

# MACHINE LEARNING WITH UPDATING FOR MILLING STABILITY

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## INTRODUCTION

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, 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), while others will not [1]. Additionally, even if stable behavior is obtained (i.e., forced vibration only), the geometric accuracy of the machined part may or may not satisfy design tolerances, again depending on the selected spindle speed-depth of cut pair [1]. 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 requirement for the vibration behavior of the tool (and sometimes the part) to predict process behavior imposes a specific measurement need. The 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 the 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 and the holder is inserted in a spindle, which is attached to

the machine, the tool point receptance prediction is not trivial [1-3].

Third, the tool point receptance and machining models are deterministic, but include inherent uncertainties. The predicted operating 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, 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. 1.

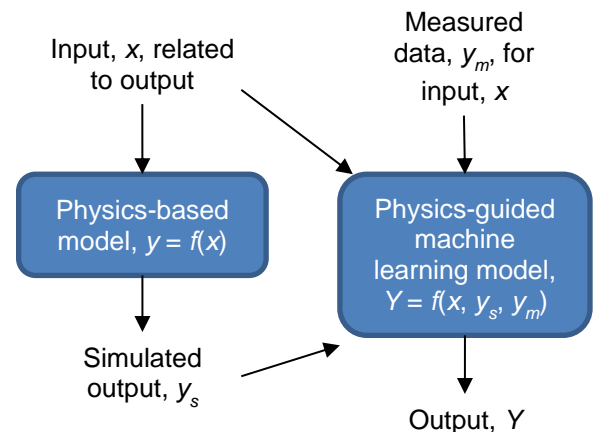


FIGURE 1. Physics-guided machine learning approach.

## PHYSICS-BASED MODEL DESCRIPTIONS

In this effort, three physics-based models are used collectively to predict the stability limit 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.

### RCSA

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 [1-3].

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).

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

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 [4]. As an alternative, the material behavior can be defined using a constitutive model (e.g., Johnson-Cook) and the cutting force predicted using finite element simulation [5].

### Frequency domain stability analysis

The analytical stability limit may be determined using the mean Fourier force analysis [6] 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.

### **PHYSICS-BASED MODEL UNCERTAINTY**

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 [7]. 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 [8]. 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 the model input parameters.

This motivates a new approach for stability model updating using milling experiments. The approach evaluated in this study is to use the (uncertain) physics-based stability model to train a machine learning (ML) algorithm. This ML model is defined in the desired test domain of spindle speed-axial depth. Updating can then proceed directly by collecting stability results and modifying the dataset used to re-train the ML stability model. This new approach falls under the emerging paradigm of data science called theory-guided data science (TGDS) that uses physical theory to augment big data techniques such as machine learning. TGDS leverages physical knowledge embedded in derived equations with experimental data to improve the predictive capability of data-driven machine learning models. In this work, domain knowledge relevant to milling stability is used to estimate the stability limit model as represented in the stability lobe diagram (SLD). The SLD accuracy is increased by the addition of "true" sampled data, which represents experiments, to the original ML training dataset.

### **PHYSICS-GUIDED MACHINE LEARNING**

Machine learning, a subset of artificial intelligence (AI), comprises a set of algorithms that are able to perform a specific task or model a process without being explicitly programmed, relying instead on recognizing patterns or making inferences from large sets of data. These algorithms can be grouped broadly into three categories based on the learning style. In supervised learning, algorithms map input data to corresponding known output data.

Unsupervised approaches develop models or functions from input data without knowing the corresponding outputs. Reinforcement learning approaches learn to achieve a goal through a series of decisions for which they are rewarded. Broadly, all of these approaches are designed to perform two tasks: classification in which data are separated into classes; or regression in which a continuous relationship is developed.

TGDS, or physics-guided machine learning, has emerged as an approach that addresses the specific limitations of both data learning models and physics-based models. Many data learning models, including ML, are black box models that do not provide insight into the underlying physics and do not reveal physical constraints for the modeled system. On the other hand, many physical processes are not completely understood, so physics-based models must make simplifying assumptions that compromise accuracy. Physics-guided machine learning offers a new approach to stability modeling that leverages experimental data while incorporating decades of process modeling efforts.

### NUMERICAL CASE STUDY

The goal of this research is to explore how physics-based milling stability models, with their associated uncertainty, can be updated with experimental data to reduce uncertainty in parameter selection for a particular milling machine operating in a factory environment under specific conditions. A numerical case study is presented, where the physics-based machine learning model is trained using an initial approximation of the system 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 to 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 teeth on the

endmill. A second stability model is created without errors, representing the unknown true stability limit. Experimental points are selected for updating the ML model from this true stability limit. Example SLDs for the physics-based stability model (with errors) and the “true” model are shown in Fig. 2.

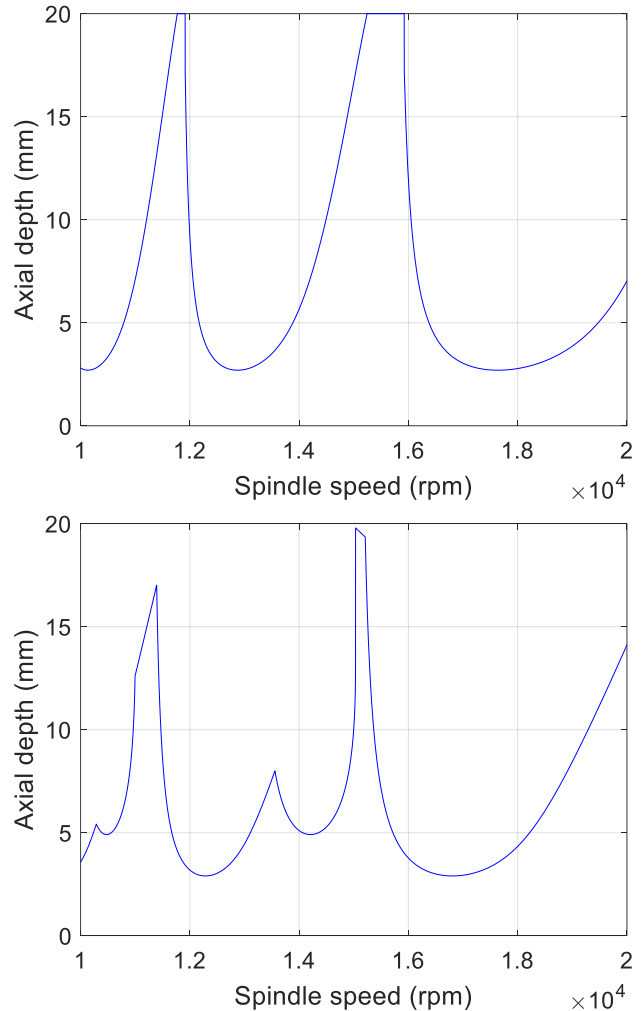


FIGURE 2. Comparison of (top) physics-based SLD with errors and (bottom) true SLD without errors.

In Fig. 2, 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<sup>2</sup>,  $k_{nc} = 262.2$  N/mm<sup>2</sup>,  $k_{te} = 0$ , and  $k_{ne} = 0$  (with errors); and  $k_{tc} = 692.8$  N/mm<sup>2</sup>,  $k_{nc} = 400.0$  N/mm<sup>2</sup>,  $k_{te} = 0$ , 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.

Data points below the stability limit represent stable behavior while data points above the stability limit give unstable behavior (chatter). Using the dataset created from the physics-based model with errors, the physics-guided machine learning model is trained. During subsequent updating, data points are sampled from the true experimental dataset and added to the training dataset. As the physics-guided machine learning model is updated using true experimental points, 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 is defined as the convergence of the physics-based ML model to the true model.

The training and updating steps are summarized.

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).
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 (chatter). For the purposes of training, testing, 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. Each combination of depth of cut and spindle speed is associated with a stability value (stable or chatter).
3. *Train the physics-guided machine learning model.* A physics-guided ML model is trained to evaluate baseline performance in predicting the stability value for combinations of spindle speed and axial depth of cut. For the purposes of training, 70% of the population of points is randomly selected for training; the remaining 30% is reserved for testing. Prediction accuracy is determined by computing the percent of the test points for which a correct prediction is obtained by the physics-guided ML model.

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 are selected, but the stability behavior is defined with the true stability limit.
5. *Update the physics-guided ML model with true experimental data and retrain.* Using the designated updating strategy, select experimental data points from the population of true data points for updating. Correct the stability values in the training dataset with the true stability values, as necessary, and retrain the physics-guided ML model.
6. *Evaluate performance of the updating strategy.* To evaluate performance of the updated physics-guided ML model, convergence,  $C$  (%) is used, where  $CP$  is the number of correct predictions compared to the true stability value and  $TP$  is the total number of 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 ability.

$$C = \frac{CP}{TP} \cdot 100\% \quad (2)$$

## TRAINING THE PHYSICS-GUIDED MACHINE LEARNING MODEL

Many ML classification algorithms are available to train the stability model and predict the stability outcome (chatter or stable) for input combinations of axial depth of cut and spindle speed. In this study, k-nearest neighbors (KNN) was used. 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 [9]. The distance between any two data points is calculated using several approaches. Common choices are Manhattan, Euclidean, and Minkowski distances. Euclidean was applied here.

## UPDATING THE PHYSICS-GUIDED MACHINE LEARNING MODEL

Updating the physics-guided ML model simulates the process by which experimental results are used to reduce prediction uncertainty (i.e., converge to the true stability condition). In this research, a “climbing” strategy was implemented.

In the first update, all points in the training set with a user-selected low depth of cut are chosen and their stability status is assessed and updated. For the stable points only, the depth of cut is increased and the stability is determined at the same spindle

speeds. If the new cutting parameters are in the training set, the incorrect stability status is replaced by the true stability status. The process is then repeated by again increasing the depth of cut for the stable points. For each updating point, additional information is available. If an experimental point (at a selected spindle speed-axial depth 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 updates are also incorporated.

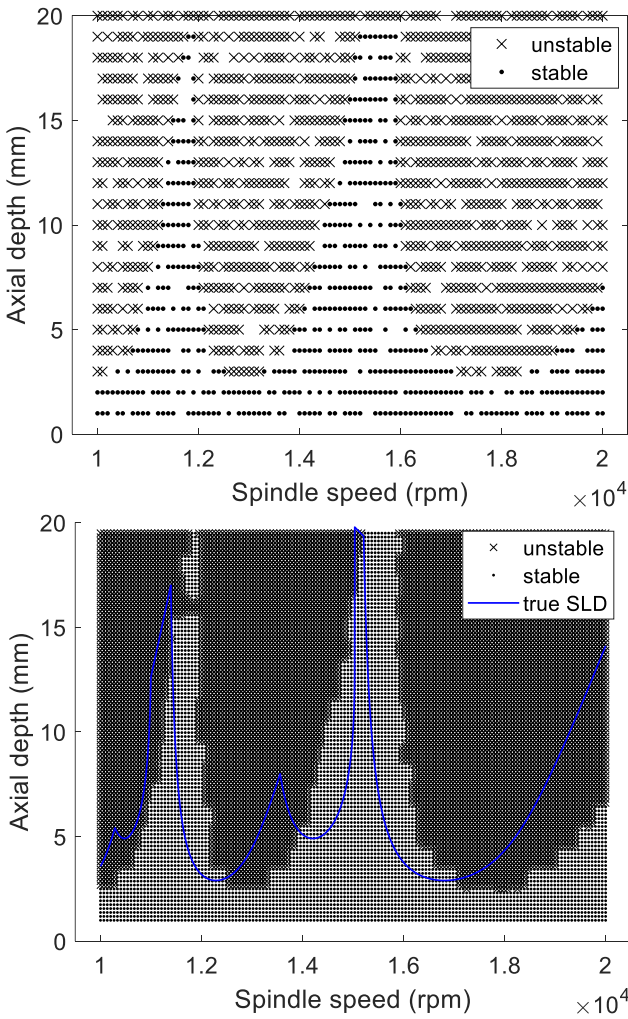


FIGURE 3. (Top) dataset used for updating the KNN model. (Bottom) Initial KNN model compared to the stability limit without errors.

Figure 3 displays the original KNN dataset used for updating. Note that the gaps in the grid appear because 30% of the original points were extracted to measure the accuracy of the original training (i.e., a comparison between the initial KNN model and the

stability limit with errors). This figure also compares the initial KNN model ( $k = 3$ ) to the stability limit without errors.

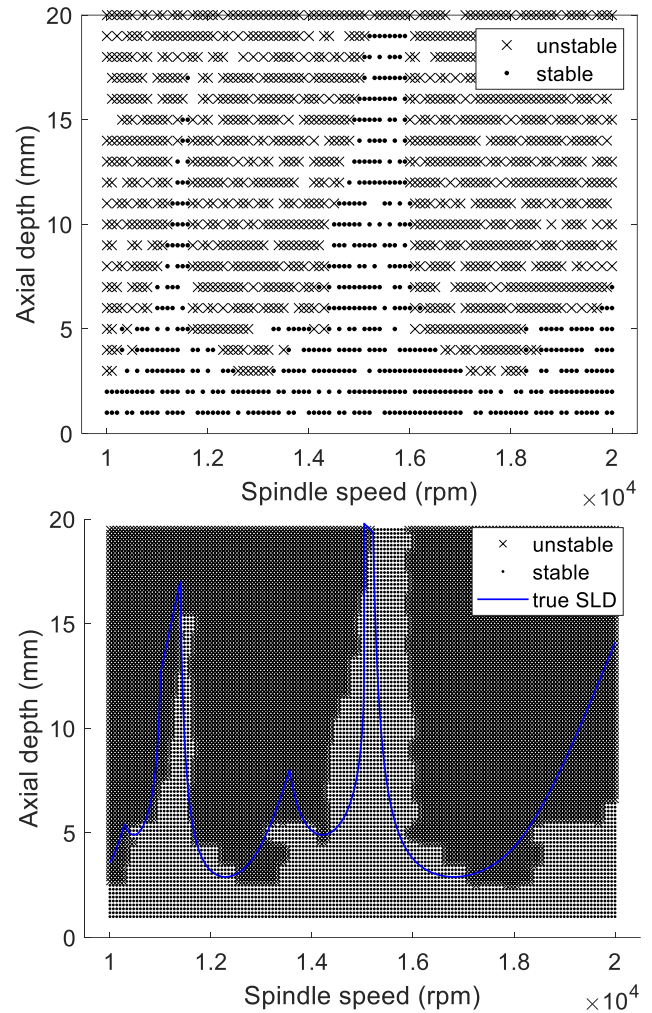


FIGURE 4. (Top) dataset after first update at a 5 mm axial depth. (Bottom) Updated KNN model compared to the stability limit without errors.

Figure 4 displays the results after updating the points at an axial depth of 5 mm. For each point, the true stability behavior was determined using the true stability limit (this represents an experiment). If the point was stable, all points at the same spindle speed with lower axial depths were also set to stable. If the point was unstable, all points at the same spindle speed with higher axial depths were set to unstable.

Figure 5 displays the results after sequential updating at axial depths of {5, 7, 10, and 13} mm. Collectively, this included 133 experiments, which yielded 1239 additional data point updates due to the strategy of modifying the state of points above

and below experiments depending on a stable or unstable outcome. The KNN model now matches the true stability limit with a convergence value of 88.37%. The results are summarized in Table 1.

TABLE 1: Updating results for climbing with KNN.

# experimental points	# additional points	Total update points	C (%)
Training			
-	-	-	76.47
Updating			
77	726	803	84.16
112	1041	1153	86.14
125	1160	1285	88.12
133	1239	1372	88.37

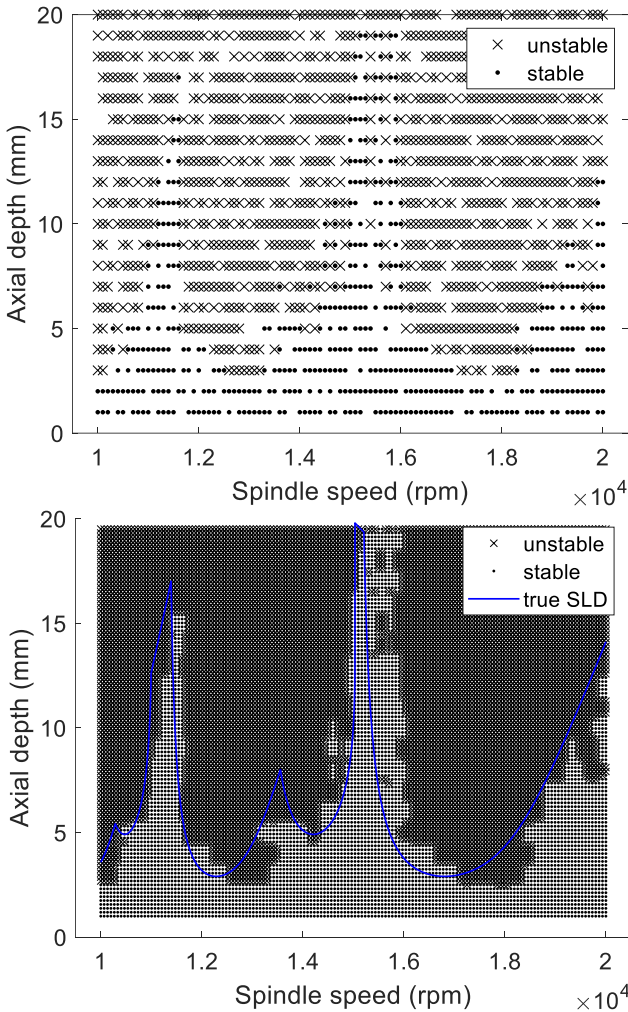


FIGURE 5. (Top) dataset after four update at axial depths of {5, 7, 10, and 13} mm. (Bottom) Updated KNN model compared to the stability limit without errors.

## CONCLUSIONS

This paper described the use of uncertain physics-based milling stability models to train a machine learning stability model and then updating this model with new data to reduce uncertainty in parameter selection. A numerical case study was presented where the machine learning model was trained using an initial approximation of the system (with errors) and then updated with new data (without errors) to better approximate the underlying true model. It was shown that the model accuracy was improved with updates and converged to the true stability behavior.

## ACKNOWLEDGEMENTS

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