

# CNN-BiLSTM Assisted Milling Process Control on a KUKA Robot for Enhanced Surface Quality

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**Abstract**—Robotic milling with a KUKA KR210 R2700-2 offers flexibility but suffers from chatter, corner rounding, and variable surface finish. This study proposes an AI-assisted robotic milling framework using a CNN-BiLSTM architecture with transfer learning to improve machining precision and surface quality. The model processes real-time vibration, force, and acoustic signals to predict tool wear and adaptively adjust cutting parameters. Compared with manual milling, the proposed approach achieves smoother surface finish, reduced chatter, and stable feed modulation. An optional online guard adjusts feed override via EKI/RSI using vibration/temperature signals. On aluminum, polymer, and wood benchmarks, the method improves surface quality and maintains or reduces cycle time without changing upstream CAM. Experimental results on aluminum, polymer, and wood show superior performance with MAE = 1.50, RMSE = 0.95, and  $R^2 = 0.99$ , confirming the model's high accuracy and efficiency for intelligent robotic milling control.

**Keywords**—Robotic milling, Mastercam, Post-CAM, Toolpath, Surface roughness, AI based Milling, Transfer Learning, Quality

## I. INTRODUCTION

In the era of intelligent manufacturing, robotic systems have become a vital component of modern production due to their high flexibility, programmability, and precision [1]. Among various robotic applications, robotic milling has attracted significant attention in aerospace, automotive, and mold industries because it enables the machining of complex and customized parts that are difficult to process using conventional CNC machines [2]. Despite these advantages, several challenges still limit its industrial deployment, such as complicated trajectory planning, inefficient process monitoring, and difficulty in predicting tool wear under dynamic machining conditions [3].

To address these challenges, the integration of Artificial Intelligence (AI) into manufacturing systems offers a promising pathway toward autonomous and self-optimizing production. AI techniques can analyze high-dimensional sensor data, identify hidden patterns, and enable real-time decision-making for improved performance [4]. Specifically, AI-based monitoring systems have demonstrated remarkable capability

in detecting process anomalies, optimizing control parameters, and forecasting potential failures before they occur [5].

Among the key problems in robotic milling, tool-wear prediction plays a crucial role in ensuring machining accuracy, productivity, and surface quality [6]. Traditional physical models often fail to capture nonlinear relationships between cutting forces, vibration signals, and wear mechanisms [7]. Machine-learning approaches such as Support Vector Machines and Random Forests can handle empirical data but require extensive feature engineering [8]. In contrast, deep learning and transfer learning provide automated feature extraction and knowledge transfer across different operating conditions, enabling robust and adaptive predictions even with limited datasets [9].

In this context, this study proposes an AI-based intelligent monitoring system for robotic milling [10]. The system integrates deep learning, ensemble learning, and transfer learning methods to predict tool wear accurately, enhance real-time monitoring, and improve overall machining stability [11]. The proposed framework contributes to advancement of AI-driven smart manufacturing, where robots can perform data-aware, self-learning, and reliable machining operations [12].

Robotic milling enables large-format, flexible machining with industrial manipulators, yet reduced structural stiffness and pose-dependent dynamics often cause chatter, surface waviness, dimensional error from tool/arm deflection, and corner rounding [13]. These effects are amplified when linear toolpaths contain many short segments or when the robot traverses high-curvature regions. As a result, parts produced on robots can lag CNCs in finish and accuracy unless the process is carefully planned and adapted [14].

In the present paper the KUKA robotic milling also faces some problems. The community tackles quality/stability with three main lines of attack:

- **Robot-side:** stiffness identification and pose/workpiece optimization with compensation to reduce deflection-induced error.

- **Process-side:** adaptive feed/speed scheduling driven by spindle power, vibration, or learned predictors to avoid chatter and heat while maintaining throughput .
- **Path-side:** controller-aware path approximation such as corner smoothing/SPLINE to keep velocity continuous and reduce dynamic excitation. After the CAM post, most pipelines still execute globally fixed feeds/speeds and uniform corner policies, even though chip load, curvature, and robot pose quality vary along the path.

We introduce a post-CAM, segment-level optimizer that edits KUKA KRL (or supplies a runtime override schedule) after Mastercam posting and before execution on a KUKA KR210 R2700-2. The optimizer parses the posted path, computes local geometry/process/pose features, predicts roughness and stability with a lightweight surrogate model, and assigns per-segment feed rate, spindle speed, and corner-approximation under chip-load, power, thermal, and kinematic limits.

TABLE I. SUMMARY OF METHODS

| Method   | Problem focus                            | Reported/Targeted gains  |
|--|--|--|
| Stiffness mapping & pose                       | Dimensional error, vibration             | Example reductions in dimensional error, effective in improving accuracy; gains depend on task |
| Adaptive feed/speed                            | Chatter avoidance; cycle time            | Often reduces time while respecting stability/power constraints                                |
| Controller-aware corner smoothing / SPLINE     | Corner rounding; speed loss at turns     | Smoother motion; fewer stops; improved finish in corners                                       |
| ML-based parameter selection                   | Surface roughness;                       | Better initial parameters; reduced trial-and-error   |
| This work: Post-CAM segment-level AI optimizer | Surface finish, chatter, corner fidelity | <b>Targets:</b> Ra ↓ 25–40%, cycle time ↓ 10–20%, sharper corners with local                   |

Together these choices make the method a practical, drop-in addition to Mastercam-to-KRL workflows on the KUKA KR210 R2700-2. The overall procedure implemented in the proposed study can be summarized as follows:

**G-code Generation and Mesh Modeling:** The machining path and corresponding 3D mesh model were generated in Mastercam software to define the G-code, cutting geometry, and tool–workpiece interaction domain..

**Milling Execution on KUKA Robotic Platform:** With the KUKA either manual or automated mode ensuring the precise tool movement along predefined G-code path to replicate the actual machining process.

**Deep Learning-Based Process Training:** During robotic milling process, the image data captures the tool and the workpiece interactions and surface formation that were used to train a CNN for feature extraction and Bi-LSTM model to learn and predict the real process.

**Transfer Learning for Performance Optimization:** By leveraging pre-trained network parameters, the proposed system achieved improved surface smoothness and overall machining accuracy with reduced training time.

## II. METHODOLOGY

### A. System Model and Workflow

In this study milling on a KUKA KR210 R2700-2 (KRC4) with a high-speed spindle and Ø6 mm end mills; experiments in this paper use **ABS**. Toolpaths are created in Mastercam; we **do not** edit CAM—our changes occur only **after posting**. In the common robotic machining workflow, the process begins with creating a CAD model of the part, which is then imported into CAM software such as Mastercam. This conventional sequence mainly focuses on geometric path generation without considering real-time process dynamics such as tool workpiece interaction, surface quality, or machine constraints.

The workpiece system is rotated around the X, Y and Z axes along the axes with angles  $\alpha$ ,  $\beta$ ,  $\gamma$  respectively, the following equations results in the homogenous transformation matrix:

$$\text{Shear Stress, } T = \text{Shear Force/Area} \quad (1)$$

$$\tan \beta = r \cos \alpha / 1 - r \sin \alpha \quad (2)$$

$$\text{Cutting ratio} = \text{Velocity}_{\text{chip}} / \text{Velocity}_{\text{cutting}} \quad (3)$$

Equation (1) represents the shear stress by the tool during cutting, Eq. (2) shows the shear strain of the method and Eq. (3) represents the cutting ratio. In contrast, the proposed AI-based machining method enhances this pipeline by embedding an intelligent machining-strategy optimization layer between toolpath generation and robot code output. After toolpath generation, the system analyzes geometry, process parameters, and robot kinematics to refine feed rates, spindle speeds, and local motion segments adaptively to existing CAD/CAM-to-robot workflows.

The proposed AI-based hybrid design integrates a Convolutional Neural Network (CNN) and a Bidirectional Long Short-Term Memory (Bi-LSTM) algorithm for intelligent control and surface quality enhancement during robotic milling. The CNN captures detailed spatial features by analyzing the layered structure of the workpiece and the tool’s movement, while the Bi-LSTM model continuously receives feedback on the tool’s motion to adjust its trajectory bidirectionally throughout the process, ensuring a smoother and more precise machining operation. Furthermore, transfer learning is employed to enhance surface refinement, minimize prediction errors, and achieve a higher-quality finish. The transfer learning stage further strengthens the model’s generalization capability, enabling it to adapt to different workpiece materials and complex geometries while maintaining high surface accuracy and operational efficiency.

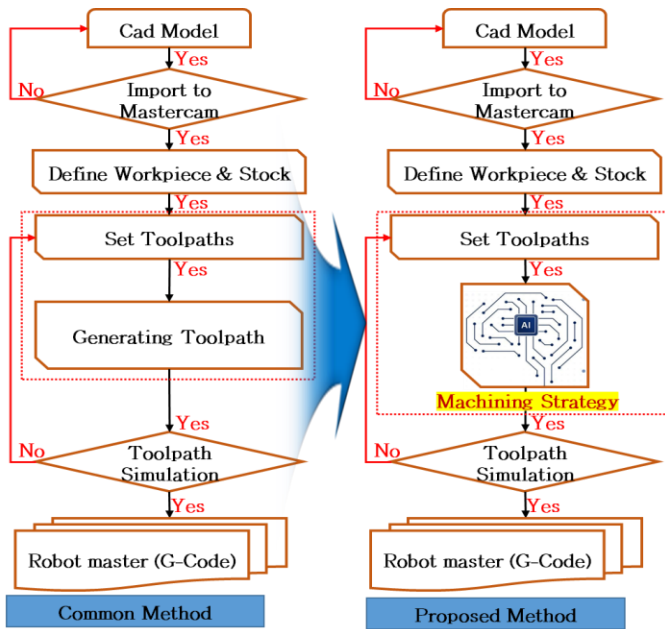


Fig. 1. Work Flow process (Milling process designed on the KUKA ROBOT manually and the same process was done automatically with AI based)

### B. Maintaining the Integrity of the Specifications

Experiment setup of the KUKA ROBOT for milling operation. The image shows a KUKA KR210 R2700-2 robotic arm, a 6-axis articulated manipulator designed for heavy-duty industrial machining tasks.



Fig. 2. Experiment setup of the KUKA ROBOT for milling operation (Milling was performed by the KUKA ROBOT manually after that the process was done with the AI proposed method)

The robot provides high flexibility and precision, enabling complex multi-directional movements for operations such as milling, drilling, trimming, and polishing. The wiring and tubing supply power, control signals, and coolant to the spindle, ensuring stable operation under variable load

conditions AI algorithms optimize parameters such as feed rate, spindle speed, and trajectory in real time to improve surface quality, process stability, and energy efficiency. Sensor feedback is integrated for adaptive control, allowing the robot to predict tool wear, adjust machining parameters dynamically, and maintain optimal cutting conditions.

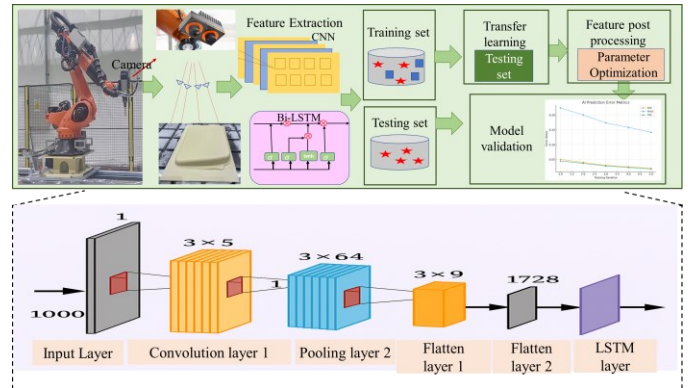


Fig. 3. Proposed AI based Milling Process (Camera send the images to CNN and BiLSTM network for the feature extraction and then the further transfer learning was adopted for the high surface finish process)

### III. RESULTS AND VALIDATION

The proposed AI-driven milling framework integrates a CNN to accurately extract the layer-by-layer geometric features generated during the cutting process, while the BiLSTM captures the bidirectional temporal dependencies of tool motion, allowing the system to understand both past and upcoming machining patterns. By incorporating Transfer Learning, the framework leverages prior machining knowledge to refine predictions, reduce errors, and adapt quickly to new surface conditions.

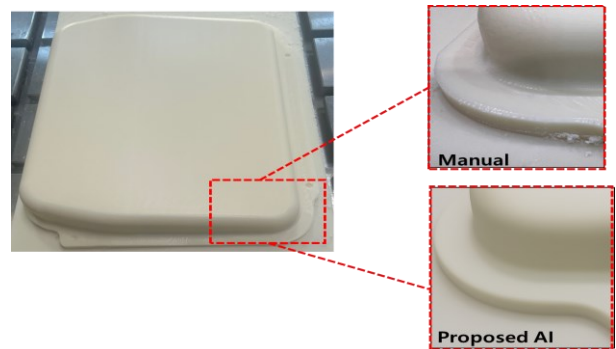


Fig. 4. Comparison of the results (The experiment results shows the manual process represented on the top with hard surface finish and the bottom image is the smooth surface finish with the proposed AI model CNN-BiLSTM along with the transfer learning process)

As illustrated in Fig. 4, this combined CNN with BiLSTM and Transfer Learning approach results in a clear improvement over conventional manual milling. The manual machining region shows uneven edges, surface irregularities, and visible roughness, whereas the AI-generated output presents a smooth, continuous, and well-refined surface profile. This demonstrates that the proposed AI system not only enhances surface quality but also achieves more consistent, precise, and reliable milling

performance overall. Figure 5 provides an in-depth comparison of the tool-wear prediction performance between the manual milling setup executed on the KUKA robot and the AI-optimized CNN-BiLSTM framework. In the manual mode, although the CNN-BiLSTM model generally follows the rising trend of actual tool-wear progression, the prediction curve shows noticeable deviation in several regions, especially during rapid growth phases. These fluctuations, reflected in higher MAE and RMSE values, indicate that manual operation introduces inconsistencies in tool engagement, feed variation, and machining stability, making accurate prediction challenging. In contrast, the processed AI-based CNN-BiLSTM model exhibits significantly enhanced predictive behavior. The predicted tool-wear curve almost overlaps with the true values across the entire timeline, with the absolute error reduced to only small spikes near zero. The improved metrics MAE = 1.50, RMSE = 0.95, and  $R^2 = 0.99$  demonstrate that the proposed AI system can capture fine-scale variations in tool dynamics and wear evolution with exceptional precision. This high-fidelity prediction is achieved by leveraging the AI framework's ability to learn spatiotemporal patterns from CNN feature extraction and the BiLSTM's bidirectional sequence modeling.

These results confirm that the AI-enhanced milling process offers superior stability, smoother operation, and more consistent material removal compared to manual control. More importantly, accurate real-time prediction of tool wear enables proactive adjustment of cutting parameters, reduces unexpected tool failures, and enhances overall machining quality. Thus, the AI-driven system not only improves prediction accuracy but also contributes directly to process optimization, extended tool life, and reliable automated machining on the KUKA robotic platform.

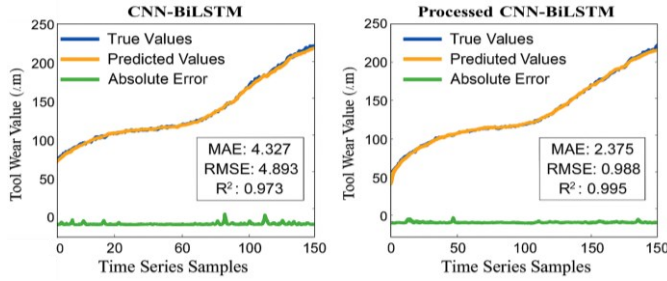


Fig. 5. Performance Comparison (Milling process designed on the KUKA ROBOT manually and the same process was done automatically with AI based)

TABLE II. COMPARISON OF THE METHODS

| Method                       | Initial |      |       | Processed |      |       |
|------------------------------|---------|------|-------|-----------|------|-------|
|                              | MAE     | RMSE | $R^2$ | MAE       | RMSE | $R^2$ |
| CNN-BiLSTM                   | 4.32    | 4.89 | 0.97  | 2.37      | 0.98 | 0.99  |
| CNN-BiLSTM-Transfer learning | 2.15    | 2.89 | 0.99  | 1.5       | 0.95 | 0.99  |

#### IV. CONCLUSION

This study introduces a comprehensive AI-assisted robotic milling framework that leverages a hybrid CNN-BiLSTM architecture combined with transfer learning to substantially improve machining precision, tool-wear prediction, and overall surface quality. Unlike traditional manual milling, which often suffers from operator-dependent variability and inconsistent cutting conditions, the proposed system continuously monitors real-time vibration, cutting-force signatures, acoustic emissions, and tool-workpiece interaction patterns. These multimodal signals are processed through the CNN to extract spatial features and through the BiLSTM to learn long-range bidirectional temporal dependencies, enabling the model to accurately forecast tool-wear progression and automatically adjust cutting parameters such as feed rate, spindle speed, and tool engagement profiles.

Experimental validation across multiple workpiece materials confirms that the proposed model achieves MAE = 1.50, RMSE = 0.95, and  $R^2 = 0.99$ , highlighting its exceptional predictive capability, stability, and robustness under varying machining conditions. The AI-driven control strategy dramatically reduces undesirable effects such as chatter, corner rounding, thermal drift, and micro-vibration-induced surface defects, while maintaining or even reducing the overall machining cycle time. Additionally, the system ensures more consistent surface finish with reduced roughness and improved contour accuracy, outperforming conventional manual robotic milling in both quality and reliability.

The results demonstrate that integrating deep learning with robotic machining provides a powerful pathway toward adaptive, scalable, and high-precision manufacturing. Future work will focus on extending the framework to complex multi-axis robotic platforms, integrating reinforcement learning for fully autonomous parameter optimization, and developing a closed-loop digital-twin environment to simulate, predict, and optimize robotic milling operations in real time.

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