Association for the Advancement of Artificial Intelligence
Spring Symposium – AI and Manufacturing
Stanford University, March 23-25, 2020

Physics-Guided Machine Learning for Self-Aware Machining

Noel P. Greis,[1] Monica L. Nogueira,[2] Sambit Bhattacharya,[3] Tony Schmitz[4]

North Carolina State University,[1,2] Fayetteville State University,[3] University of Tennessee, Knoxville[4]
npgreis@ncsu.edu,[1] mdnoguei@ncsu.edu, [2] sbhattac@uncfsu.edu [3] tony.schmitz@utk.edu [4]

Abstract

Physics-guided machine learning offers a new approach to stability modeling for self-aware machining that leverages experimental data generated during the machining process, while incorporating decades of theoretical process modeling efforts. Physics-guided machine learning is a new paradigm of artificial intelligence that addresses some specific limitations of both machine learning models and physics-based models. Machine learning models are black box models that typically do not provide insight into the underlying physics and do not reveal physical constraints for the modeled system, sometimes yielding solutions that violate physical laws or operational constraints. In addition, acquiring the large amounts of manufacturing data needed for machine learning can be very costly. On the other hand, many physical processes are not completely understood by domain experts, so physics-based models must make simplifying assumptions that compromise accuracy. In this research, we ask the question whether data generated by an uncertain physics-based milling stability model to train a machine learning stability model, and then updated with experimental data, provides useful approximation to the "true" stability model for a specific set of factory operating conditions, therefore reducing uncertainty in optimal parameter selection to avoid chatter during the machining process. Using a numerical experiment, we demonstrate that the accuracy of a machine learning model trained using an uncertain physics-based model with errors, and subsequently updated with "true" experimental data shows improved convergence towards the underlying true stability model with minimal investment in data collection.

Introduction

Self-aware machines, as their name suggests, maintain "self-awareness" of both their own health and operational constraints and, as required, "self-control" to make parametric adjustments that maintain their continued performance to target levels. For example, self-aware machines can make parametric adjustments to keep themselves operational while waiting for service; they can adjust their machining parameters to assure process stability during machining; and they can adjust their load to balance production yields in their cell in the event of excess demand or machine downtime. This level of machine intelligence has considerable potential to enhance productivity in the manufacturing environment and to maintain optimal operational performance for maximum efficiency.

As a key enabler of self-aware manufacturing, machine learning has been an area of keen and accelerating interest by academic researchers (Sharp et al. 2018; Olega et al. 2018; Cherukuri et al. 2019; Tao et al. 2019). A range of methods have been studied to optimize processes for milling, turning and grinding and several recent review papers have been published (Kim et al. 2018; Wang et al. 2018). Due in part to the aging installed machine base, industrial manufacturers have been slower to take practical advantage of tools of artificial intelligence when compared with industries such as healthcare and finance. However, most large machine tool manufacturers now offer product suites designated as "smart". The majority of these "smart" applications address aspects of predictive maintenance to anticipate and avoid machine failure and support process control for CNC machining. Machine learning models can learn normal operational performance in order to track performance degradation and anticipate machine failure. Similarly, machine learning can be used to determine appropriate machining parameters, thereby minimizing problems such as tool breakage, tool deflection, and tool wear. Tool paths can also be optimized using machine learning to improve productivity and minimize cost.

This research builds on the existing trajectory of research on data-driven machine learning in machining by exploring a new paradigm—a new hybrid modeling approach referred to as physics-guided machine learning (PGML). In this approach, physics-based process models are combined with data-driven models to enable a new approach for machining and measurement applications for products ranging from aerospace components to freeform optics. The innovation of PGML is to combine process measurements with physics-based assessments that penalize model predictions that are inconsistent with physical knowledge. This capability will enable physically meaningful model output that not only provides increased accuracy and optimized processes, but also be incorporated into new scientific discovery efforts, such as improvements in physics-based models themselves. This new research stream is being explored under the leadership of the Center for Self-Aware Manufacturing and Metrology (CSAM), a consortium of universities in North Carolina focused on providing a physical and computational testbed for evaluating self-aware machining and measurement strategies enabled by physics-guided machine learning. CSAM's research goal is to develop physics-guided machine learning approaches that improve the accuracy, physical consistency, traceability, and generalizability of model predictions over traditional data-driven or physics-based methods solely. CSAM serves as a resource for both academic researchers and industry practitioners in developing and promoting best practices when applying physics-guided machine learning models to the manufacturing community. Current use cases being explored include chatter avoidance during machining, ultra-precision machining of freeform optics, semantic data management for machining and metrology, and machining force diagnosis. CSAM includes more than 20 industry members, as well as researchers from the collaborating universities.

Physics-Guided Machine Learning

Physics-guided machine learning is emerging as a new paradigm for modeling and scientific discovery that combines scientific theory with data science techniques such as machine learning. Traditionally, theory-based models of physical processes have served as the foundation for both academic research and operational best practices in the manufacturing environment. More recently, with the introduction of CNC machines and advances in sensor technology, data-driven techniques have become both popular and useful. In recognition of the limitations of solely data-driven models with respect to generalizability and physical interpretability however, a new approach—physics-guided machine learning—has been proposed. These models use physical principles to inform the search for the best machine learning model, thereby capturing the best attributes of both physics-based and data-learning models, as shown in Fig. 1 below.

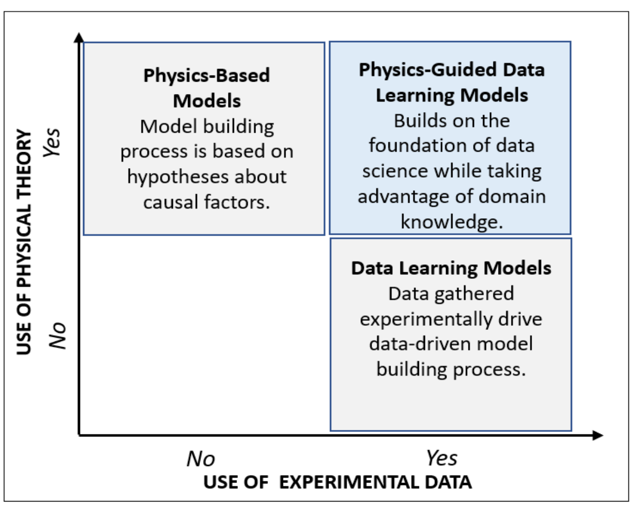

FIGURE 1. Physics-Guided Data Learning.

When modeling complex machining processes, the practical choice—and associated best practice—has been to choose between physics-based and data-driven models for prediction. Both approaches have distinct advantages when applied to complex systems with integrated mechanical, electrical, and software components. However, individually, they fall short of delivering the broad capability needed for self-aware machining. The hybrid models proposed herein are a relatively unexplored multidisciplinary methodology. Successful integration of physics-based and data-driven models represent a transformative breakthrough in intelligent system development for manufacturing, broadly, and self-aware machining, in particular.

Data-driven approaches such as statistical models and machine learning are built on historical and/or real-time data and can learn directly from sensor data (e.g. vibration, temperature, acoustic emissions, etc.) collected during machining. Advantages include the ability to model highly complex physical systems for which there is no underlying physical model that completely defines the system, or where the relationships between the input and output variables are difficult to describe using physics, or when the ability to include contextual data (e.g. environmental conditions, changes in operating regime, etc.) is important.

A challenge with data-driven (black box) models is that they are agnostic to physical laws because they rely only on data. They are, also, therefore dependent on data quality which can lead to relationships that do not generalize beyond the training data set. Data-driven model predictions are subsequently limited to the training data range and cannot, in general, be used for generating new scientific knowledge. Physics-based models are still preferred for scientific discovery. However, especially for highly complex physical systems, obstacles to their implementation include: 1) every model is an approximation of reality; 2) the model input parameters require identification, estimation and calibration; and 3) the model may be more complex and computationally intensive than required.

Early work in theory-guided data learning focused on applications characterized by degrees of complexity that resisted capture by traditional physical models, but for which large amounts of data were available for machine learning (Karpatne et al. 2017). These included physical phenomena such as turbulent flow (Singh, Medida and Duraisamy, 2017) and geoscience applications such as hydrologic modeling and climate change [Karpatne et al. 2017; Sheikh and Jahirabadkar 2018; Faghmous and Kumar 2014]. This research addresses the modeling of industrial processes where data is often limited by cost or time constraints but for which the underlying physical models are often more specific. A critical difference for mainstream manufacturing applications is that the models much keep pace with the surrounding industrial processes. The application presented here is focused on determining the optimized operational parameters offline. However, a major challenge for future applications in manufacturing is to develop sensor-enabled physics-based machine learning models with decision-making latencies that match the speed of the process in real-time.

Motivation for Physics-Guided Data Learning

There is currently no universal reference model for combining physics-based and data-driven models. In this paper we focus on the application of physics-guided machine learning to determine operational parameters that maintain the stability of the machining process when milling complex metal parts that require excellent surface quality, for example precision aviation or automotive parts. Milling is a cutting process that uses a cylindrical cutting tool to remove material from the surface of a workpiece. During the milling process, the cylindrical tool follows a predetermined tool path to achieve the desired geometry in the workpiece. Under certain dynamic conditions, the milling process will exhibit chatter—a self-excited vibrational state that leads to instability and uncontrollability of the system. Chatter is associated with undesirable effects such as poor surface quality of the part, poor part accuracy, and accelerated tool wear. Fig. 2 illustrates poor surface quality due to chatter.

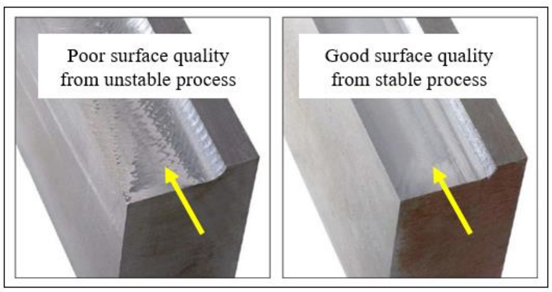

FIGURE 2. Poor Surface Quality Due to Chatter

Machine learning approaches have been directed towards predicting and detecting chatter in order to control the milling process [Oleaga et al., 2018; Cherukuri, et al. 2019]. The stability model governing milling is the physics-based model that predicts stable and unstable milling regimes as a function of machining parameters such as spindle speed and axial depth of cut. The representation of the stability model, the Stability Lobe Diagram or SLD, contains errors that reflect both the incompleteness of the model and the variability from one operating environment to another. In this numerical experiment, we use data generated by the SLD to train a machine learning stability model ("theory-based" machine learning model), and then update this model with experimental data to better approximate the "true" stability model, thereby reducing uncertainty in parameter selection.

Although many advances in machining have been achieved in recent decades, challenges for high productivity machining remain. First, CAD/CAM software generally treats machining as a geometric effort. Provided the cylindrical tool follows the required path through the prismatic work material to leave the desired geometry, it is assumed that the machining process is acceptable. This approach does not consider the constraints imposed by the process dynamics. For example, as noted above, some spindle speed-depth of cut combinations will exhibit self-excited vibrations, or chatter, which produces large forces, large vibrations, unacceptable surface finish, and potential damage to the tool, part, and spindle. Additionally, even if stable behavior is obtained, the geometric accuracy of the machined part may not satisfy design tolerances, again depending on the selected spindle speed-depth of cut parameters. Machining dynamics models are therefore required to select spindle speed-depth of cut combinations that avoid chatter, while providing the required geometric accuracy.

Second, the ability to predict process behavior by understanding vibrational behavior of the tool (and sometimes the part) imposes a specific measurement need. Vibration behavior is traditionally described by the frequency response function (FRF), which is obtained through modal testing. A popular approach is to excite the structure in question using an instrumented hammer and a low mass accelerometer attached to the structure to record the subsequent time domain vibration response. The frequency domain displacement-to-force ratio is the FRF, or receptance, for the tool or part. While the measurement procedure is well-understood, the lack of widespread availability of modal testing equipment and associated expertise has hindered the implementation of machining modeling on the shop floor. This points to a second modeling need; the tool point receptances must be identified without a measurement of each. Because the tool is clamped in a holder that is inserted in a spindle attached to the machine, tool point receptance prediction is not trivial.

Third, the tool point receptance and machining models are deterministic, but include inherent uncertainties. The predicted machining parameters are therefore also uncertain. This establishes the need for uncertainty reduction through testing. In this research, the (uncertain) physics-based process models are used to train machine learning models. Once these machine learning models are created, they are updated as process data is gathered. This leverages Industry 4.0 practices, where data collected during and after machining is used to achieve process improvement. In this way, each part becomes an experiment and operating parameter uncertainty can be reduced over time. The physics-guided machine learning approach is summarized in Fig. 3.

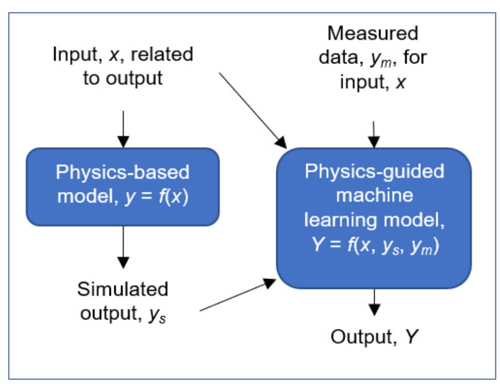

FIGURE 3. Physics-Guided Machine Learning Approach

Physics-Based Model Descriptions

Three physics-based models are used collectively to predict the stability lobe diagram (SLD) for milling. First, receptance coupling substructure analysis (RCSA) is used to predict the tool point receptance. Second, a mechanistic force model is used to relate the cutting force to the commanded chip area through cutting force coefficients. Third, a mean force frequency domain analysis is used to predict the stability limit using the first two models as input.

Receptance Coupling Substructure Modeling

Using three-component RCSA for tool point dynamics prediction has been demonstrated. In prior efforts, the free-free boundary condition tool and holder were modeled as cylindrical cross-section Timoshenko beams. These beam receptances were coupled analytically to measured receptances of the spindle-machine [Schmitz and Donaldson 2000; Schmitz and Duncan 2005; Schmitz and Smith 2009]. The sequence of steps for tool point receptance prediction are: 1) calculate the tool receptances (free-free boundary conditions) using the Timoshenko beam model; 2) calculate the holder receptances (free-free boundary conditions) using the Timoshenko beam model; 3) measure the spindle-machine receptances using impact testing; and 4) couple these receptances to predict the tool-holder-spindle-machine assembly dynamics using either rigid or flexible-damped compatibility conditions.

Force Model

In mechanistic force modeling for milling, the cutting force components, k, are calculated using the commanded axial depth of cut, b, and chip thickness, h. The model shown in Eq. 1 includes force components that are tangential, t, and normal, n, to the rotating cutting edge. Force coefficients that relate the force to chip area, bh, are identified by a c subscript (cutting or shearing force). Those that relate the force to axial depth alone have an e subscript (edge or rubbing force).

$$\begin{aligned} F_t &= k_{tc}bh + k_{te}b \\ F_n &= k_{nc}bh + k_{ne}b \end{aligned} \tag{1}$$

These coefficients may be determined by experiments where the cutting force is measured using a force dynamometer and the commanded axial depth of cut and chip thickness are known. Linear regression over a range of chip thickness values and nonlinear least squares fitting to the time domain force have been applied [Rubeo and Schmitz 2016]. As an alternative, the material behavior can be defined using a constitutive model and the cutting force predicted using finite element simulation [Shi and Liu 2014].

Frequency Domain Stability Analysis

The analytical stability limit may be determined using the mean Fourier force analysis [Altintas and Budak 1995] to transform the dynamic milling equations into a time invariant, but radial, immersion dependent system. This analysis expands the frequency domain dynamic milling equations into a Fourier series and then the series is truncated to include only the mean component. This analysis uses the tool point receptance and force model as inputs. The output is the limiting axial depth of cut as a function of spindle speed for a selected radial depth of cut, milling orientation (up and down), and number of teeth on the endmill.

As noted earlier, the deterministic models described in the previous section include uncertainty. For example, the actual extension length of the endmill from the holder is subject to setup and measurement uncertainties. This results in uncertainty in the tool point receptance which, in turn, leads to uncertainty in the stability limit. Propagation of uncertainties in the tool and holder models, spindle receptances, and cutting force coefficients to uncertainty in the stability limit may be completed using Monte Carlo simulation [Karandikar, Zapata and Schmitz 2010]. This provides a predictive model, where a probabilistic, rather than deterministic, stability limit is presented. However, if a test is performed to determine the actual stability behavior of a spindle speed-axial depth combination, there is no straightforward mapping between this result and input parameters.

Numerical Experiments

A numerical experiment was performed to illustrate how physics-based milling stability models, with their associated uncertainty, can be updated with experimental data to reduce uncertainty in parameter selection. In this numerical experiment, the physics-guided machine learning model is trained using an initial approximation of the process and then updated with experimental data to better approximate the underlying true model. Errors are intentionally introduced into the inputs to the physics-based model so that the predicted stability limit used to train the machine learning model includes uncertainty. However, because the input errors are known, it is possible to determine the true (zero uncertainty) stability limit. This error-free stability model is used to generate experimental data, which replaces the uncertain data in the original uncertain training dataset during the updating step.

The physics-based stability model is created by adding uncertainty to both the RCSA and force models. Errors are added to the extension length from the holder in the RCSA model and the cutting force coefficients in the force model. The stability model with errors is then created from the error-induced inputs of both these models; the result is presented in a stability lobe diagram (SLD) that provides the limiting axial depth of cut as a function of spindle speed for a given radial depth of cut, milling orientation, and number of endmill teeth. A second stability model is created without errors, representing the unknown true stability limit. To update the machine learning model experimental points are selected from this true stability limit (true experimental dataset). Example stability lobe diagrams for the physics-based stability model (with errors) and the "true" model are shown in Fig. 4.

In Fig. 4, the model parameters for the tool were: 12 mm diameter, 4 teeth, 50 mm extension from the holder (with errors); and 12 mm diameter, 4 teeth, 53 mm extension (without errors). The force model coefficients were: k_{tc} = 649.0 N/mm^2, k_{nc} = 262.2 N/mm^2, k_{te} = 0, and k_{ne} = 0 (with errors); and k_{tc} = 692.8 N/mm^2, k_{nc} = 400.0 N/mm^2, k_{te} = 0, and k_{ne} = 0 (without errors). The same spindle and holder receptances were used in both cases. Up milling with a radial depth of 2 mm was applied.

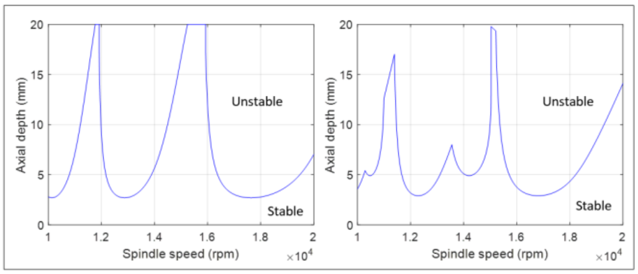

FIGURE 4. Comparison of (left) Physics-Based SLD with Errors and (right) True SLD without Errors.

Data points below the stability limit represent stable behavior while data points above the stability limit represent unstable behavior (chatter). Using the dataset created from the physics-based model with errors, the physics-guided machine learning stability model is trained to create the "theory-based" machine learning model. During subsequent updating, data points are sampled from the true experimental dataset and their true stability values updated in the training dataset. As the physics-guided machine learning model is updated, it is expected that the "learned" stability model will approach the underlying and unknown "true" model. Correspondingly, as true experimental data is added to the physics-guided machine learning model during updating, the number of correct stability predictions is expected to increase. This increasing number of correct predictions after updating defines the (stability) convergence of the physics-guided machine learning model to the true model.

Many data-learning algorithms are available to train the physics-based stability model and to predict the stability outcome (chatter or stable) for input combinations of axial depth of cut and spindle speed. In this study, three machine learning methods were used, as follows:

1) **K-Nearest Neighbors** (**KNN**) is one of the simplest classification algorithms, which makes decisions by referring to the k data points closest to the data point of interest. The distance between any two data points is calculated using several approaches. Common choices are Manhattan, Euclidean, and Minkowski distances. Euclidean distance was applied here.
2) **Support Vector Machines** (**SVM**) is a supervised learning machine learning model that is used largely for classification. Binary classification is performed by finding the hyper-plane that best differentiates between two classes, i.e. maximizes the margin between the hyperplane and the support vectors, or closest values to the classification margins. The use of kernels can transform linearly inseparable problems into separate ones.
3) **Nesterov-Accelerated Adaptive Moment Estimation** (**NADAM**) is an optimizer used in neural network models that minimizes the cost function by finding the optimized values for the weights during updating. NADAM is typically used in the case of noisy gradients or gradients with high curvatures.

Similarly, three strategies for selecting experimental updating points were selected, as illustrated in Fig.5 below. Updating the physics-guided machine learning model simulates

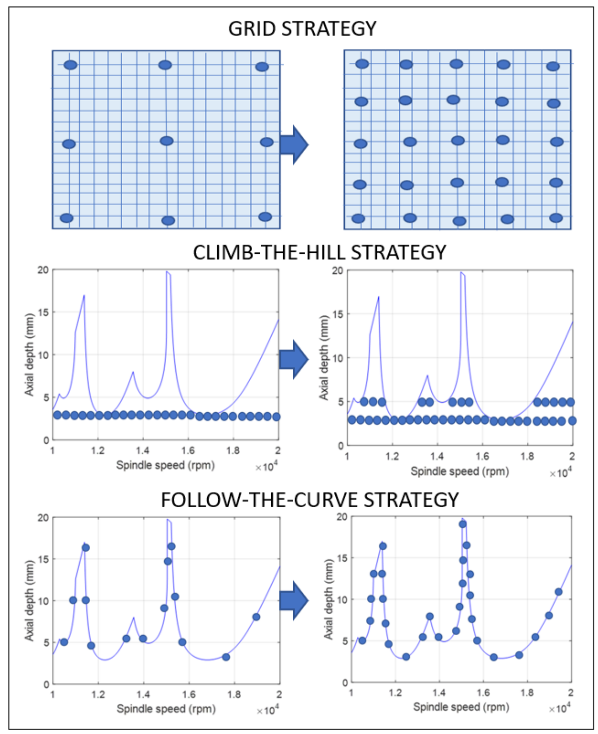

FIGURE 5. Concepts for Three Updating Methods

the process by which experimental data can reduce prediction uncertainty (i.e., converge to the true stability condition). The three updating strategies are: 1) a grid-based approach where experimental points are obtained at regular intervals across the operational domain of spindle speed and depth of cut; 2) a "climb-the-hill" strategy where update points are selected at regular intervals as it "climbs" the SLD hill; and 3) a "follow-the-curve" strategy where update points are selected at regular intervals along the SLD curve. For each updating strategy, the density of points increases at each iteration. To implement the experimental design in a balanced experiment, each of the three machine learning methods is paired with each of the updating strategies.

Implementing Physics-Guided Machine Learning

The training and updating steps of the physics-guided machine learning approach are summarized below.

Step 1: Build a physics-based milling stability model. This model is populated by the best information about the structural dynamics, relationship between the cutting force and chip area, and other process parameters. Using these inputs, the model predicts the limiting axial depth of cut to avoid chatter over a range of spindle speeds (i.e., the stability boundary). For the case study, known errors are intentionally inserted in the input data. This enables the incorrect model to be later updated with new points, corresponding to experimental data, which are generated using the true error-free stability limit (Step 4).

Step 2: Generate training data from the physics-based model. The stability boundary separates the spindle speed-axial depth of cut domain into two zones, stable and unstable and each combination is associated with a stability value of stable or unstable. For the purposes of training and updating the model, a grid of 2020 points was defined using: 101 spindle speeds from 10000 rpm to 20000 rpm in increments of 100 rpm; and 20 axial depths of cut from 1 mm to 20 mm in increments of 1 mm.

Step 3: Train the physics-guided machine learning model. A physics-guided machine learning model is trained to predict baseline stability values for combinations of spindle speed and axial depth of cut. For the purposes of training, all 2020 points defined above are included in the training set. For testing, a sample of 500 points corresponding to the midpoints between each two consecutive points on the x- and y- axis were selected as the test set. Prediction accuracy is determined by computing the percent of the test points for which a correct prediction is obtained by the trained model.

Step 4: Generate true experimental data. The true stability model (without errors) is used to predict the limiting axial depth of cut. Experimental points are then defined using this stability limit. The same spindle speed-axial depth points of the training and test sets are selected, but the stability behavior is defined with the true stability limit.

Step 5: Update the physics-guided machine learning model with true experimental data and retrain. Using the designated updating strategy, experimental data points from the population of true data points are selected. These stability values in the training dataset are updated with the true stability values, as necessary, and the model is retrained.

Step 6: Evaluate performance of the updating strategy. To evaluate performance of the updated model at each iteration, stability convergence C (%) is calculated, where CP is the number of correct predictions compared to the true stability value and TP is the total number of true predictions; see Eq. 2. A higher C value means that the machine learning model agrees more closely with the true stability limit. This indicates that updating has improved the model's predictive capability with respect to the true stability limit.

$$C = \frac{CP}{TP} * 100\% \qquad (2)$$

Numerical Results

Once the physics-guided machine learning classification model is trained, we evaluate its performance by running the model for both the training and testing sets one at a time. The model's *training accuracy* is measured by presenting the training set inputs to the trained model and computing the fraction of its predictions that are correct with respect to their expected outputs. Similarly, presenting the testing set inputs to the trained model and computing the fraction of its predictions that are correct with respect to their expected outputs, we measure the *testing accuracy*.

As shown in Table 1, accuracy results obtained with the KNN, SVM, and NADAM machine learning methods are high and indicate that these methods can become useful in improving identification of the chatter phenomenon in the manufacturing environment. *Testing accuracy* results, for the various models, are slightly inferior to their *training accuracy* counterparts. Usually, accuracy results for the training set are higher than the accuracy results for the test set, because the data points in the test set have not been evaluated, or "seen", by the model during training.

			ACCURACY		CONVERGENCE	
	K=	*RUNS*	TRAINING	TESTING	TRAINING	TESTING
KNN	1	1,000	100.00%	96.18%	79.62%	79.51%
	3	1,000	99.31%	95.88%	79.61%	79.76%
	5	1,000	98.66%	95.38%	79.74%	79.94%
	7	1,000	98.03%	95.25%	79.98%	80.43%
	9	1,000	97.77%	95.99%	80.35%	80.60%
SVM		1,000	99.58%	98.63%	79.61%	79.26%
NADAM		100	99.90%	99.10%	79.92%	77.86%

TABLE 1. Convergence and Accuracy Results Before Updates

Accuracy is a good measure of how well a classification model fits the data, especially when the distribution of the training and testing sets is similar, such as the two datasets generated from the physics-based model for this application (cf. step 3 above). However, given that the stability value (stable or chatter) provided by the physics-based model may contain errors, it is desirable to measure the performance of the machine learning methods against the stability values generated by the true stability model (without errors). For the purposes of this research, such a measure is called stability convergence and attempts to express how far the model trained with physics-based data is from capturing the true stability limit of the operational environment. The model's stability convergence during training is measured by presenting the training set inputs to the trained model and computing the fraction of model predictions that are correct with respect to the corresponding stability value provided by the true stability model. Similarly, stability convergence is measured for the test set.

As presented in Table 1 above, the convergence results are much lower than the accuracy results, as expected, given the limitations of the current physics-based model to completely capture the complex relationships among machining parameters. Fig. 6 illustrates the “performance gap” between the physics-based model and the true stability model, when running the KNN model, by computing the misclassification error for both the accuracy and stability convergence measures as the difference between 1 and each measured value. The graph helps visualize that a 20% to 25% improvement is possible and additional updating methodologies need to be attempted to resolve it. Overall, SVM and NADAM algorithms performed better than KNN.

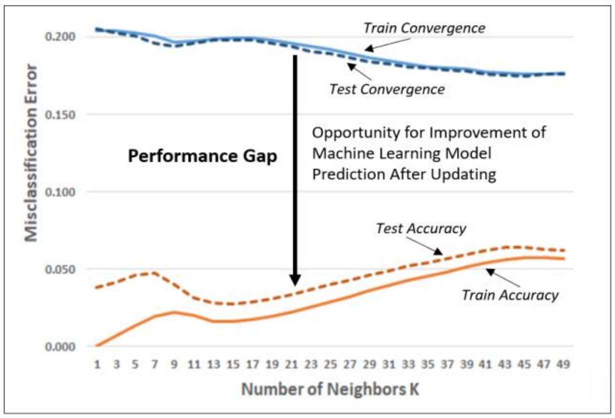

FIGURE 6. Accuracy and Stability Convergence Error for KNN Machine Learning Model

The physics-guided machine-learning model is updated in stages to assess the rate at which it approaches the true underlying SLD. In the first updating iteration, a subset of update points in the training set is selected depending on the updating method. The stability values in the training dataset are corrected with the true stability values, as necessary, and the physics-guided machine learning model is trained. At the next iteration, the subset of points is expanded, their stability status is again replaced by the true stability value, and the model is retrained. The process can then be repeated for increasing subsets of update points. For each updating point, additional information is available. If an experimental point (at a selected spindle speed-axial depth of cut pair) is stable, then all points for that spindle speed at lower axial depths are also stable. Conversely, if a point is unstable, then all points for that spindle speed at higher axial depths are also unstable. These additional points are incorporated into the set of experimental update points.

Updating experiments are currently underway for the three methods described above. However, preliminary experiments from our research group, shown in Fig. 7, suggest that a small number of experimental points selected using the Climb-the-Hill updating approach may assist in improving stability convergence of the initial KNN model (k=3) to the true stability limit [Jiang et al., 2019]. The left image in Fig. 7 compares the physics-based stability model with the true SLD, shown as a solid blue line. As seen in the figure, discrepancies between the physics-based and true model exist at spindle speed 13,500 rpm and for spindle speeds greater than 18,000 rpm. The image on the right illustrates stability convergence after sequential updating at axial depths of 5mm, 7mm, 10mm and 13mm. In that image the updated model with 133 update points now captures areas at 13,500 rpm and greater than 18,000 rpm that were not previously captured by the physics-based SLD.

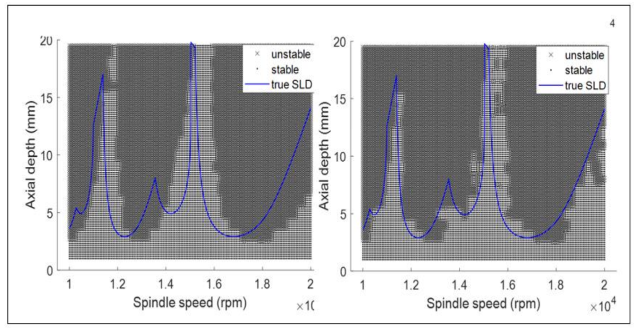

FIGURE 7. Preliminary Results Comparing Stability Convergence of the Physics-Guided KNN to True SLD After Updating

Summary, Conclusions and Next Steps

Our research focuses on developing new methodologies that apply physics-guided machine learning for manufacturing process control. Specifically, this paper reports experiments with machine learning models that can classify the stability condition of milling operations and assist with milling machine parameter selections to avoid chatter instability. We have developed novel strategies for updating the machine learning model with domain knowledge to improve productivity on the factory floor and the quality of the final product. A numerical case study was presented in which the machine learning model was trained using an initial approximation of the milling process (with errors) and then updated with new data (without errors) to better approximate the underlying true stability model. It was shown that model accuracy was improved and converged to the true stability behavior.

Since this research is on-going, more questions have been raised than answered. Most significantly, we are developing a framework for combining physics-based and data-driven models. There are currently no accepted or universal principles for the practical or theoretical application of these new methods. Our research explores distinct archetypes that represent different approaches to incorporating domain knowledge into the machine learning method. Each archetype uses a different implementation of machine learning to corroborate or contradict the outputs of the physical models. Other approaches, such as embedding the machine learning components directly into the physical model, are also being considered.

New research questions have been suggested by the specific milling example studied here. While prior research has provided guidelines for machine learning model selection and associated parameter specification during training, the best strategy for update point selection is an open question. Our preliminary results suggest that the strategy for selecting experimental update points can have a significant impact on the magnitude and rate of stability convergence. For this paper, we created three systematic approaches, each with implicit assessments about the value of the points selected (c.f. near the curve, near an inflection point, etc.). We are in the process of developing an information-theoretic updating strategy that uses a "value of information" criterion to determine which (and how many) points should be selected for updating. This question has practical, as well as theoretical implications. The cost of gathering manufacturing data can be quite costly within a production environment. Thus, achieving stability convergence with fewer experimental points is desirable in an operational setting. Further, physics-guided machine learning models will need to be compared against physics-based and data-driven models with respect to trade-offs between complexity and cost, estimation accuracy, and suitability across a range of applications.

Acknowledgements

The Center for Self-Aware Manufacturing and Metrology (CSAM), and the research described in this paper, are supported by the University of North Carolina's Research Opportunities Initiative. The authors wish to thank Research Assistant Catherine Spooner for her many contributions to this paper.

References

Altintas, Y. and Budak, E., 1995. Analytical prediction of stability lobes in milling. *Annals of the CIRP* 44(1), 357-362.

Cherukuri, H., Perez-Bernabeu, E., Selles, M. and Schmitz, T., 2019. Machining chatter prediction using a data learning model. *Jour. of Manufacturing and Materials Processing* 3(2), 45. doi.org/10.3390/jmmp3020045.

Faghmous, J.H. and V. Kumar, 2014. A big data guide to understanding climate change: The case for theory-guided data science, *Big Data* 2(3), 155–163, 2014.

Jiang, J., Nogueira, M., Greis, N., Bhattacharya, S. and Schmitz, T., October 2019. Machine Learning with Updating for Milling Stability. *American Society for Precision Engineering*, Pittsburgh, PA.

Karandikar, J., Zapata, R., and Schmitz, T., 2010. Incorporating stability, surface location error, tool wear, and uncertainty in the milling super diagram. *Trans. of the NAMRI/SME* 38: 229-236.

Karpatne, A., Atluri, G., Faghmous, J.H., Steinbacj, M., Banerjee, A., Ganguyly, A., Shekhar, S. Samatova, N. and Kuman, V., 2017. Theory-Guided Data Science: A New Paradigm for scientific Discovery from Data. *IEEE Transactions on Knowledge and Data Engineering* 29(10), 2318-2331. doi.org/10.1109/TKDE.2017.2720168.

Kim, D.H., Kim, T J.Y., Wang, X., Kim, M., Quan, Y.-J., Oh, J. W., Min, S.-H., Kim, H., Bhandar, B., Yang, I. and Ahn, S.-H., 2018. Smart Machining Process Using Machine Learning: A Review and Perspective on Machining Industry. *International Journal of Precision Engineering and Manufacturing Green Technology* 5(4), 555-568.

Oleaga, I., Pardo, C., Julaika, J.J. and Bustillo, A., 2018. A machine-learning based solution for chatter prediction in heavy-duty milling machines. *Measurement* 28: 24-44.

Rubeo, M. and Schmitz, T., 2016. Mechanistic force model coefficients: A comparison of linear regression and nonlinear optimization. *Precision Engineering* 45: 311-321.

Sheikh, R. and Jahirabadkar, S., 2018. An Insight into Theory-Guided Climate Data Science—A Literature Review. *Advances in Data and Information Sciences, Lecture Notes in Networks and Systems 38*, M. L. Kolhe et al. (eds.), doi.org/10.1007/978-981-10-8360-0_11.

Schmitz, T.L. and Smith, K.S., 2009. *Machining Dynamics: Frequency Response to Improved Productivity*, Springer, New York, NY.

Schmitz, T. and Donaldson, R., 2000. Predicting high-speed machining dynamics by substructure analysis. *Annals of the CIRP* 49 (1), 303-308.

Schmitz, T. and Duncan, G.S., 2005. Three-component receptance coupling substructure analysis for tool point dynamics prediction. *Journal of Manufacturing Science and Engineering* 127(4), 781-790.

Sharp, M., Ak, R. and Hedberg, T., 2018. A survey of the advancing use and development of machine learning in smart manufacturing. *Journal of Manufacturing Systems* 8(Part C), 70-79. doi.org/10.1016/j.jmsy.2018.02.004.

Shi, J. and Liu, C.R., 2004. The influence of material models on finite element simulation of machining. *Journal of Manufacturing Science and Engineering* 126/4, 849-857.

Singh, A.P., Medida, S., and Duraisamy, K., 2017. Machine-Learning-Augmented Predictive Modeling of Turbulent Separated Flows over Airfoils. *AIAA Journal* 55(7), 2215-2227. doi.org/10.2514/1.J055595

Tao, F., Qi, Q., Liu, A. and Kusiak, K., 2018. Data-driven smart manufacturin.. *Journal of Manufacturing Systems* 48(Part C), 157-169. doi.org/10.1016/j.jmsy.2018.01.006.

Wang, J., Ma, Y., Zhang, L., Gao, R., and Wu, D., 2018. Deep learning for smart manufacturing: Methods and applications. *Journal of Manufacturing Systems* 48: 144-156.