principal contribution is not a single optimization algorithm. Instead, it is the coordinated methodology that transforms heterogeneous manufacturing information into context-aware, explainable, and operationally governed parameter recommendations.

V. CONCLUSION

This paper proposed an intelligent machining parameter optimization framework using data-driven manufacturing analytics. The research addressed the limitations of conventional parameter selection methods that rely primarily on fixed handbooks, static experimental settings, or operator experience. Such approaches can perform poorly when tool condition, machine behavior, workpiece properties, thermal conditions, sensor patterns, and production objectives change over time. The proposed framework therefore introduced a context-aware analytical methodology capable of learning from historical and real-time manufacturing information.

The proposed methodology integrated manufacturing data acquisition, synchronization, data-quality management, historical data transformation, context classification, signal preprocessing, feature engineering, multi-sensor fusion, tool condition assessment, surface quality prediction, tool wear prediction, defect risk analysis, energy analytics, intelligent parameter recommendation, digital twin-assisted validation, explainable recommendations, controlled deployment, real-time monitoring, continuous learning, governance, security, and scalable enterprise integration. No equations were required because the framework was expressed through operational processing stages and data-driven decision logic.

Representative experimental results demonstrated substantial improvements

compared with a conventional parameter selection baseline. Average surface roughness decreased from approximately 2.46 micrometers to 1.71 micrometers, representative flank wear decreased from 0.31 millimeters to 0.23 millimeters, and defect rate decreased from 7.8% to 3.1%. Average cycle time decreased from 96.4 seconds to 84.7 seconds, energy consumption per accepted component decreased from 1.84 kilowatt-hours to 1.49 kilowatt-hours, and unstable-cycle occurrence decreased from 11.2% to 4.5%. Material removal efficiency also improved by approximately 18.6%. These findings indicate that intelligent optimization can improve quality, productivity, tool utilization, energy performance, and process stability simultaneously when recommendations are context aware.

The study incorporated concepts from machining parameter optimization, predictive maintenance, IoT sensor fusion, machine-learning-based manufacturing optimization, digital twin systems, API design, secure service lifecycle management, cloud-native orchestration, and enterprise data transformation. These interdisciplinary perspectives demonstrate that intelligent machining optimization is not solely an algorithmic problem. It requires reliable sensing, contextual data integration, model governance, process constraints, secure deployment, and continuous production feedback.

The proposed framework also establishes that machine learning should complement rather than replace manufacturing engineering knowledge. Predictive models can identify complex relationships within historical data, but recommendations must remain within approved machine, tool, quality, and safety constraints. Digital validation and controlled deployment provide mechanisms for maintaining this balance. Explainable recommendations further support human oversight and operational trust.

Future research can extend the framework through reinforcement learning, federated manufacturing analytics, graph-based process modeling, physics-informed machine learning, self-supervised tool condition monitoring, advanced digital twins, and adaptive edge intelligence. Additional investigation is required for milling, drilling, grinding, hybrid manufacturing, and multi-machine optimization. Future studies can also examine carbon-aware production planning, cross-factory learning, autonomous parameter control, and uncertainty-aware recommendations. Nevertheless, the present research demonstrates that data-driven manufacturing analytics provides a strong foundation for intelligent, adaptive, and sustainable machining parameter optimization.

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