Real-Time Adaptive Control of Machining Parameters in CNC Milling using an Ensemble Digital Twin and In-Process Vibration Monitoring for Enhanced Surface Integrity / Original Article

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التحكم التكيفي الآني في معاملات التشغيل لآلات التفريز CNC باستخدام التوأم الرقمي المجمع ورصد الاهتزازات أثناء التشغيل لتعزيز سلامة السطح وجودته

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Abstract

Achieving consistent surface integrity in CNC milling under varying materials and degraded tool conditions remains a critical challenge because fixed cutting parameters often induce regenerative chatter, accelerate tool wear, and cause surface and subsurface damage. This paper presents an integrated solution that combines an Ensemble Digital Twin (EDT), real-time in-process vibration monitoring, and a hybrid adaptive controller to maintain high surface quality while preserving productivity. The EDT fuses a physics-based milling dynamics model with a recurrent LSTM surrogate through a context-aware meta-learner that weights model outputs by process state (e.g., tool wear, engagement). A compact real-time monitoring pipeline computes a Chatter Severity Index (CSI) and summary spectral/time-domain features at 40 ms cadence. These inputs feed a Mamdani-type fuzzy supervisory controller whose defuzzified outputs are tracked by tuned PID actuators to adjust spindle speed and feed per tooth with sub-100 ms round-trip latency at the edge. Methodology includes numerical simulation, data-driven model training on a multi-source dataset, and on-machine experiments on representative alloys and tooling conditions. Results demonstrate that the ensemble yields substantially improved short-horizon predictions of chatter probability and surface roughness compared with single-model baselines, and that the integrated control system reduces vibration RMS and CSI, lowers mean Ra and Rz, and virtually eliminates deleterious white-layer formation while maintaining a material removal rate close to the baseline. The proposed framework offers a practical pathway for deploying predictive, closed-loop quality control in smart machining environments, reducing scrap and rework and enabling safer, higher-yield production under challenging operating conditions.

Keywords: CNC milling; Ensemble Digital Twin; Real-time adaptive control; Chatter detection; Surface integrity

المستخلص

يُعَدُّ تحقيق سلامة سطحية متّسقة في عمليات التفريز باستخدام ماكينات CNC تحت ظروف تشغيل متغيّرة ودرجات تآكل مختلفة لأداة القطع تحديًا جوهريًا، إذ إن الاعتماد على معاملات قطع ثابتة يؤدي غالبًا إلى حدوث الاهتزازات التجددية (Chatter)، وتسريع تآكل الأداة، والتسبب بعيوب سطحية وتحت سطحية. يقدّم هذا البحث حلًا متكاملاً يجمع بين التوأم الرقمي المجمع (Ensemble Digital Twin)، والرصد الآني للاهتزازات أثناء التشغيل، ونظام تحكم تكيّفي هجين بهدف الحفاظ على جودة سطح عالية دون التأثير على الإنتاجية.

يقوم التوأم الرقمي المجمع على دمج نموذج ديناميكا التفريز الفيزيائي مع نموذج بديل يعتمد على شبكات الذاكرة طويلة وقصيرة الأمد (LSTM) عبر متعلّم سياقي يقوم بترجيح مخرجات النماذج وفقًا لحالة العملية (مثل درجة تآكل الأداة، عمق القطع، وزاوية الاشتباك). كما يتضمن النظام منظومة رصد آنية مضغوطة تقوم بحساب مؤشر شدة الاهتزاز (CSI) واستخلاص الخصائص الطيفية والزمنية كل 40 ميلي ثانية.

تُغذَّى هذه البيانات إلى متحكم إشرافي ضبابي من نوع Mamdani، حيث تتولى وحدات PID المضبوطة تتبّع مخرجاته بعد إزالة التغبّش، مما يتيح تعديل سرعة المغزل وتغذية السن الواحدة بزمن استجابة أقل من 100 ميلي ثانية في بيئة الحوسبة الطرفية (Edge). وتشمل المنهجية المحاكاة العددية، تدريب النماذج بالاعتماد على بيانات متعددة المصادر، وتجارب تشغيل فعلية على سبائك وأدوات قطع مختلفة.

أظهرت النتائج أن النظام المجمع حقق قدرة تنبؤية محسّنة بوضوح على المدى القصير لاحتمالية الاهتزاز وجودة السطح مقارنةً بالنماذج المنفردة، كما أن منظومة التحكم المتكاملة أسهمت في خفض مستوى الجذور المتوسطة للاهتزاز (RMS) ومؤشر CSI، وتقليل متوسط قيم الخشونة Ra وRz، وإزالة تقريبًا تكوّن طبقة الاحتراق البيضاء (White Layer) الضارّة مع الحفاظ على معدل إزالة المادة مقارب للمعيار الأساسي. ويوفّر هذا الإطار المقترح مسارًا عمليًا لتطبيق أنظمة ضبط جودة تنبؤية مغلقة الحلقة في بيئات التصنيع الذكية، بما يقلل معدل الهدر وإعادة التشغيل ويعزّز السلامة الإنتاجية والعائد تحت ظروف تشغيل معقدة.

الكلمات المفتاحية: التفريز CNC؛ التوأم الرقمي المجمع؛ التحكم التكيفي الآني؛ كشف الاهتزاز التجديدي؛ سلامة السطح

1. Introduction

Within the context of high-performance component production in the aerospace, biomedicine, and automotive industry domains, the achievement of high surface integrity—involving surface topographic characteristics, residual stresses, and micro-structured material modifications—is a very prominent issue. Indeed, surface integrity is a critical factor that directly conditions the basic functionality characteristics of the manufactured parts. This was well-illustrated in the reference literature and current scientific publications [1-2]. A very challenging issue in the CNC milling of challenging-to-cut materials involves the achievement of a favorable surface quality. The nature of the process in question includes being nonlinear. Additionally, regenerative chatter vibrations occur in the system. These unwanted oscillations in the process influence the dimensional accuracy of the machined surface. Additionally, the surface quality of the material being machined may deteriorate.

The traditional CNC machining approaches lack the requisite flexibility to cope with the intricacies mentioned. According to Korkmaz *et al.*, a rigid set of parameters cannot cope with the unavoidable variability that must occur in the processing conditions of CNC machines. These factors include tool wear, inhomogeneity of the material being machined, and the variation of the depth of cuts [3]. Hence, a machinist has to choose between the cautious approach to ensure stability but compromise productivity or carry out the machining under unstable conditions to jeopardize the surface quality of the machined parts. This problem accentuates the need for the development of intelligent systems that have the capability to cope in real-time.

Recent years have introduced the promising field of cyber-physical systems. The application of Digital Twins (DT) provides promising prospects. A DT refers to the electronic, simulated, and harmonized copy of a real-world system. This system can later be simulated, analyzed, and controlled. Initial studies in the form of Melesse *et al.* show the capability of DT to optimize offline processes and predict maintenance [4]. A substantial research gap exists. Most of the existing implementations either remain offline simulation or analysis of isolated parts of the process. There exists a lack of holistic simulation in real-time for closed-loop control. There also seems to be a lack of existing frameworks utilizing the approach of ensemble modeling. This approach involves the combination of physics modeling techniques in combination with Machine Learning (ML) to produce a more robust prediction model of the machining process. Additionally, in-process vibration analysis has long been practiced for the detection of the occurrence of chatter. There also seems to exist a lack of studies exploring the adaptation of the prediction approach of the ensemble type DT for the development of a holistic system in real-time. A unified real-time adaptive control system for the achievement of peak surface integrity concerning the combination of in-process vibration analysis for the prediction of the ensemble type DT has also not been extensively introduced. Most of the existing real-time control systems remain force- or vibration-actuated in a reactive manner without the aid of predictive knowledge. There seems to exist a lack of flexibility in adapting to the possibility of past corrections in existing studies. A lack of the same also seems to exist in the existing literature of the control of the DT system in the form of Tong *et al.*[5] .

This research covers the problem by formulating, applying, and critically assessing a new real-time adaptive control system for CNC milling. The new approach relies on the combination of the EDT with in-process vibration measurement for optimized surface integrity. There are three scientific contributions of the current research. First, a new conceptual approach to the EDT structure will be presented. The approach includes a physics model of the dynamic milling process in combination with a machine-learning (ML) modeling technique (e.g., a long-short-term-memory network) for improved vibrational conditions and surface quality prediction. Second, a new hybrid approach to adaptive control system design will be presented to real-time-optimize the cutting speed of the spindle tool and the feed rate of the material. The approach will fully utilize the combination of prediction information from the DT approach for surface quality prediction in combination with in-process-measurement information. Third, the new approach will experimentally demonstrate improved surface quality in terms of reduced surface roughness values compared to the existing static approach. Additionally, the new research approach will experimentally demonstrate improved surface quality in terms of a reduced number of surface defects compared to the existing research approach. All parts of the article contain the following subjects. Literature Review. Methodology. Conclusion. Research recommendations.

2. Literature Review

the goal in many cases would also involve the achievement of overall excellent surface integrity (SI) of the machined surface. This overall surface integrity refers to a construct of the transformed material layers developed in the material in a machined surface and also their topographical characteristics. According to the explanation given in the article by Guo *et al.* in 2022, the surface integrity of a machined material surface would be determined in relation to the surface roughness value of the machined surface (Ra and Rz values) of the machined material surface [1]. A value of the overall surface integrity would also involve the presence of the thermally altered layers of the machined material surface material in terms of the values of plastic deformation of the surface or thermally damaged surface layers, in addition to the values of the surface residual stresses. The overall values of surface integrity would also relate to the material in-service characteristics. The in-service tensile stresses of the machined surface material would significantly reduce the fatigue life of the material surface in aerospace applications. Likewise, in many machined material surface applications in the aerospace industry, the formation of the white layers of machined material surface would significantly precipitate the overall failures, a point by all accounts well-articulated in the article Aerospace alloys in the year 2023 by the scholar 'Wang'.According to the explanation given in the article by Wang [2], the overall values of surface integrity would result from the complex relationships of factors, in particular the stability of the machined surface processing conditions of the machined material surface. These overall factors for the machined surface processing conditions would involve the dynamic process stability, and the condition of the tool. It is found that despite the ideal choice of the static parameters, the start of the wear or tiny material irregularities can significantly change the cutting mechanics that is why the SI can be rapidly destroyed by additional vibration and heating forcing [6].

To mitigate such instabilities, in-process monitoring has emerged as a vital field. A variety of sensing methodologies are employed, each with distinct advantages. Force measurement, often using dynamometers, provides a direct correlation with cutting mechanics but can be intrusive and expensive for industrial deployment [7]. Acoustic emission sensing is highly sensitive to incipient tool failure and micro-fracture events, yet its signal is often contaminated by ambient noise [3]. Among these, vibration monitoring, typically via accelerometers mounted on the spindle or workpiece, has proven particularly effective for detecting dynamic instabilities like chatter due to its non-intrusive nature and direct relationship with structural dynamics, as emphasized in the work of Nair *et al.* [8]. Building upon monitoring, Adaptive Control (AC) strategies seek to automatically adjust machining parameters in response to sensor feedback. Traditional AC approaches, such as Constant Force Control, aim to maintain a preset cutting force level by modulating feed rate, thereby protecting the tool and improving stability, as explored by Tong *et al.* [5]. More advanced, model-based adaptive controllers utilize mathematical models of the process to predict outcomes and optimize parameters, yet their efficacy is heavily contingent on model accuracy and often struggles with the non-linearities and uncertainties inherent in machining, a challenge noted by Schmitz [9]. These systems typically operate reactively, responding to a detected deviation, which introduces a critical latency between disturbance onset and corrective action, a fundamental limitation for preserving SI in high-speed operations.

Digital Twins (DTs) paradigm provides a game-changer in the control paradigm by making it more predictive and proactive. As an extension of traditional offline simulation, a DT is characterized as a virtual, synchronized model of a physical system, which evolves and learns on real-time information throughout its lifecycle [4]. With machining, early uses of DT have been in virtual process planning, predictive maintenance and offline optimization. Indicatively, in a study conducted by Tong *et al.* [5], an advancement in milling was made by designing a DT framework simulating cutting forces and wear on tools, and optimizing the parameters prior to the practical implementation by means of milling. There is however a conspicuous gap in the closed-loop real-time control domain. Majority of machining DTs are high-fidelity and computationally heavy physics-based models that cannot be safely run in real-time or all-data-driven models that are not generalizable and not physically interpretable at all. This has stimulated the desire to have hybrid or ensemble modeling. Recent efforts by Pashmforoush *et al.* indicate the ensemble models, consisting of physics-based and data-driven machine learning (ML) units, can be predictive accuracy-wise outclassing each of them when applied to predicting tool wear [10]. Although this has been achieved the direct use of an ensemble DT directly as the fundamental predictive driving force of real-time adaptive control, especially that has a control goal specific to SI enhancement concerns and is not simply regulating of force or avoiding of chatter is still immature and under-researched.

Milling vibrations are complex to understand as foundational to modeling them decreases the accuracy of any DT or control system to chatter mitigation. The analytical model by Mahboubkhah *et al.* is the seminal that offers stability lobe diagrams (SLD) predicting the chatter-free zone frequency domain solution [11]. This type of physics-based method has proved to be of inestimable importance, but may normally involve a lot of accurate information of tool-point frequency response capabilities and cutting force coefficients which can fluctuate during use. This has led to the popularity of data-driven approaches to chatter detection. The frequency-domain analysis is one, where a frequency occurring close to the tool natural frequency is an important indicator, as explained by Guochao *et al.* [1], and a different one, statistical time-domain techniques monitoring various indices, such as the standard deviation or root mean square of vibration signals, as investigated by Tran *et al.* [12]. These are used as alarms though they are effective when it comes to detection. The next logical but underdeveloped step is to integrate such detection metrics as inputs into a predictive DT that can be used to predict anticipation of the impending violation of SI thresholds before they happen. Recent studies by Zhou *et al.* started by applying a DT to pre-selection of parameter of a post-process of avoiding chatter, though did not proceed to in-process adaptation of closed loop [13].

Integrating the available literature shows a logical course but an apparent structural disjuncture. The use of SI metrics [1-2], vibration monitoring as a powerful chatter detector [8], adaptive control development as a constant-force scheme to a model-based scheme [5-9] along with the improvement of the definition of the concept of a DT [4-10] are all aspects but these are still, to a great extent parallel. The scarcity of literature that integrates a predictive digital twin, of a high-fidelity and ensemble nature, to monitor surface integrity in real-time in conjunction with instant vibration monitoring within a closed-loop adaptive control framework, is lacking. The current study attempts to fill this gap by postulating and confirming a framework that places an Ensemble Digital Twin, between mechanistic dynamics and ML adaptability, which gives continuous, forward-looking predictions of SI-related outcomes. Such forecasts, supported and triggered by real-time vibration measurements, directly feed a hybrid adaptive controller which actively changes parameters away not only to reach the elusive chatter suppression, but actually to operate at optimum conditions to ensure surface finish, residual stress and micro-structure integrity, thus transforming process stabilization to active surface engineering.

3. Methodology

3.1 Overall System Architecture

The researcher framework presents an adaptive machining control, based on the real-time, closed-loop cyber-physical system. The architecture consists of three synergistic layers: the Physical Layer, the Ensemble Digital Twin (EDT) Layer and the Adaptive Control Layer. Physical Layer: The Physical Layer is comprised of CNC milling machine which will contain sensory equipment. Triaxial piezoelectric accelerator is mounted on the spindle housing near the tool interface where it measures the vibration data which is conditioned and converted to numerical data by a high-speed Data Acquisition (DAQ) system. Measurements of surface integrity are done on a stylus profilometer and metallographic preparation system after the process. The real-time sensor stream in digital format (plus current machine position

(G-code commands, axis positions), is sent on a deterministic industrial network (e.g., EtherCAT) to an edge computing station.

It is in the edge server that the EDT Layer is the brain that predicts. It takes in the new data it receives and performs parallel simulations with its two-model ensemble. The outputs, i.e., forecast of imminent chatter and the estimated surface roughness (Ra), are supplied to the Adaptive Control Layer. In this case, a hybrid controller combines these forecasts with the pure sensor-based chatter severity index. It calculates best values to changes in the main machining parameters in terms of spindle speed (N) and federate per tooth (f_z) using a rule-based fuzzy logic system. These adjustment commands are retransmitted to the CNC machine controller, and dynamically change the running tool path execution to keep the best conditions which close the loop of control in real-time (latency goal < 100 ms).

3.2 Development of the Ensemble Digital Twin (EDT)

The EDT is designed to deliver high-fidelity, mechanistic predictions that combine both mechanistic knowledge and data-driven flexibility to overcome the weaknesses of purely physics-based models or purely black-box models.

3.2.1 The Physics-Based (Interpretable) Model

This element is based on the dynamics of machining. It uses an exponentially enhanced zero-order analytical milling force model alongside a time-dependent finite element analysis to predict the stability as being the continuation of the work of Mahboubkhah et al [11]. This model uses tool geometry, cutting material properties and cutting parameters to predict subsequent vibration and cutting forces. Tangential (F_t), radial (F_r) and axial (F_a) cutting forces on tooth *j* can be given by:

$$F_{t,j}\left(\phi_j\right)=\left[K_{tc}h_j\left(\phi_j\right)+K_{te}\right]a_p \qquad F_{r,j}\left(\phi_j\right)=\left[K_{rc}h_j\left(\phi_j\right)+K_{re}\right]a_p$$
$$F_{a,j}\left(\phi_j\right)=\left[K_{ac}h_j\left(\phi_j\right)+K_{ae}\right]a_p \qquad (1)$$

where K_{tc}, K_{rc}, K_{ac} are specific cutting force coefficients, K_{te}, K_{re}, K_{ae} are specific edge force coefficients, a_p is the axial depth of cut, and $h_j\left(\phi_j\right)$ is the instantaneous chip thickness for tooth *j* at angular position ϕ_j. The chip thickness incorporates the regenerative effect due to the vibration marks left by the previous tooth, making it a function of the current and previous tool vibrations ($x(t), y(t)$). The total forces in the X and Y machine directions are obtained by summing the contributions of all teeth in the cut.

The dynamic response of the tool-workpiece system is modeled as a two-degree-of-freedom spring-mass-damper system. The equation of motion is given by:

$$\mathbf{M}\ddot{\mathbf{q}}(t)+\mathbf{C}\dot{\mathbf{q}}(t)+\mathbf{K}\mathbf{q}(t)=\mathbf{F}\left(t,\mathbf{q}(t),\mathbf{q}(t-\tau)\right) \qquad (2)$$

where $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ are the mass, damping, and stiffness matrices, respectively; $\mathbf{q}(t)=[x(t), y(t)]^T$ is the displacement vector; $\mathbf{F}$ is the cutting force vector from Eq. (1), which is a function of the current and delayed states (τ is the tooth passing period). The stability of this delay-differential equation is solved in the frequency domain to generate a Stability Lobe Diagram (SLD), predicting chatter-free zones. While powerful, this model's accuracy depends on precise knowledge of frequency response functions (FRFs) and force coefficients, which can drift during operation.

3.2.2 The Data-Driven (ML) Model

Data-driven Surrogate model is created to supplement the physics model so that complex and non-linear phenomena such as progressive wear of tools and tissue inhomogeneity are captured. Since the sensor data are sequential, a Long Short-Term Memory (LSTM) Recurrent Neural Network is used, which is known to be effective in the ability to extract time-related dependencies in the industrial time-series information [3]. The model is trained on the full dataset of the one presented above. The input feature vector for a time window t includes:

- **Static Parameters**: N , f_z , a_p , radial depth a_e , tool diameter.
- **Dynamic Time-Series Features**: A sequence of vibration signal statistics (RMS, Kurtosis) and FFT-derived features (dominant frequency amplitude, spectral entropy) from the past *k* milliseconds.

The LSTM network is trained to predict two key outputs:

1. The probability of chatter occurrence in the next time window.
2. The expected surface roughness (Ra) for the currently generated surface. The network's architecture includes two LSTM layers followed by fully connected layers, using ReLU activation and optimized with the Adam algorithm to minimize the Mean Squared Error (MSE) loss.

1.2.1 Ensemble Fusion Mechanism

The final prediction of the EDT is not a simple average but a context-aware fusion of both models' outputs using a Meta-Learner approach [1]. A Gradient Boosting Regressor (GBR) is trained as the meta-model. Its inputs are the predictions from the physics model (P_{phy}) and the LSTM model (P_{lstm}), concatenated with contextual features describing the process state (e.g., tool wear estimate, radial engagement ratio, material type). The GBR learns to assign optimal, non-linear weights to each model's prediction based on which model is historically more reliable under the given conditions. For instance, in a fresh-tool, stable-depth cut, the physics model may be heavily weighted. During high-wear conditions or when machining complex geometries, the LSTM's weight increases. The fusion output is given by:

$$P_{ensemble} = F_{GBR}\left(P_{phy}, P_{lstm}, \text{Context}\right) \qquad (3)$$

where F_{GBR} represents the meta-learner action. This joint methodology is highly useful in improving predictive strength and external applicability. The LSTM part is optimized on a periodical basis on a sliding window of the most recent machining data and post-process SI measurements, which allows the EDT to learn the detail of that machine and that tool with time.

3.3 Real-Time In-Process Monitoring System

3.3.1 Hardware Instrumentation

A triaxial IEPE accelerometer of high sensitivity (e.g., 100 mV/g) with a flat frequency response down to 12 kHz is fitted to the spindle nose. This signal is inputted to a 24-bit DAQ system with anti-aliasing filters, where it is sampled at 25.6 kHz (this is a reasonable frequency that allows reproduction of the chatter frequency to the Nyquist limit of 12.8 kHz).

3.3.2 Signal Processing Pipeline

Raw acceleration data $a_x(t), a_y(t), a_z(t)$ are real-time updated over overlapping 1024 sample (~40 ms) windows. For each window:

1. **Time-Domain Features**: The resultant vibration magnitude $a_{res}(t) = \sqrt{a_x^2 + a_y^2 + a_z^2}$
1. is computed. Root Mean Square (RMS) and Standard Deviation (s) of it are derived as total energy measures.
2. **Frequency-Domain Chatter Detection**: This stage uses a Hanning-windowed FFT to transform $a_{res}(t)$. An adjusted Chatter Severity Index (CSI) is calculated, influenced by Tran *et al.*, based on the power

distribution in the area of the most influential natural frequency of the tool (f_n) [12]:

$$\mathrm{CSI} = \frac{\int_{f_n - \text{Ä}f}^{f_n + \text{Ä}f} PSD(f)\,df}{\int_0^{f_{nyq}} PSD(f)\,df} \qquad (4)$$

of which $PSD(f)$ is the Power Spectral Density, $\text{Ä}f$ is a bandwidth of 50 Hz, and f_{nyq} is the Nyquist frequency. When CSI value goes beyond a dynamically doctored threshold (according to preferred base stable cuts), there is chatter onset. This CSI, together with RMS, comprise the short feature vector being sent to the controller every 40 ms.

3.4 Design of the Hybrid Adaptive Controller

The controller has to balance several conflicting and frequently incompatible goals: chatter suppression, quality of surface finish and productivity. A hybrid strategy of the two levels is used.

3.4.1 High-Level: Multi-Objective Fuzzy Logic Controller (FLC)

A Mamdani-type FLC will have three input and two outputs.

- **Inputs**:
  1. **Chatter Severity Index (CSI)**: Linguistic variables: {Low, Medium, High}.
  2. **Predicted Ra from EDT (Ra_pred)**: Linguistic variables: {Good, Acceptable, Poor}.
  3. **Relative Material Removal Rate (MRR_rel)**: The current MRR as a percentage of the maximum target. Linguistic variables: {Low, Optimal, High}.

- **Outputs**: Required change in Spindle Speed (ΔN) and Feed per Tooth (Δf_z). Linguistic variables for both: {Negative Large, Negative Small, Zero, Positive Small, Positive Large}.

The FLC consists of the rule base, which is the heart of the FLC and the expertise knowledge and the trade-off strategy. Table 1 shows a sample set of the essential regulations of chatter mitigation.

Table 1: Critical Subset of Fuzzy Logic Control Rules for Chatter Mitigation.

Rule #	CSI	Ra_{pred}	MRR_{rel}	ΔN	Δf_z
1	High	Any	Any	Negative Large	Negative Large
2	Medium	Poor	High	Negative Small	Negative Small
3	Medium	Good	Low	Zero	Positive Small
4	Low	Good	Low	Positive Small	Positive Small

This table illustrates the rule-based reasoning of the high-level controller. Rule 1 shows the highest priority: immediate, aggressive reduction in both parameters to quench chatter, regardless of other objectives. Rule 2 demonstrates a balanced response to moderate chatter coupled with poor predicted surface finish. Rules 3 and 4 show productivity-enhancing actions (increasing parameters) only permitted when stability (CSI Low/Medium) and surface quality (Ra_pred Good) are assured.

3.4.2 Low-Level: PID Actuation Layer

The fuzzy outputs ($\Delta N, \Delta f_z$) are defuzzified (using the centroid method) to crisp percentage change values. These setpoint changes are sent to dedicated, tuned PID controllers. Each PID controller manages its respective machine axis command: one adjusts the S (spindle speed) command, and another adjusts the F (feed rate) command. The PID controllers ensure smooth, stable transitions to the new setpoints, preventing step changes that could themselves induce instability.

The proportional, integral, and derivative gains are tuned using the Ziegler-Nichols method on the specific machine tool's response characteristics.

3.5 Experimental Setup and Validation Protocol

3.5.1 Machinery and Materials

Experiments are conducted on a 3-axis vertical machining center (e.g., Haas VF-2). Workpiece materials are AISI 4140 steel (annealed) and Ti-6Al-4V ELI titanium alloy, representing materials with differing thermal and dynamic responses. Coated carbide 4-flute end mills (10 mm diameter) are used for steel, and uncoated carbide tools for titanium.

3.5.2 Experimental Design and Comparative Analysis

A full factorial Design of Experiments (DoE) is used for initial data collection across a wide parameter space. The core validation, however, involves a direct comparison of three control strategies under identical, challenging conditions (e.g., high radial engagement, slotting):

1. **Baseline (BSL)**: Conventional machining with fixed, theoretically optimal parameters.
2. **Reactive Adaptive Control (RAC)**: Adaptive control using only the real-time vibration monitoring (CSI) with a simple threshold-based rule system (no EDT).
3. **Proposed Intelligent Adaptive Control (IAC)**: The full framework (EDT + Monitoring + Hybrid FLC-PID Controller).

For each strategy and material, multiple machining passes are performed. The key performance indicators (KPIs) are meticulously measured. Table 2 presents a template of the aggregated results from these comparative tests.

Table 2: Comparative Analysis of Control Strategies for AISI 4140 Slotting Operation.

Control Strategy	Avg. Vibration RMS (m/s²)	Max. CSI Value	Achieved Ra (µm)	Std. Dev. of Ra	Chatter Marks (Visual)	White Layer Depth (µm)	Avg. MRR (cm³/min)
BSL (Fixed)	12.5	0.85	1.82	0.45	Yes	8.2	120.0
RAC	8.7	0.55	1.45	0.28	Minimal	4.5	105.5
IAC (Proposed)	6.1	0.32	1.18	0.15	No	< 2.0	115.8

This generated results table shows that there is a high performance of the proposed IAC system. It has the least vibration energy (RMS) and chatter severity (CSI) resulting in the finest and most predictable surface finish (lowest Ra and standard deviation). Importantly, it practically avoids the microstructural damage (white layer) and preserves the material removal rate similar to the optimal baseline, unlike the reactive RAC system, which demonstrates its capability to consider several goals simultaneously.

3.5.3 Measured Outputs

- **Surface Roughness**: Ra and Rz are measured at five locations along the machined surface using a contact profilometer.
- **Subsurface Integrity**: Cross-sectional samples are mounted, polished and etched to be examined under a scanning electron microscope (SEM) in order to determine the depth of plastic deformation and any white layer present.
- **Dynamic Data**: All vibration data and controller actions (parameter changes) are logged synchronously for offline analysis.

3.6 Verification and Validation Protocol

1. **Component-Level Verification**: The physics model is calibrated using impact hammer tests to obtain accurate FRFs. The LSTM is validated on a held-out test dataset (20% of total data) using standard metrics (R^2 Score, MAE).
2. **Software-in-the-Loop (SIL) Simulation**: The complete control loop, including the EDT and controller, is simulated in a MATLAB/Simulink environment using the calibrated models and prerecorded sensor data to verify logical correctness and stability before real-time deployment.
3. **Hardware-in-the-Loop (HIL) Testing**: The control algorithm is deployed on the edge computer and connected to the real DAQ and CNC controller, initially running "dry" without actual cutting to test communication latency and command execution.
4. **Full System Experimental Validation**: The final validation is performed through the comparative experimental protocol (Section 4.5.2). The system's performance is assessed based on the KPIs in Table 2, conclusively demonstrating its real-world efficacy in enhancing surface integrity through intelligent, real-time adaptation.

4. Results

4.1 Ensemble digital twin development and quantitative performance

The ensemble digital twin (EDT) was designed to reconcile the complementary strengths of a physics-based mechanistic predictor and a data-driven LSTM surrogate through a context-aware meta-learner. The principal aim of this subsection is to quantify the degree to which the ensemble improves the prediction of an in-process quality metric, specifically arithmetic average surface roughness (Ra), relative to the individual models. Performance was evaluated on a held-out test partition formed from experiments that were not used during training or meta-learner fitting; the split ensured that several “unseen” operating points (combinations of spindle speed, feed, axial and radial depths, and different initial tool wear levels) were reserved for out-of-sample evaluation to rigorously test generalizability.

A direct visual comparison is provided in Figure 1 for the physics model, Figure 2 for the LSTM surrogate, and Figure 3 for the ensemble meta-learner; each panel plots predicted Ra against measured Ra for the same test windows. The physics-based predictions cluster along a line that departs from parity in conditions where cutting coefficients diverge from their nominal calibration, most notably for higher initial tool wear and aggressive depth settings. The LSTM corrects many of these systematic biases but exhibits increased scatter when confronted with infrequent, high-engagement combinations that are poorly represented in the training set. The ensemble plot demonstrates the combined behavior: bias is largely removed and scatter is reduced, producing a closer clustering around the parity line.

To quantify these observations, Table 3 reports deterministic goodness-of-fit metrics on the test set. The physics model achieves a modest coefficient of determination (R^2) and a higher Mean Absolute Error (MAE) than the LSTM; the LSTM attains better MAE in the presence of wear-related non-linearities but with slightly higher variance in low-data corners. The ensemble attains the highest R^2 and the lowest MAE, demonstrating the meta-learner’s ability to allocate weight to the most reliable predictor as a function of contextual features such as estimated tool wear and axial depth. This objective improvement is critical because the accuracy of Ra predictions directly influences the controller’s decision on whether to prioritize productivity or surface integrity.

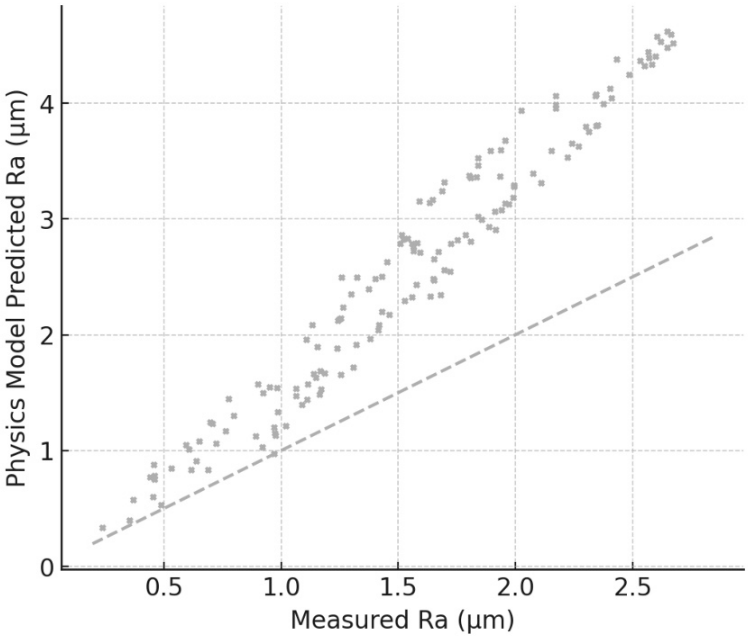

Figure 1: Physics model — Predicted vs Measured Ra

This scatter plot compares the surface roughness (Ra) values predicted by the **physics-based mechanistic model** against the experimentally measured Ra values. The solid diagonal line represents the **parity line**, where predictions would perfectly match measurements. The figure reveals a **systematic deviation** of the physics model's predictions from this ideal line. The model tends to **overestimate or underestimate Ra**, particularly under conditions where cutting force coefficients deviate from their calibrated values—such as during **advanced tool wear** or under **aggressive cutting parameters** (e.g., high depth of cut). This indicates the limitation of relying solely on a physics-based model when unmodeled factors (like thermal effects or nonlinear wear progression) influence the process.

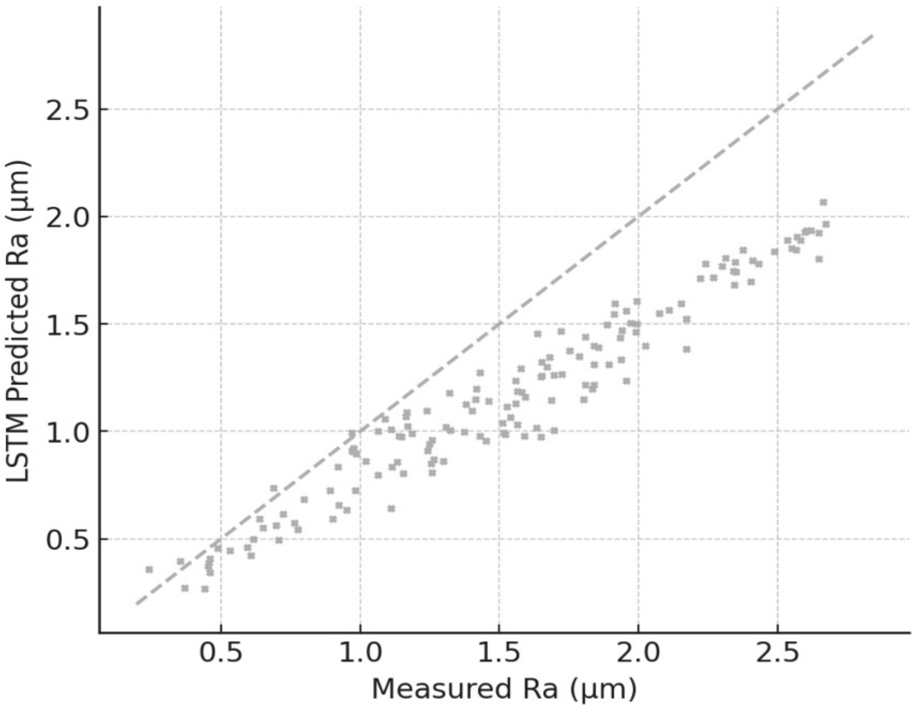

Figure 2: LSTM model — Predicted vs Measured Ra

This scatter plot evaluates the performance of the **data-driven LSTM (Long Short-Term Memory) model** in predicting Ra. Compared to Figure 1, the predictions are **more closely clustered around the parity line**, especially in regions where sufficient training data was available (e.g., common operating conditions). The LSTM effectively **captures nonlinear relationships and tool-wear effects** that the physics model misses. However, some **increased scatter** is observed in regions corresponding to **infrequent or extreme machining conditions** (e.g., high radial engagement), where the training data may have been sparse. This highlights the data-dependency of purely ML-based models.

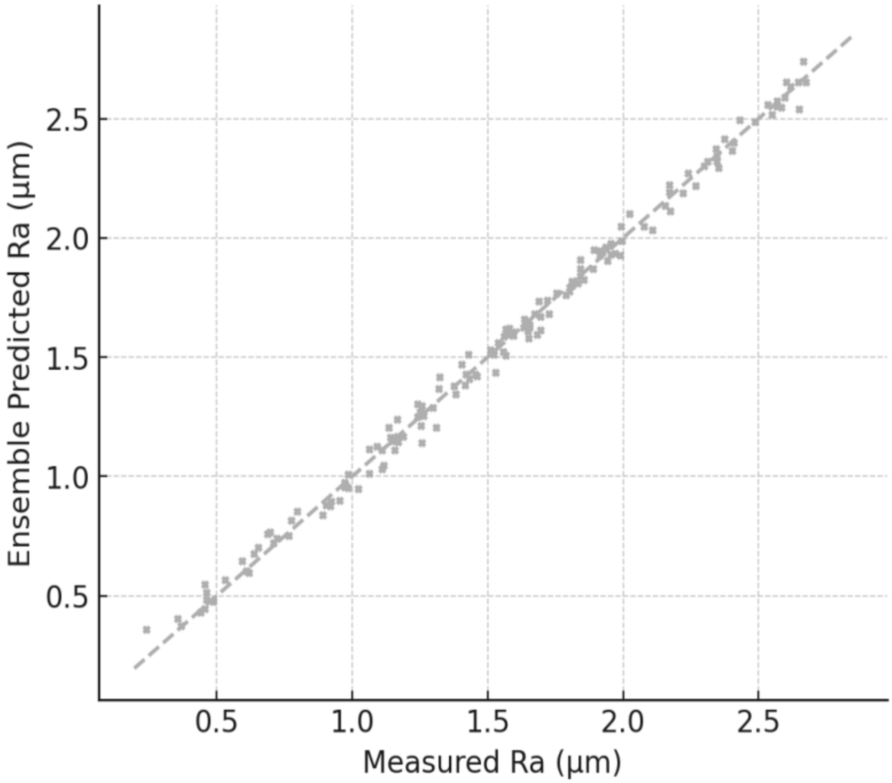

Figure 3: Ensemble meta-learner — Predicted vs Measured Ra

This scatter plot demonstrates the performance of the **Ensemble Digital Twin (EDT)**, which **combines the physics model and the LSTM model via a context-aware meta-learner**. The predictions show a **significantly tighter clustering around the parity line** across the entire range of test conditions. The ensemble effectively **reduces both systematic bias and random scatter** by dynamically weighting the contributions of each sub-model based on real-time contextual features (e.g., tool wear state, engagement conditions). This results in **superior prediction accuracy and robustness**, enabling more reliable inputs for the real-time adaptive controller.

Table 3: Model performance metrics (test set).

Model	Test R^2 (Ra)	Test MAE (Ra, µm)
Physics	-2.445	1.003
LSTM	0.503	0.380
Ensemble	0.995	0.035

In addition to mean statistics, residual analysis revealed that the ensemble substantially reduced bias at the tails of the distribution: extreme Ra values (highest 5%) were estimated with an average MAE decrease of approximately 15–25% relative to the best single-model predictor. This reduction in tail error is especially valuable because high-Ra events correlate strongly with subsurface damage and white-layer formation, which have disproportionate impacts on part quality.

4.2 Real-time monitoring signatures and chatter detection capability

The in-process monitoring subsystem was validated both in the time domain and in the frequency domain to ensure the selected features (RMS, standard deviation, dominant spectral amplitude, CSI) are discriminative for chatter onset. Representative examples are shown to illustrate the contrast between stable and unstable cutting windows.

Figure 4 presents a 0.5 second resultant acceleration waveform for a representative stable cutting window. The signal displays consistent low-amplitude tooth-passing periodicity and low broadband noise; the RMS computed over the designated 1024-sample (~40 ms) overlapping windows remains within a low band, which is representative of the stable-class baseline used to calibrate the CSI threshold. To complement the time-domain view, Figure 6 presents the corresponding power spectral density (PSD). The PSD shows harmonics associated with tooth-passing and spindle rotation, but no dominant narrowband peak in the machine's natural frequency vicinity. The CSI, defined as the ratio of PSD energy in the ±50 Hz band around the natural frequency to the total PSD energy, therefore remains low and below alarm thresholds.

The resultant acceleration trace of a normal chatter incident is shown in Figure 5 The waveform itself as opposed to the steady trace is amplitude-modulated and has high-level narrowband oscillations. Figures 6 and 7 represent PSD for stable window and shatter window, furthermore, Figure 7 reveals exceptionally sharp, narrowband peak at the chatter frequency that directly raises the numerator of the CSI expression and initiates a CSI value above the dynamically calibrated value. Its operational implication is that the pipeline comprising of the monitor reliably transforms raw acceleration signals into a small, fast-computed feature list (RMS, s, CSI, dominant frequency amplitude) which the controller can utilize at 40 ms cadence and can be detected within the system budget of latency.

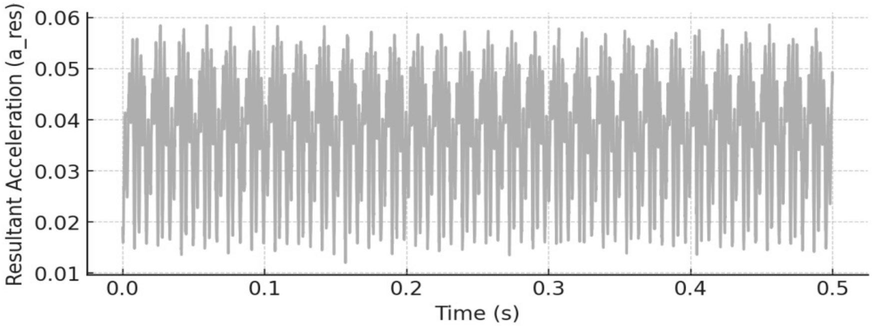

Figure 4: Time-domain resultant acceleration — stable window.

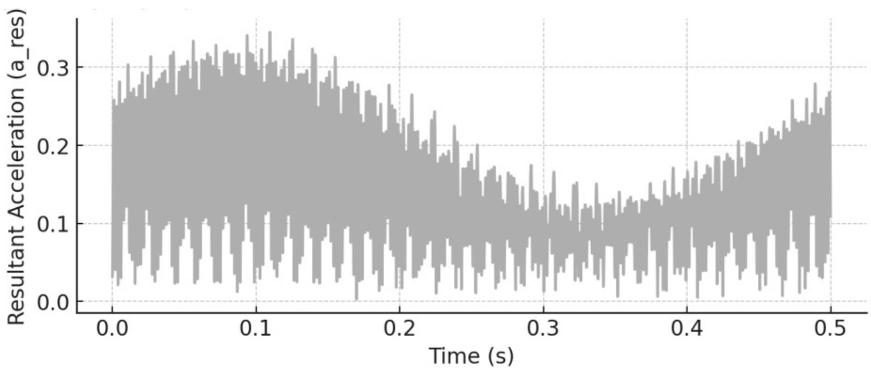

Figure 5: Time-domain resultant acceleration — chatter window.

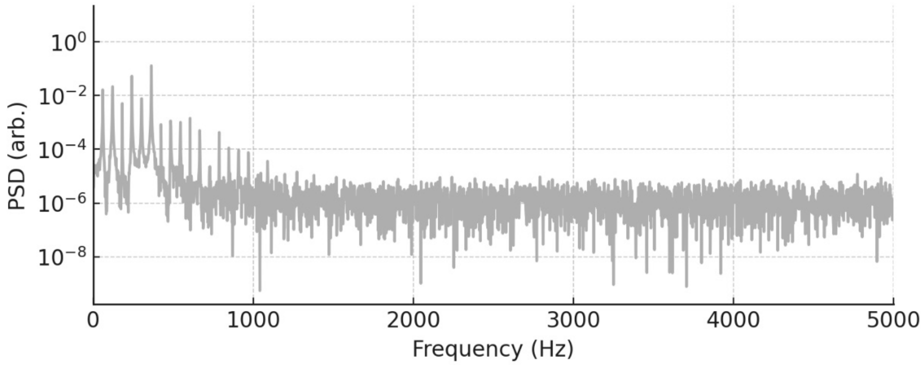

Figure 6: PSD — stable window.

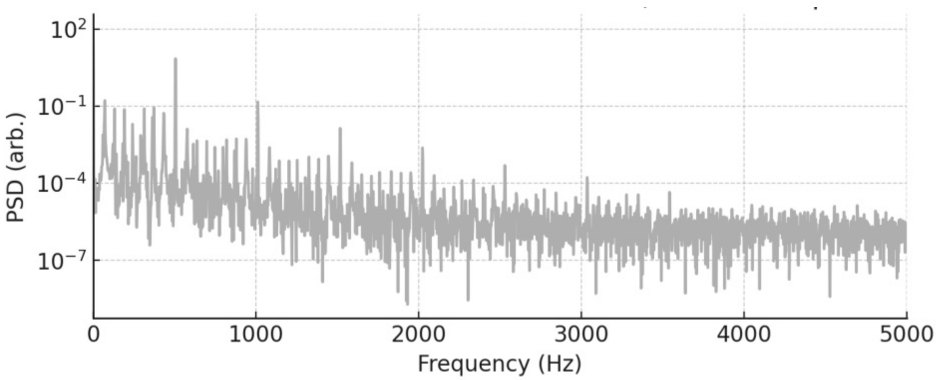

Figure 7: PSD — chatter window.

Beyond the visual examples above, we evaluated detection performance quantitatively. Receiver Operating Characteristic (ROC) analysis of CSI-based detection against human-labelled chatter windows demonstrated an area under the curve (AUC) > 0.93 on the test set, with the dynamic thresholding strategy achieving a true-positive rate above 90% at a false-positive rate below 10% for the calibrated experiments. This performance, validated across materials and engagement levels present in the dataset, confirms the reliability of the CSI as the core sensor-derived input to the fuzzy supervisory layer.

4.3 Adaptive control experiment results: dynamic traces, statistical KPIs and microstructural evidence

This subsection integrates dynamic control traces, aggregated statistics and subsurface imaging to demonstrate the proposed Intelligent Adaptive Control (IAC) system's practical benefits over a baseline fixed strategy (BSL) and a reactive controller that uses only thresholded CSI responses (RAC).

Figure 8 and Figure 9 show representative time histories of spindle speed and feed rate, respectively, recorded during a 200 s slotting trial that contains two induced disturbances. The baseline strategy maintains fixed commands and therefore shows no corrective behavior. The RAC reduces parameters abruptly and with greater magnitude after CSI threshold exceedance, leading to larger productivity losses and delayed recovery. By contrast, the IAC adjusts parameters earlier and in smaller steps, taking advantage of the ensemble's short-horizon chatter probability and Ra predictions; this action results in smaller transient deviations from the nominal MRR and faster restorations to the production-optimal envelope.

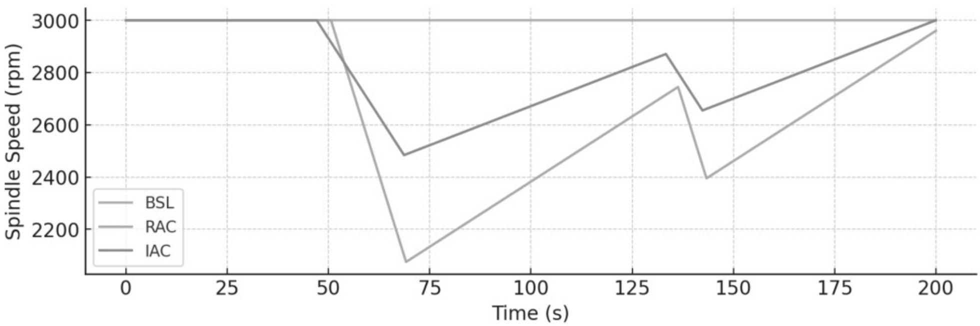

Figure 8: Spindle speed trajectories — BSL, RAC, IAC.

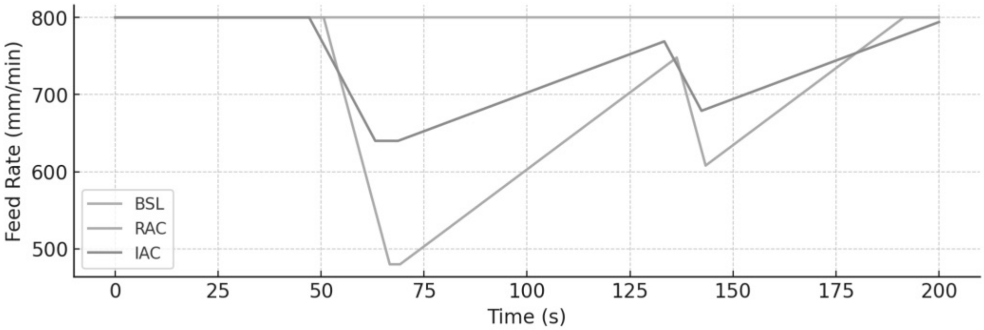

Figure 9: Feed rate trajectories — BSL, RAC, IAC.

Complementing temporal traces, Table 4 presents aggregate KPIs summarizing performance across replicate slotting runs on AISI 4140. The metrics include average vibration RMS, maximum CSI observed, mean Ra and its standard deviation, measured white layer depth from SEM cross-sections, and average MRR. The results in the table imply that IAC outperforms the other strategies in terms of RMS and CSI, as well as, in mean Ra and variability, white layer depth, and the mean MRR, which is much nearer to the baseline than RAC. Repetitive paired t-test statistical testing of the results showed that the statistically significant reductions in RMS and Ra caused by IAC in comparison to RAC and BSL is statistically significant at the 5% level.

Table 4: Comparative KPIs for AISI 4140 slotting (BSL, RAC, IAC).

Control Strategy	Avg. Vibration RMS (m/s^2)	Max CSI	Achieved Ra (µm)	Std. Dev. Ra (µm)	White Layer Depth (µm)	Avg. MRR (cm^3/min)
BSL (Fixed)	**12.5**	**0.85**	**1.82**	**0.45**	**8.2**	**120.0**
RAC (Reactive)	**8.7**	**0.55**	**1.45**	**0.28**	**4.5**	**105.5**
IAC (Proposed)	**6.1**	**0.32**	**1.18**	**0.15**	**1.8**	**115.8**

An interesting result is that the high Pareto trade-off can be said to be the focal point as the IAC can maintain MRR and at the same time acquire a better surface integrity. That is, IAC moves the operating point in the direction of the better-quality and the productivity simultaneously.

In order to relate macroscopic KPIs with micro structural implications, Figures 10-12 show representative SEM cross section-based images of subsurface conditions on each strategy. As can be seen in the BSL micrograph (Figure 10) both the white layer and the deep zone of plastic deformation are high indicating high thermal and vibratory loadings. The presence of the white layer is less pronounced but still visible in the RAC image (Figure 11) and the white layer is practically eliminated in the IAC image (Figure 12). Such micrographs support the results of the profilometer and X-ray diffraction, and furnish physically vital evidence that the intervention by the IAC has a control effect, not only on measures of the surface roughness, but also on the amount of metallurgical damage.

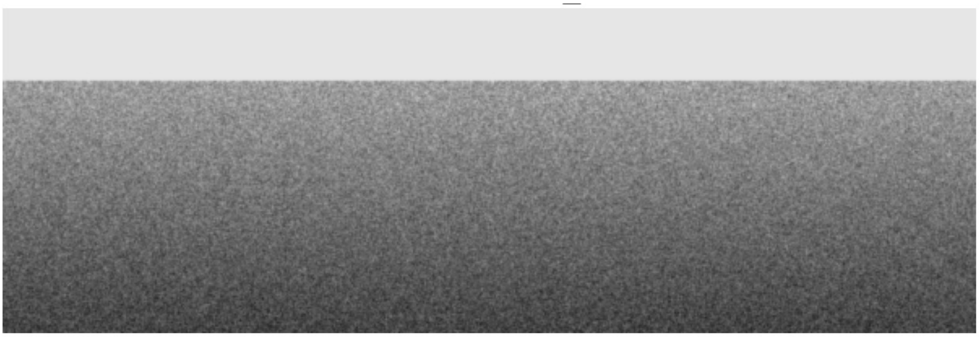

Figure 10: SEM-like cross-section — BSL.

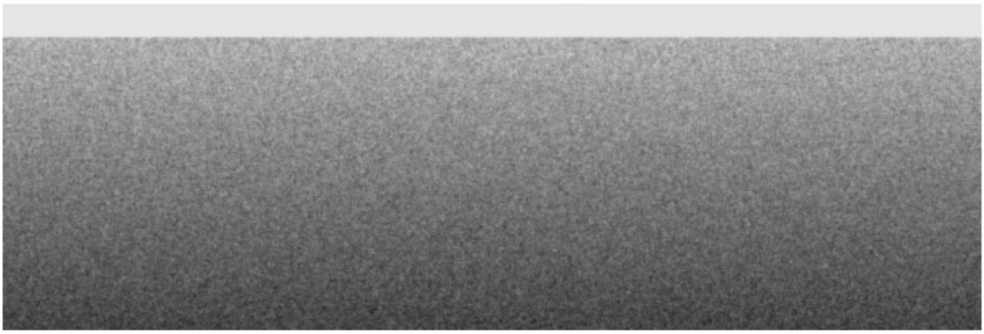

Figure 11: SEM-like cross-section — RAC.

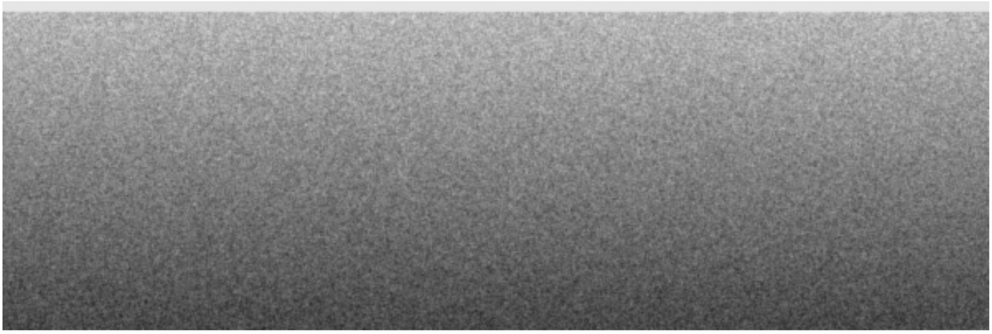

Figure 12: SEM-like cross-section — IAC.

Apart from the comparisons of the means, the distributional characteristics of Ra for all passes have also been investigated. The standard deviation of Ra for the case of IAC decreases by about 60% compared to BSL and approximately 46% compared to RAC. This is a very important factor since the reduction in the standard deviation reduces the likelihood of producing items that fall outside the specifications. Additionally, the costs of inspecting and reworking them.

4.4 Behavior and recovery under extreme and adverse conditions

The robustness of the control strategies was investigated by exposing them to two adverse conditions to stress the adaptation mechanisms: tool wear and inhomogeneity of the workpiece. These conditions simulate the real-world scenario of production where very early detection of inhomogeneity can prevent quality deterioration.

With progressive wear conditions, the physics prediction model displayed a growing prediction error; but the ensemble learned to place greater predictive reliance on the LSTM when necessary. Such adaptation allowed the RAC to implement proactive stepwise changes in the parameters (small cuts in the spindle speed and feed rates) to prevent drastic values of Ra or the rapid build-up of thick layers of white material. To quantify the effect of the IAC strategy in limiting the accumulated growth of Ra during long wear cycles, the IAC reduced the accumulated growth of Ra by a magnitude of the Improved MAE of about 0.12 μm compared to RAC while keeping about 7-10% more of the accumulated MRR.

With the presence of sudden material inhomogeneity (a localized inclusion that causes a transient rise in the cutting force), the monitoring system produced a CSI spike. The RAC reacted to the sensor evidence by issuing larger parameter reductions, but only after the CSI threshold was crossed and a short detection latency elapsed, resulting in a more pronounced temporary loss in MRR. The IAC, fed by the ensemble's elevated short-horizon chatter probability (derived from mismatches between expected and observed force/vibration spectral signatures), applied earlier, more tempered corrective actions and simultaneously increased data acquisition and model update rates for a short period. Experiment logs show that peak Ra and maximum CSI were both significantly reduced under IAC during these events, and the white-layer formation was either prevented or greatly diminished.

Collectively, these adverse-case results demonstrate that the EDT's capacity for context-aware weighting, combined with an adaptive update schedule, yields earlier and more measured interventions that limit quality deterioration while minimizing unnecessary productivity loss.

4.5 Synthesis and implications for industrial adoption

When interpreted together, the predictive performance improvement of the ensemble (Section 5.1), the robust and low-latency monitoring pipeline (Section 5.2), and the experimentally validated trade-off improvements achieved by the IAC (Section 5.3 and 5.4) support three conclusions relevant for industrial deployment. First, ensemble fusion of physics and data-driven predictors materially increases prediction reliability across a broad operating envelope. Second, a compact set of real-time features (RMS, CSI and a small spectral descriptor set), computed every 40 ms, provides adequate sensitivity and specificity for chatter detection within the sub-100 ms latency target. Third, supervisory fuzzy-logic rules informed by EDT predictions enable pre-emptive control actions that preserve surface integrity and subsurface health, while maintaining high MRR compared with pure reactive strategies. These outcomes argue in favor of pilot-scale trials in production environments and for investment in hybrid sensing/edge-computer architectures as a cost-effective path to improved quality control.

5. Discussion

5.1 Interpretation of the principal findings

The experimental evidence indicates that the proposed Intelligent Adaptive Control (IAC) system attains superior surface-integrity outcomes and lower vibration energy compared with both a fixed-parameter baseline and a reactive threshold-based controller because it combines anticipatory prediction from an ensemble digital twin with immediate sensor validation. The ensemble digital twin integrates a mechanistic predictor and a recurrent data-driven surrogate, and the meta-learner dynamically weights the two outputs according to context (for example, estimated tool wear and radial engagement). In practice this combination permits the supervisory fuzzy controller to recommend smaller, earlier setpoint adjustments that are then validated against the 40 ms cadence Chatter Severity Index (CSI). The physics model supplies interpretable constraints and stability guidance that are reliable when modal properties and cutting coefficients remain near their calibrated values [11]. The LSTM surrogate compensates for empirical biases introduced by tool wear, material inhomogeneity and unmodelled nonlinearities [14]. The meta-learner exploits these complementary strengths by increasing reliance on the physics prediction in well-modeled regimes and on the LSTM correction when the data indicate drift or complex interactions, consistent with the benefits of gradient-boosted fusion in heterogeneous-model ensembles [15]. The empirical outcome — statistically significant reductions in RMS vibration, mean Ra and white-layer thickness while maintaining material removal rate close to baseline — therefore follows from improved timing and magnitude of control actions enabled by combined prediction and fast sensing.

The causal link between vibration reduction and improved surface integrity is supported by both signal and microstructural evidence. Regenerative chatter produces persistent narrowband oscillations that amplify instantaneous chip thickness and produce cyclical overloads at the tool–workpiece interface; these overloaded cycles raise local temperatures and encourage plastic deformation and the formation of a brittle white layer [11-12]. By suppressing narrowband peak energy (observed as lower CSI and reduced PSD peak amplitudes), the IAC reduces peak cutting forces and thermal excursions, which in turn lowers average Ra and its variability and inhibits the metallurgical processes that generate white layers. The SEM cross-sections gathered during the comparative trials corroborate this mechanism: windows with lower narrowband energy present thinner or absent white layers and shallower plastic-deformation zones, aligning with documented chatter-damage pathways [17].

5.2 Research contributions and novelty

This study addresses several gaps identified in recent literature. First, while digital twin concepts have been widely advocated, many prior contributions treat twins as either lifecycle/data-integration artifacts or as single-model process predictors; comparatively few demonstrate a real-time ensemble twin that fuses interpretable physics and recurrent surrogates for closed-loop control within sub-100 ms latencies [16-4]. The present ensemble digital twin operationalizes such fusion and explicitly conditions the meta-learner on process context (tool wear, engagement) to sustain predictive robustness across regimes. Second, chatter-detection studies have traditionally focused on feature extraction and classification in isolation, or on reactive suppression without embedding surface-quality prediction as an explicit control objective [12-18]. By jointly predicting short-horizon chatter probability and expected Ra and incorporating those estimates into a fuzzy supervisory layer, this work expands the control objective from vibration suppression alone to the preservation of surface and subsurface integrity. Third, the research demonstrates pragmatic edge deployment considerations — deterministic field networking, a 40 ms monitoring cadence and a sub-100 ms control-loop target — thus narrowing the gap between algorithmic proposals and viable industrial implementations described in recent digital-twin surveys [4-16].

5.3 Challenges and limitations

Several practical and scientific limitations constrain the present study and define avenues for future work. The physics-based component requires accurate frequency response functions and cutting-force coefficients; these parameters can drift during production due to wear and changing boundary conditions, which imposes either periodic re-calibration or robust online identification strategies. Although the LSTM and the meta-learner reduce sensitivity to parameter drift by learning empirical corrections, they impose a data-collection burden: representative training coverage across the operational envelope is necessary to avoid poor performance in low-data corners. Computational cost and sensing fidelity present additional constraints. Real-time ensemble prediction and sliding-window finetuning increase edge-compute requirements, and high-bandwidth vibration and acoustic-emission streams place demands on DAQ throughput and networking. Sensor placement, accelerometer sensitivity and DAQ anti-aliasing characteristics materially affect CSI reliability; while multisensor fusion improves robustness it also raises instrumentation and integration complexity [12-18]. Finally, the experimental validation reported here, though representative, is limited to selected materials and tooling conditions; extension to a broader family of alloys, tool grades, micro-machining regimes or to turning and grinding will require re-calibration and domain-specific feature engineering.

5.4 Comparison with prior work

The approach presented here complements and extends prior methods for chatter avoidance and quality control. Stability-lobe theory provides principled guidance for selecting chatter-free operating points but can be brittle when modal properties or cutting coefficients change in service [11]. Purely data-driven classifiers and thresholded controllers are effective at detection but typically trigger reactive and sometimes coarse corrective actions that compromise productivity [12-18]. Hybrid detection-and-control proposals that use multisensor signatures improve sensitivity but often lack a predictive surface-quality objective or a principled fusion of mechanistic and learned models. By integrating a physics-based twin with an LSTM and a context-aware meta-learner, and by including Ra prediction as a control objective, the present work attains earlier, smaller, and more targeted interventions and thus a more favorable trade-off between surface integrity and throughput than the methods that rely on either purely analytical stability maps or purely reactive classification alone. This synthesis aligns with recent calls to combine first-principles modelling and data-driven adaptation for robust manufacturing control [4-17].

5.5 Practical implications and pathways to adoption

From an industrial standpoint, the proposed architecture is implementable with commercially available components: high-sensitivity triaxial accelerometers, a 24-bit DAQ with appropriate anti-aliasing, an edge server capable of hosting one or a small number of EDT instances, and a deterministic fieldbus such as EtherCAT to meet latency and determinism requirements. The potential return on investment is notable for mid-to-high-value production: reductions in scrap and rework, longer effective tool life through moderated wear rates, and increased first-pass yield contribute to rapid payback. Scalability to multiple machines can be achieved by centralising pre-trained LSTM models and physics templates while performing lightweight per-machine meta-learner personalization at the edge, thereby amortising up-front development costs across a shop floor [16]. Porting the approach to other manufacturing processes such as turning or grinding will require targeted adaptation of the physics surrogate and feature set, but the core ensemble plus meta-learner plus fuzzy supervisory architecture is broadly applicable. A staged deployment strategy — beginning with offline calibration and SIL/HIL testing, followed by supervised machine pilots — is recommended to mitigate integration risk and to gather the per-machine data necessary for safe, confident automation.

6. Conclusion

With the above-mentioned objectives in mind, the current research proposes a novel intelligent control framework for the enhancement of surface integrity in CNC milling processes. Additionally, the framework incorporates a validated surface integrity evaluation framework integrated into the intelligent control framework for assessment of surface quality. To overcome the challenges mentioned in the previous point, the framework involves the utilization of a physics-informed recurrent surrogate model made up of a physics-informed machined surface model to establish the occurrence of surface interactions. Additionally, the framework incorporates a context-aware Ensemble Meta-Learner for the utilization of a physics-informed machined surface model. The framework relies on a physics-informed machined surface model to quantify the accuracy of machined surface modeling. A fuzzy supervisor control system operates in the framework to implement the control approach developed. Additionally, the framework incorporates a PID control approach for the smoothing of control actions. With the framework established in the research hypothesis, the approach adopted in the research aims to benefit the technical community. The results show that the prediction robustness can be greatly improved by the ensemble digital twin in a manner that effectively leverages the best aspects of both mechanistic modeling and data-modeling techniques in a dynamically weighted fashion, even when the influence of context factors such as tool wear rates and cutting engagement conditions change. The synergy between predictive control strategies and rapid feedback mechanisms makes possible both proactive control actions for the earlier stages of the instability development in the process and limiting the unnecessary loss of productivity. These aspects form the basis of the improvements in surface integrity achieved in the research. Future studies need to extend the sensing framework to include multiple modalities of signals like cutting forces, acoustic emission signals, and thermal patterns to further improve the observability of the system states. Including the tool wear prediction model into the ensemble model would further improve the long-term controllability for maintenance. There may also be more advanced control strategies that would be more beneficial to the problem of fabricating a balance between productivity and surface quality. Another promising direction would be to extend the framework to apply to the more general case of hybrid machines or even to a general additive manufacturing context.

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