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Design of Control System Architecture for Intelligent Fixture

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Abstract: We present a compact architecture for an intelligent fixture aimed at stabilizing the milling of thin-walled aerospace parts. The system fuses multi-sensor inputs tri-axial accelerometers (5–30 kHz) for vibration/chatter, strain or dynamometer signals (1–5 kHz) for cutting/clamping loads, and low-rate pressure/temperature (≤ 100 Hz) for thermal/fixturing state with an "edge to cloud" computing stack. A Raspberry Pi 5 performs synchronized windowing (0.5–1.0 s, 50% overlap), time–frequency analysis (STFT/wavelets), and lightweight features (RMS, crest factor, band energies, relative wavelet energy, entropy). Unsupervised detectors (one-class models, LSTM autoencoders) provide fast on-device deviation alerts, while server services handle training/retuning, dashboards, a model registry, and over-the-air deployment. Telemetry uses MQTT for efficient streaming and OPC UA for typed information models, PTP (IEEE-1588) aligns timestamps. A private QoS-aware 5G link carries features and event-driven raw snippets, supporting a split control strategy, safety-critical actions stay local, and supervisory updates (feeds/speeds, ae/ap, clamping) close over 5G. Anticipated benefits include improved accuracy and surface integrity, reduced scrap/rework, and better adaptability across parts and machines. Validation will proceed via stability-lobe experiments and trials on aerospace-grade components, with a planned upgrade to simultaneous-sampling IEPE acquisition and Acoustic Emission sensing for higher bandwidth and earlier wear detection.

Keywords: Intelligent fixtures, thin-walled components, in-process monitoring, edge computing, private 5G, machining.

1. Introduction

In high-precision manufacturing sectors such as aerospace and space technology, fixtures are critical to achieving dimensional accuracy and surface integrity for thin-walled components. Traditional passive fixtures do not sense or adapt to dynamic changes (e.g., chatter, thermal drift, elastic deflection), which leads to errors, rework, and reduced efficiency. The goal of this paper is to present a concept architecture of an intelligent control system that integrates sensing, communication, and predictive algorithms to stabilize the process and enable data-driven decisions [1–5, 14].

Intelligent fixtures embed sensors and actuators to actively support compliant parts, suppress chatter, and reduce deformation by piezo-actuated elements and magnetorheological soft jaws exemplify these advances [1, 2, 8–10]. Concurrently, the IIoT and Industry 4.0 enable distributed, real-time monitoring with edge-to-cloud data pipelines. 5G provides low-latency, high-throughput backhaul suitable for shop-floor analytics [3, 4, 14, 15]. Existing reference architectures emphasize modular sensing (force/strain, vibration/Acoustic Emission, temperature), edge computing gateways for feature extraction and buffering, and server-side model training/serving for fleet-level learning [3, 5–7, 23].

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2. System Architecture Design

We choose to combine tri-axial accelerometers (5–30 kHz) for vibration/chatter with dynamometer/strain channels (1–5 kHz) for cutting and clamping loads, and pressure/temperature (≤100 Hz) to capture thermal and fixturing state. Tri-axial sensing is necessary because milling stability is directional. Coupling across x–y–z axes govern regenerative chatter, and single-axis signals can miss early cross-axis precursors. The 5–30 kHz span covers tooth-passing fundamentals/sidebands and transient bursts that appear before visible instability [5, 32–34]. Strain/load channels disambiguate elastic-deflection-driven geometry error from genuine loss of dynamic stability, while low-rate pressure/temperature contextualize slow drift recommended in in-process monitoring stacks [5, 7].

A Raspberry Pi 5 (8 GB) serves as the edge gateway. It provides sufficient compute and I/O to run concurrent Data Acquisition, windowing, time–frequency transforms and encrypted publish, aligning with edge-to-cloud guidance where compute near the source reduces latency/bandwidth and training remains centralized [3, 17].

For the initial iteration we decide use an NI USB-6001 (20 kS/s aggregate, 14-bit). It satisfies a minimum viable sampling plan—two vibration axes at ~10 kS/s plus strain/temperature for rapid bring-up, accepting constraints (no IEPE excitation, aggregate-rate ceiling, no built-in anti-alias filters) [16]. Our defined upgrade path is a simultaneous-sampling IEPE front end to preserve inter-channel phase for multi-axis stability analysis and enable Acoustic Emission sensing (typically 100–500 kS/s) for earlier tool-wear detection as shown in recent studies [5, 27]. The 5G modem we choose (Quectel RM530N-GL) provides private, Quality of Service-aware backhaul without tethering the fixture to wired infrastructure [18].

We plan streaming telemetry via MQTT and OPC UA. MQTT affords lightweight publish/subscribe of features and event-triggered raw snippets over constrained links. OPC UA contributes typed information models that integrate cleanly with OT systems and can be auto-generated to reduce integration cost [14, 15]. Local digital outputs support safety interlocks (e.g., feed-hold/ESTOP) and future active-fixture actuation with on-device latency, while server-side recommendations flow back to the edge/CNC for supervisory parameter updates [3, 4, 14].

Synchronized acquisition and on-edge feature computation will start at the fixture. Compact features (and raw snippets on alarm) will be published via MQTT to the server for inference/confirmation. Decision-making follows a split the edge raises fast-path alarms for imminent chatter or deviation, the server issues supervisory recommendations (feeds/speeds/clamping) and manages the model lifecycle. Feedback is applied locally for safety-critical actions and through CNC/fixture controllers for supervisory adjustments. This arrangement is consistent with IIoT best practice and preserves latency where it matters [14, 16, 24–27, 30, 31].

The edge node attaches to a private 5G network using the Quectel RM530N-GL (3GPP Rel-16, SA/NSA), enabling QoS-aware uplink of features and event-driven raw windows. Latency budgets of ~10–50 ms are sufficient for supervisory control. Hard real-time inner loops (e.g., active damping) remain on-device. PTP (IEEE-1588) provides precise time synchronization across edge/server to align events, while MQTT and OPC UA carry data and typed models, respectively [4, 14, 18–21]. The proposed system architecture is shown in the Figure 1.

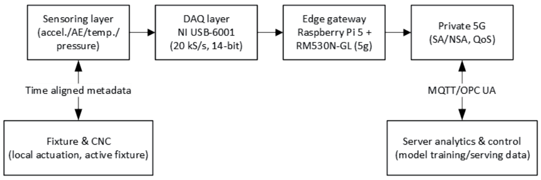

Figure 1: Sensing → DAQ → Edge → Private 5G → Server; paths.

Machining signals are non-stationary, so we use synchronized windows of 0.5–1.0 s with 50 % overlap to balance detection delay and spectral stability, followed by time–frequency front-ends (Short-Time Fourier Transform and wavelet packets) that expose evolving spectral content and transients [24, 25, 32–34]. We extract Root Mean Square (overall energy/load), crest factor (impulsiveness), band energies around tooth-passing/sidebands (canonical chatter markers), Relative Wavelet Energy (energy redistribution across scales typical of milling), and entropy (spectral complexity robust to operating-point shifts). These features are lightweight enough for edge execution and repeatedly shown to improve detectability versus fixed-band FFT alone [5, 24, 25, 27, 32–34]. For inference, unsupervised detectors

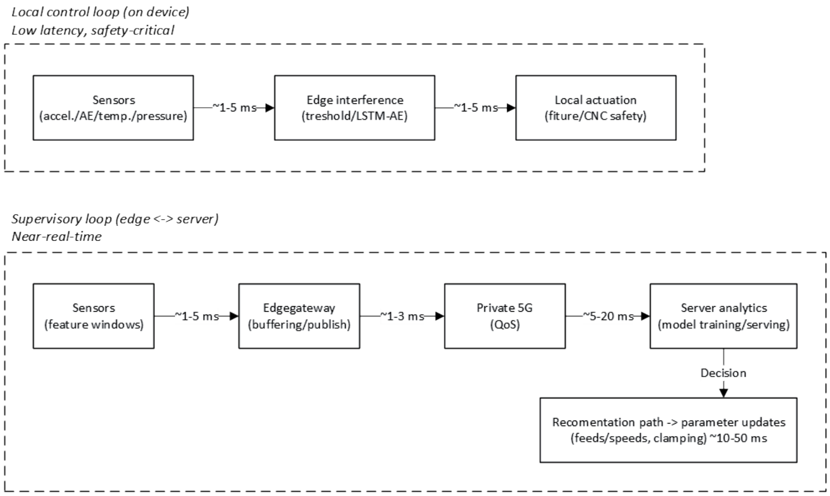

Figure 2: Local low-latency loop vs. near-real-time supervisory loop over 5G.

particularly LSTM autoencoders learn the manifold of "normal" and raise alarms on reconstruction/prediction error; they have demonstrated strong performance on CNC and broader condition-monitoring tasks [23, 28, 30, 31]. A simple one-class model serves as an ultra-low-latency fallback at the edge, while the server handles training/retuning on fleet data, drift monitoring, dashboards, and Over-the-Air deployment via a model registry with governance (signing, mTLS, audit, canary/rollback) [3, 36]. See Figure 2.

3. Results and Discussion

The proposed architecture is expected to improve dimensional accuracy and surface quality, reduce scrap and rework through earlier anomaly detection, widen stability windows with data-informed parameter adjustments, and enhance adaptability across part variants. It targets aerospace and space components, thin-walled structures, and high-precision manufacturing where dynamic effects dominate quality. For firms, the value lies in higher yield and OEE, faster troubleshooting via traceable telemetry, and a scalable analytics foundation that compounds learning across machines and parts.

4. Conclusions

We presented a concept for an intelligent fixture control architecture that fuses multi-sensor acquisition, edge preprocessing with private 5G backhaul, and server-side learning for deviation prediction and adaptive optimization. Key elements-modular sensing, MQTT/OPC UA integration, LSTM-autoencoder-based detection, and a hybrid edge-server split-align with current evidence and industrial constraints. Next steps are to prototype the universal control unit (Raspberry Pi 5 + NI USB-6001 + RM530N-GL) with PTP time-sync, run stability-lobe experiments to calibrate thresholds and quantify detection delay, validate in aerospace machining scenarios, and iterate toward closed-loop actuation and an IEPE/Acoustic Emission upgrade.

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Abbreviations

IIoT	*Industrial Internet of Things*
5G	*Fifth-Generation Mobile Network*
3GPP	*3rd Generation Partnership Project*
SA / NSA	*Standalone / Non-Standalone (5G)*
PTP	*Precision Time Protocol*
IEEE-1588	*IEEE Std 1588*
MQTT	*Message Queuing Telemetry Transport*
OPC UA	*Open Platform Communications Unified Architecture*
OT	*Operational Technology*
CNC	*Computer Numerical Control*
ESTOP	*Emergency Stop*
IEPE	*Integrated Electronics Piezo-Electric*
FFT	*Fast Fourier Transform*
LSTM	*Long Short-Term Memory*

CNN	*Convolutional Neural Network*
OEE	*Overall Equipment Effectiveness*
mTLS	*Mutual Transport Layer Security*
QoS	*Quality of Service*
I/O	*Input/Output*
kS/s	*kilo-samples per second*
kHz	*kilohertz*

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