Generating machine learning-based state maps from real-world friction-induced vibration data

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Abstract. Understanding the rich bifurcation behavior of friction-excited mechanical structures such as brake systems remains a challenge in engineering today. Currently, a complete bifurcation map that represents the system state over a large bifurcation parameter range cannot be obtained from physics-based models or experimental data alone. This work presents a machine-learning based method for obtaining bifurcation maps of the entire parameter space in a purely data-driven fashion. A machine learning model is built to predict the system's dynamical state from experimental data, picking up hidden bifurcation mechanisms. This model is then exploited to assess the system state for a wide range of synthetic, physics-conform data, yielding a complete map of the bifurcation parameter space. Results suggest that the method can detect hidden dimensions and parameters driving the bifurcation which were inaccessible previously.

Introduction

Friction-induced vibrations represent a major challenge in mechanical engineering structures, such as brake systems, clutches, drill-strings, and others. Under specific loading conditions, the dynamical systems undergo bifurcations that will feed frictional energy into the structure, thereby exciting unwanted and potential vibrations. Today, the complete bifurcation parameter map cannot be obtained from either physics-based models or directly from experimental data [1, 2]. While the former is limited due to modeling assumptions and parameter uncertainties, the amount of available measurement data is inherently sparse. Recently, it has been shown that machine learning-based approaches can yield digital twins for friction-induced dynamical systems [3]. These data-based models are a powerful tool for the prediction of system stability. This work proposes a purely data-driven approach to generating bifurcation maps from real-world measurement data of a friction brake system.

Results and Discussion

A machine learning model is trained to predict the brake system state using external load data obtained from a brake system undergoing commercial vibration testing. After training and validation, the digital twin of the brake system has picked up the complex parametric relations and hidden mechanisms which drive the systems dynamics. As the load parameter space is sampled only sparsely by experiments, the digital twin can be used to predict behavior in the remaining space, thereby drawing complete bifurcation maps, see Figure 1. To do so, a physics-conform data augmentation is installed to generate synthetic measurement data for all requested load parameter combinations. Thereby, a full bifurcation map is generated even though the original measurement space was only sparsely sampled. Validation of those maps is achieved using the experimental data at hand.

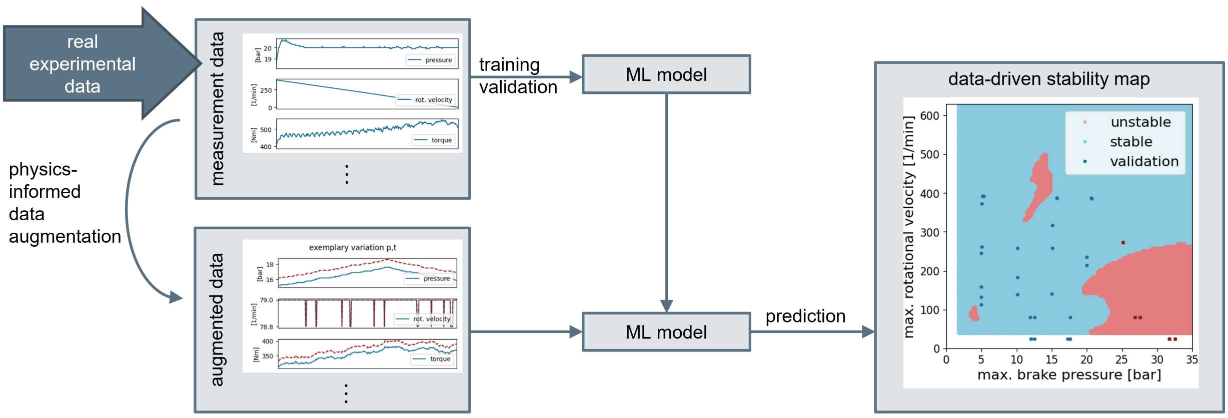

Figure 1: Generation of a data-based bifurcation map from measurement data of real-world data of a brake system.

Results indicate that this method yields consistent results. The complex bifurcation pattern of a real-world brake system is revealed, i.e. hidden mechanisms and driving (bifurcation) parameters that were previously impossible to grasp. Machine learning bifurcation maps can therefore be a powerful tool for the understanding of complex dynamical systems.

References

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