INTEGRAL BLADE ROTOR MILLING IMPROVEMENT BY PHYSICS-GUIDED MACHINE LEARNING

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INTRODUCTION

In this paper, an integral blade rotor (IBR), or blisk, is used as the test case for the development and implementation of a physics-guided machine learning (PGML) framework for milling performance improvement. The project is motivated by the importance and inherent challenges of the computer-numerically controlled (CNC) machining industry. There is significant cost embedded in the starting material, capital resources, and hourly rates, making it essential that parts are not scrapped and the machine/tooling is not damaged. Part production that conform to design drawing specifications in a first-part-correct, high-profit scenario requires that the machining parameters, including depths of cut, spindle speed, and feed rate, as well as the material removal strategy embedded in the computer-aided manufacturing (CAM) toolpath, are optimized.

PGML

The first step of the PGML approach is the selection of: 1) cutting tools applicable to the design geometry; and 2) initial machining parameters provided by tool manufacturer recommendations and common industry handbooks; the latter provides a baseline to benchmark performance improvement. Second, a digital twin of the machining process is defined by physics-based models. This includes measurement of the tool tip frequency response function (FRF) using tap testing, where an instrumented hammer is used to excite the tool tip and the response is measured using a low-mass accelerometer. The cutting force model is selected using the workpiece material and prior experience/literature review. The cutting force model and tool tip dynamics are then used to define stable spindle speed-axial depth of cut combinations that avoid self-excited vibration, or chatter, which results in large cutting forces and poor surface finish [1]. Third, the machining parameters are used to generate toolpaths in HyperMill™, a CAM software. Finally, the Production Module™ software from Third Wave Systems is used to update the feed rates, optimize tool paths, and predict cycle times [2].

Within the PGML framework, the machining stability predictions from the physics-based models are used as training data for a Bayesian machine learning model [3]. The prior (initial beliefs about milling stability) is defined using two approaches: 1) uninformed, where the only information used is the tendency for stability to decrease with increasing axial depth; and 2) informed, where the physics-based models are incorporated in a Monte Carlo simulation to include input uncertainties and define the spindle speed and axial depth-dependent probability of stability.

Given the prior, milling tests are completed to update the probability of stability as a function of spindle speed and axial depth of cut. The frequency content of sound data collected during the milling process is analyzed to label a test as stable (content only at the tooth passing frequency and its multiples), or unstable/chatter (content also present at other frequencies) [1]. The tests are used to update the probability of stability using the Bayesian machine learning method [3]. The updated probability of stability

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(which represents new beliefs about stability after several tests) is finally used to select optimal material removal conditions.

EXPERIMENTAL SETUP

For an initial machining trial, a mock IBR geometry was designed with straight blades. This design consisted of three blades that were 2 mm thick and 25.4 mm tall. The material was 6061-T6 aluminum. See Fig. 1.

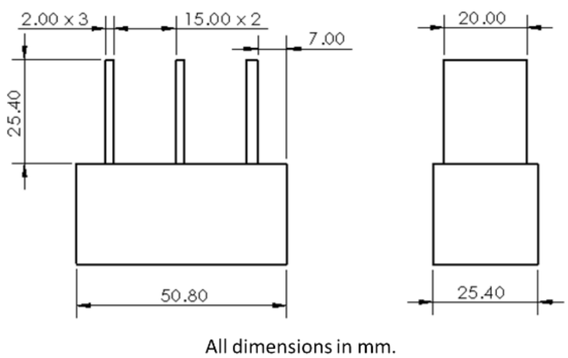

FIGURE 1. Straight blade IBR design.

An endmill was selected and the spindle speed and feed rates for partial radial immersion and slotting conditions were recorded from the tool manufacturer. The recommended feeds and speeds were used as input parameters for part programming. The tool dimensions and recommended machining parameters are provided in Table 1.

TABLE 1. Tool geometry and machining conditions.

Teeth	Corner style	Diameter (mm)	Max axial depth (mm)	Material
3	Square	12.7	25.4	PVD coated carbide
Recommended down milling for 6061-T6 Al				
Condition	Spindle speed (rpm)	Axial depth (mm)	Feed per tooth (mm)	
Slotting	6264 - 24828	6.35	0.102	
Side milling (10% radial immersion)		25.4		

The machining strategy was as follows:

- face the workpiece top;
- profile the width of the blades;
- rough the blades at maximum stable slotting depth;
- finish blades;
- repeat roughing and finishing operations in axial steps (equal to maximum stable slotting depth) down the blade height.

This machining strategy was chosen to retain the blade stiffness. Finishing passes only took place at the current bottom of the blades (stiffest location) as the cycle progressed. Alternatively, roughing the entire height of the blades would have significantly increased the compliance of the blades and, subsequently, the time required for the finishing process. This strategy enabled the stability analysis to consider only the tool dynamics.

Machining trials were completed on a Haas VF-4 three-axis computer numerically controlled (CNC) milling machine. A low-mass accelerometer and instrumented hammer were used to measure the tool tip FRF in both the *x* and *y* machine axes; see Fig. 2. The measured FRF and cutting force model were used to construct a stability map for the selected tool-holder-spindle-machine assembly [1]. This map was used to establish the prior (initial beliefs) for the PGML updating. This was done by assigning uncertainties in the cutting force coefficients and propagating them through the stability model using a Monte Carlo simulation [4].

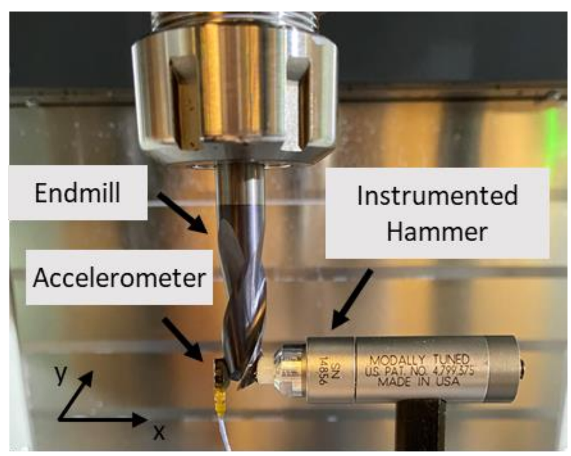

FIGURE 2. Endmill modal tap test.

To update the PGML model, audio content from test cuts was recorded using a Shure SM94 instrument microphone. Best results were obtained with the microphone located inside the enclosure.

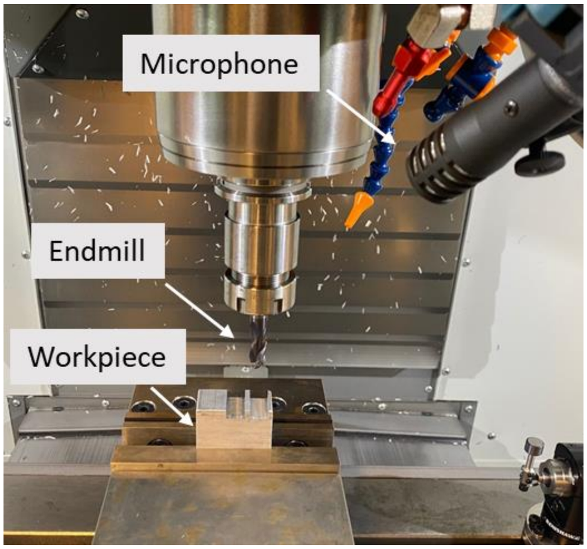

FIGURE 3. Machining audio sampling.

The time domain audio content was converted to the frequency domain using the fast Fourier transform (FFT). Test cuts were performed for slotting and 50% radial immersion (6.35 mm radial depth). The audio signal frequency content and visual inspection of the surface finish were used to determine if the spindle speed-axial depth combination was stable or unstable. For a stable combination, the frequency content occurs at the tooth passing and its multiples. FIGURE 4 shows a comparison of the frequency content for stable, 2.3 mm, and unstable, 3.0 mm, axial depths for slotting passes with a spindle speed of 7310 rpm (365.5 Hz tooth passing frequency).

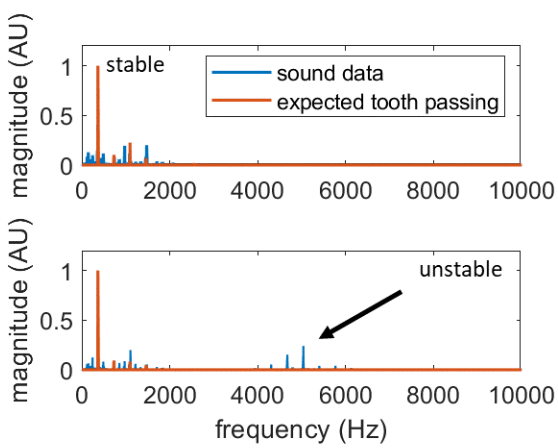

FIGURE 4. Stable (top) and unstable (bottom) frequency domain content for slotting tests.

The results from the trials were used to update the probability of stability using the Bayesian machine learning method. The test parameters were determined using an expected improvement in material removal rate criterion [3]. The tests were terminated when the expected improvement in material removal rate was less than 5%. The details of the Bayesian learning algorithm and test parameter selection are described in [3].

The straight bladed IBR design was used as the initial test case for the PGML framework. The geometry was then updated to include more realistic curved blades; see Fig. 5.

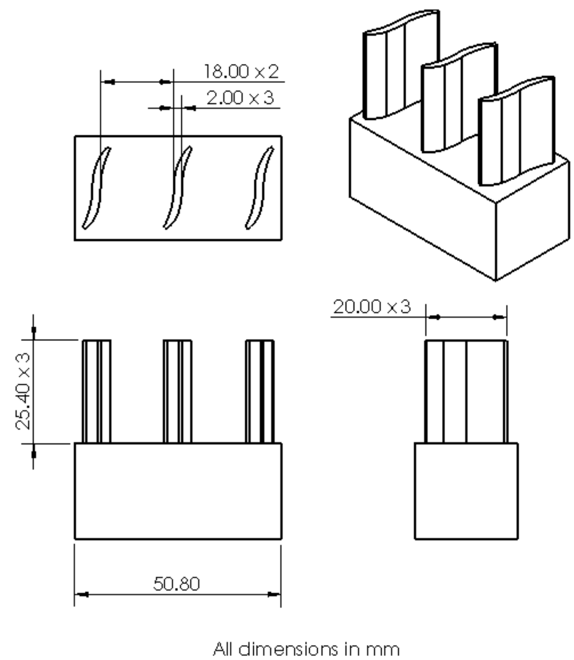

FIGURE 5. Curved blade IBR design.

The fixed-level roughing and finishing strategy previously detailed was adapted for the curved blade design. Videos were recorded for all machining cycles to document time savings seen at the machine and compare to software predictions.

PRODUCTION MODULE

Production Module™ (PM) is a toolpath level analysis and optimization software offered by Third Wave Systems [2]. PM has configurable machine kinematics that refine cycle time predictions as compared to CAM software by including acceleration/deceleration rates for rapid and feed motions. For cycle time reduction and program optimization, gain multipliers were set to increase the calculated mean tangential force on the tool while limiting the maximum in-cut feed rate and load per unit length (average tangential force divided by tool-workpiece interference length). PM's optimization process overwrites the commanded feed rate in the toolpath program to achieve the scaled tangential force. The optimization values used for both toolpath programs in this study are described in Table 2.

TABLE 2. Production Module optimization multipliers.

Tangential force	1.2
Load per unit length	1.3
Max in-cut feed rate	1.5

The roughing and finishing cycles were separated in PM to accurately scale the mean tangential force for each respective machining operation.

RESULTS AND DISCUSSION

Modal tap testing provided the vibrational response for the tool-holder-spindle-machine assembly used in this study. A stability map was constructed for slotting conditions; see FIGURE 6. Any spindle speed and axial depth combination contained under the solid boundary (in the unshaded region), was expected to be stable. Meanwhile, combinations greater than the boundary were expected to be unstable.

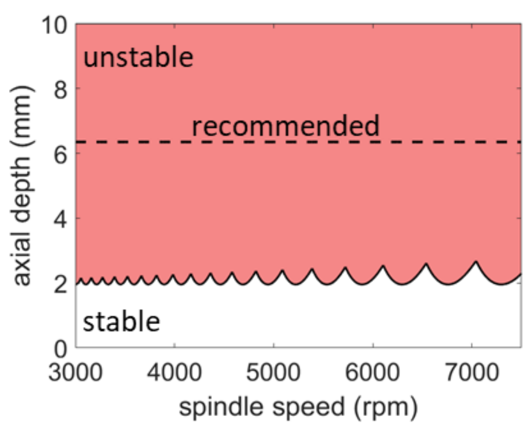

FIGURE 6. Slotting stability map.

The dotted line in Fig. 6 shows the recommended axial depth for slotting provided by the tool manufacturer. The recommended depth was significantly greater than the measured stability limit for the machine's entire spindle speed range. Results for machining tests using the recommended cutting conditions are displayed in Fig. 7.

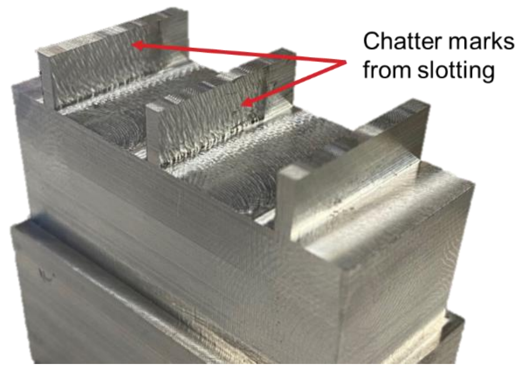

FIGURE 7. *Machining results using manufacturer-recommended parameters.*

FIGURE displays the probabilistic stability diagram for slotting that the PGML framework produced with an uninformed prior. In this case, the tap test and force model data were not used to determine the prior probabilities. The prior probability was assumed to reduce linearly with increasing axial dept. The color gradient represents the probability of stability, with 1.0 (gray) indicating stable and 0.0 (white) indicating unstable parameters. The results of 18 test cuts are included. The predicted stability limit for slotting was identified to be 2.3 mm at 7130 rpm.

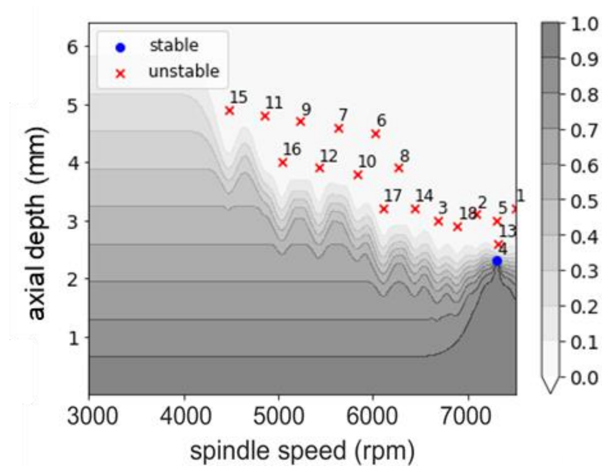

FIGURE 8. Probabilistic stability lobe diagram with uninformed prior.

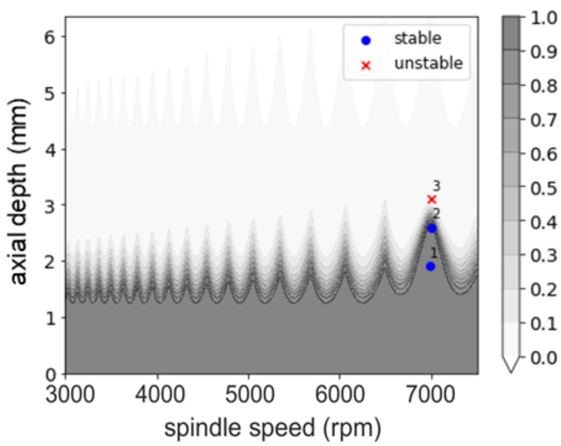

FIGURE 9. Probabilistic stability lobe diagram with informed prior.

FIGURE shows the probabilistic stability limit where an informed prior was implemented. In this case, the tap test FRFs, cutting force model, and corresponding uncertainties were included in a Monte Carlo simulation to establish the probability of stability. For this prior, only three test cuts were required. The maximum stability limit was 2.6 mm at 7000 rpm. The informed prior stability limit was used to program the toolpaths for both the straight and curved blade geometries.

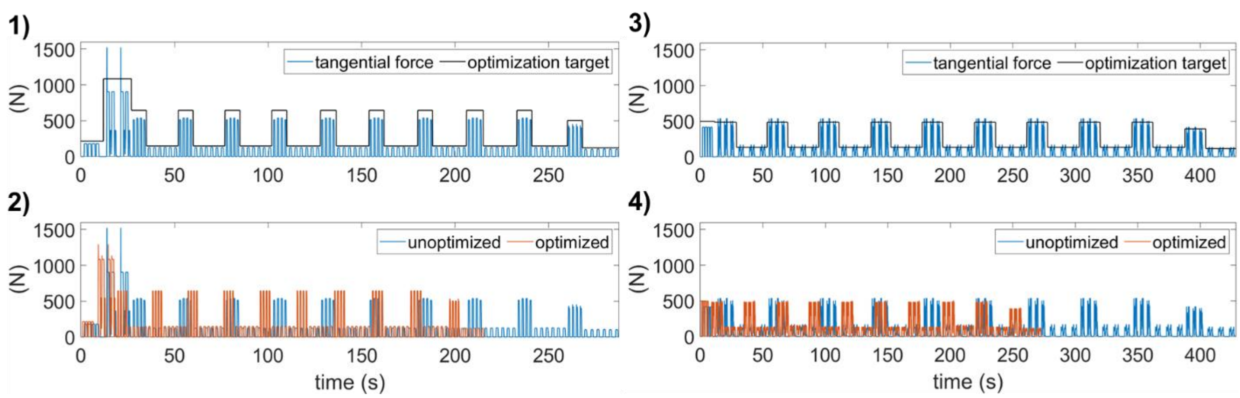

FIGURE 10. Production Module results: 1) force analysis and optimization targets for straight blade program; 2) optimized and unoptimized comparison for straight blade program; 3) force analysis and optimization targets for curved blade program; and 4) optimized and unoptimized comparison for curved blade program.

TABLE 3. Cycle time predictions and recorded improvements for PM toolpath optimization.

Program	Unoptimized		Optimized		Improvement	
	source	time (s)	source	time (s)	(%)	time (s)
Straight blade	hyperMILL	159	hyperMILL	-	-	-
	Production Module	287	Production Module	216	24.7	-71
	actual	304	actual	240	21.1	-64
Curved blade	hyperMILL	350	hyperMILL	-	-	-
	Production Module	429	Production Module	273	36.4	-156
	actual	441	actual	286	35.1	-155

FIGURE 1010 shows the PM force analysis and optimization effort for the straight and curved blade programs. The cycle times for both programs were reduced significantly within PM and as recorded on the machine. The mean tangential force in the straight blade program was nearly constant for the roughing and finishing operations. The optimization process resulted in a consistent increase of the feed rate, and subsequent force, that resulted in the cycle time reductions listed in TABLE 3TABLE 3. Cycle time predictions and recorded improvements for PM toolpath optimization.

The tangential force in the curved blade program fluctuated much more due to the changing radial engagement and curvature of the design geometry. The feed rate adjustments resulted in a more continuous force profile with maximum values that were less than the peak forces observed in the original toolpath. For both programs, the out-of-cut time was decreased considerably. The in- and out-of-cut optimization of the straight and curved blade programs resulted in cycle time reductions of 21.1% and 35.1%, respectively. The recommended parameters from the tool manufacturer did not provide suitable machining conditions (i.e., chatter occurred) and, therefore, no comparative improvement through the PGML process was available. This shows that accurate recommendations for CAM programming requires knowledge of the tool tip dynamics.

CONCLUSIONS

This paper demonstrated a physics-guided machine learning (PGML) framework for milling performance improvement. The application was integral blade rotor (IBR), or blisk, machining.

The PGML framework provided optimized machining conditions using two scenarios: 1) an uninformed prior, where the only information used was the tendency for stability to decrease with increasing axial depth; and 2) an informed prior, where a physics-based stability model was implemented that used the tool tip FRF and force model together with a Monte Carlo simulation to include input uncertainties and define the spindle speed and axial depth-dependent probability of stability.

Given the prior, milling tests were completed to update the probability of stability as a function of spindle speed and axial depth of cut. The frequency content of sound data was collected during the milling process and analyzed to label a test as stable or unstable/chatter. The tests were used to update the probability of stability using Bayesian machine learning approach. The updated probability of stability (which represents new beliefs about stability after several tests) was finally used to select optimal material removal conditions. It was shown that the machining parameters recommended by the manufacturer did not produce acceptable IBRs (chatter occurred), while the optimized parameters were stable and provided the required surface finish.

Additionally, the toolpaths were optimized using Production Module™ (PM), a toolpath level analysis and optimization software offered by Third Wave Systems. Cycle time reductions of 21.1% and 35.1% were obtained for the two IBR designs (straight and curved blades).

ACKNOWLEDGEMENTS

This research was supported by MxD project number 20-11-04 Physics-Guided Machine Learning (PGML) for CNC Milling. This material is based on research sponsored by Office of the Under Secretary of Defense for Research and Engineering, Strategic Technology Protection and Exploitation, Defense Manufacturing Science and Technology Program under agreement number W15QKN-19-3-0003 between MxD and the Government. The U.S. Government is authorized to reproduce and distribute reprints for Governmental purposes.

REFERENCES

[1] Schmitz, T. and Smith, K.S., 2019, Machining Dynamics: Frequency Response to Improved Productivity, Second Edition, Springer, New York, NY.

[2] https://thirdwavesys.com/machining-modeling/productionmodule/

[3] Karandikar, J., Honeycutt, A., Schmitz, T. and Smith, S., 2020. Stability boundary and optimal operating parameter identification in milling using Bayesian learning. *Journal of Manufacturing Processes*, *56*, pp.1252-1262.

[4] Duncan, G., Schmitz, T.L. and Kurdi, M.H., 2000. Uncertainty propagation for selected analytical milling stability limit analyses. Society of Manufacturing Engineers.