Concept for predicting vibrations in machine tools using machine learning

D. Barton[1,*] and J. Fleischer[1]

[1] wbk Institute of Production Science, Karlsruhe Institute of Technology (KIT), Kaiserstraße 12, 76131 Karlsruhe, Germany
*Corresponding david.barton@kit.edu

Abstract. Vibrations have a significant influence on quality and costs in metal cutting processes. Existing methods for predicting vibrations in machine tools enable an informed choice of process settings, however they rely on costly equipment and specialised staff. Therefore, this contribution proposes to reduce the modelling effort required by using machine learning based on data gathered during production. The approach relies on two sub-models, representing the machine structure and machining process respectively. A method is proposed for initialising and updating the models in production.

Keywords: Machine tools; Machining; Vibration; Machine learning.

1 Introduction

The performance of machine tools, measured in terms of productivity, availability, product quality, and production costs, depends strongly on the choice of process settings for the machining process. Vibrations during the process are an important factor when defining process settings, as excessive vibrations have a significant effect on tool wear and surface quality. In extreme cases they may cause tool breakage and damage to the machine. A prediction of these vibrations enables an informed choice of settings to achieve the best possible productivity while taking into account quality and cost requirements. [1, 2]

This contribution examines existing experimental and numerical methods to characterise and predict machine vibrations. These existing methods have not achieved widespread use in industry due to high costs and limited scalability. A new concept is proposed to predict vibrations based on a regression model, thus automating the costly modelling process (Fig. 1). The enhanced machine tool could then assist its user in evaluating settings.

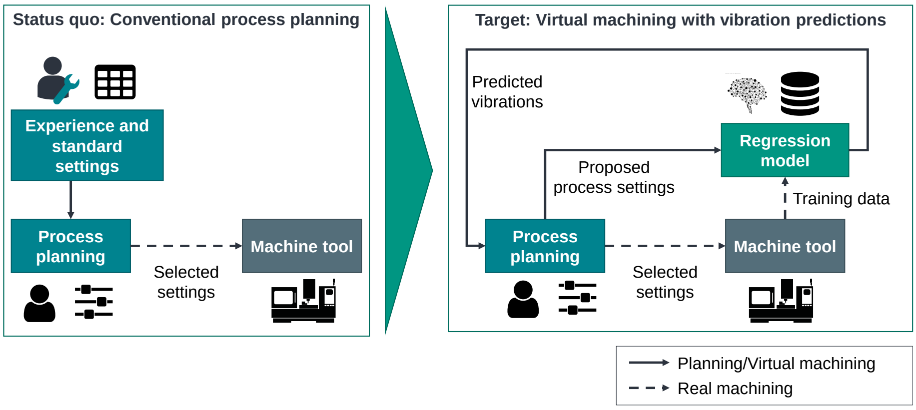

Fig. 1. Enhanced process planning using virtual machining

2 Existing modelling methods for machine tool vibrations

In the design process of machine tools, numerical simulation models are required in order to predict the behaviour of structures that have not yet been built. With existing machines, it is possible to identify vibration properties experimentally. In both cases, a model of the machine can be integrated into a simulation of the process-machine interaction.

2.1 Numerical simulation of machine vibrations

Vibration properties of mechanical structures, including machine tools, can be simulated using the finite element method (FEM). Once such a model has been built for a given machine type, predictions can be made concerning static properties (e.g. stiffness) and dynamic behaviour (natural frequencies and modes) [3]. Before complex FEM models can be used to assist in finding suitable process settings, a smaller surrogate model needs to be derived from the original using order reduction methods or machine learning, thus reducing the required computing resources [4, 5].

In order to predict the amplitude of vibrations or to increase the accuracy of the prediction, the model must contain a high level of detail including accurate damping properties. As there are no suitable models to predict damping properties in complex machines, these must be determined experimentally and added to the FEM model, thus increasing the cost of modelling [3]. The relevant mechanical properties of machine components, especially relating to friction and damping, vary widely among machines of the same type. Additionally, due to wear, these properties change over time for a given machine. Thus a model that was tuned for one particular machine will not always be valid for another machine of the same type or a different state of wear [6].

2.2 Experimental identification and data-driven approaches

Instead of simulating the structure of a machine tool using the methods described above, the vibration behaviour can be determined by performing experiments on a real machine. Currently a method known as experimental modal analysis (EMA) is typically used. This requires the machine structure to be excited by an external force, e.g. using an electromagnetic shaker. The transfer function mapping the measured excitation force to the resulting vibration is known as the frequency response function (FRF). This describes the machine's dynamic stiffness as a function of the excitation frequency. [7]

EMA is a costly process requiring specialised equipment and machine downtime, therefore it is not usually performed on every machine. Recent research has focused on identifying machine properties during operation [8–10]. These approaches aim to use cutting forces to replace the external excitation, however they still require targeted experimentation and thus a loss of production time.

Other approaches use machine learning and experimental data to map process settings directly to machining results related to the machine's vibration properties. Using an artificial neural network (ANN), Karkalos et al. predict surface roughness after milling [11]. Several studies focus on predicting the stability of processes, i.e. the occurrence of chatter, thus representing a stability lobe diagram (SLD): Cheruruki et al. use ANN for chatter prediction in turning [12], Friedrich et al. estimate a stability lobe diagram using support vector machines (SVM) and ANN [13], Denkena et al. use kernel interpolation [14]. All these approaches model a setup with a single combination of one machine and one tool. Postel et al. propose a hybrid approach for stability prediction relying on ensemble transfer learning, showing potential for deployment to a broader range of machines and tools [15]. Denkena et al. propose a process planning approach that relies on machine learning models to predict surface roughness in turning operations [16].

2.3 Simulation of process-machine interactions

Once the machine has been modelled using either an FEM simulation or an experimentally determined FRF, this model must be combined with a physical model of the cutting process itself in order to predict the vibrations occurring during operation. This may be achieved by performing a geometric-physical simulation. In this time-domain simulation, the frequency response function of the machine structure is approximated by a set of harmonic oscillators. In each time step, the intersection of geometric models representing the cutting tool and workpiece is determined. Based on this intersection and the cutting speed, empirical cutting force models predict the resulting force, which is applied to the oscillators in the structure model to predict the machine deformation. For the following time step, the workpiece geometry is updated by subtracting the intersection with the tool, and the tool position is updated based on the feed rate and deformation. [1, 17]

Geometric-physical simulation is conventionally used to assist when planning machining processes. Recent studies also aim to simulate in real time, parallel to the real machining process. Saadallah et al. train a surrogate model with machine learning using simulation results [18]. Finkeldey et al. use pre-calculated simulations results to deliver online predictions, taking into account the effect of tool wear during the process, by switching between several process models, each describing a different state of tool wear [19].

3 Regression model of vibration amplitudes in machining

All the methods presented above require significant expert knowledge, costly specialised measurement equipment and targeted experiments. To achieve widespread use in an industrial setting, an ideal modelling method for machine tools should be entirely automated. Instead of costly experiments, the method should rely on data acquired during regular operation of the machine tool in production. The approach presented in this contribution aims to fulfil these requirements by setting up a regression model to map process settings to the corresponding vibrations measured on the main spindle.

3.1 Overall architecture

Unlike the existing data-driven approaches mentioned above, the scope of this contribution is to predict vibration amplitudes through a regression model rather than determine whether a process will be stable. The aim is to deliver predictions for multiple tools, materials and machines, while taking into account changes over time in machine behaviour. The present concept covers stable vibrations resulting from open-loop dynamical behaviour. In future work, the authors plan to add a closed feedback loop to the model in order to include the influence of the vibrations on process forces, thus aiming to cover self-excited vibrations.

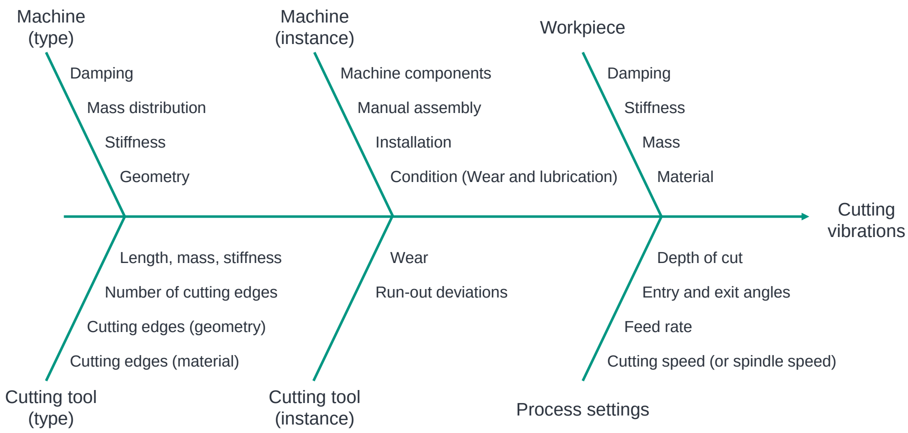

Fig. 2. Cause-and-effect diagram for cutting vibrations in milling [7, 20–22]

An overview of factors influencing cutting vibrations during machining processes is given in Fig. 2 using the example of milling. Additionally, machine tools display noncutting vibrations due to other excitations [22]. Given the aim of keeping the model up-to-date throughout the lifecycle of machine tools, the relevant time scales must be considered (Table 1). Depending on the rate of change over time, different strategies are required to take the change into account in the regression model. The factors with the highest rate of change over time (cutting conditions, machine pose, tool wear) are included in the input data of the model, while factors that change slowly are covered by updating the model.

Table 1. Changes in machine behaviour over time.

Approximate time scale	Cause of change
Days - years	Machine wear and maintenance work
Days	Model update
Minutes - seconds	Tool wear
Seconds - milliseconds	Cutting conditions, machine pose

Special consideration is attached to the cutting tool: while properties of the machine itself may remain constant over the course of several process steps and workpieces, machine tools and especially machining centres are typically used with multiple tools. A tool may potentially be used on multiple machines. The tools differ in their geometry (in particular the number of teeth or blades). Additionally the preferred process settings will depend on the tool and the workpiece material. These tool-specific properties influence the frequencies at which the machine structure will be excited by the process. In order to accurately model the machine structure for a wide range of frequencies, the corresponding model should be trained with data from several different tools. Therefore it is proposed to separate the model into two parts: a model of the cutting process and a model of the machine structure's dynamic stiffness (Fig. 3). The process model maps process settings and conditions to the cutting force, which the machine model then maps to the measured vibration. Thus the machine model can be trained using all the available data for a given machine, whereas each process model is trained using the data gathered for this individual process, potentially spanning multiple machines. A machine model is specific to a machine instance, whereas a process model describes a generic combination of a workpiece material with a tool type.

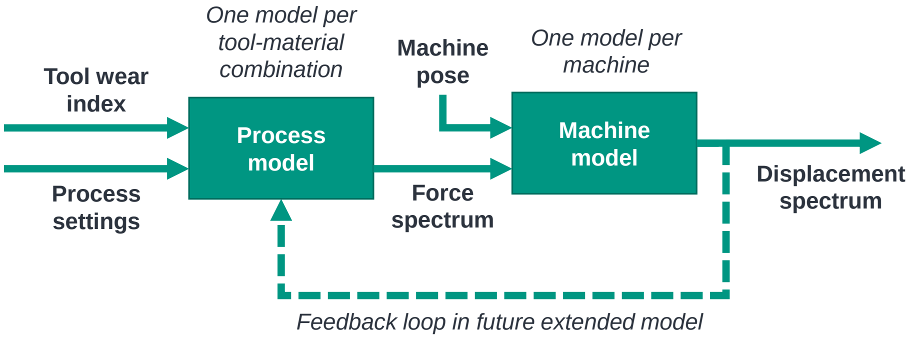

Fig. 3. Model architecture

The effects of workpiece mass and workpiece stiffness on the dynamic behaviour of the machine are not considered in the present article, based on the assumption of small and stiff workpieces. The effects of the tool mass, stiffness and length are also not taken into account, based on the assumption of stiff tools of equal length. However, the concept may be extended to consider modifications in dynamic behaviour based on the principles of receptance coupling [23].

3.2 Input and output formats

Inputs for the process model are the cutting conditions, in the case of milling these are the spindle speed n, feed rate v_f, axial depth of cut a_p, and tool engagement angle φ. A wear index for the tool instance, based on the tool's previous load history, is introduced as an additional input. The output from the process model consists in three force signals (one for each direction in space). In accordance with the state of the art, excitations and the resulting vibrations are modelled in the time-frequency domain, therefore the measured force (if available) and acceleration data are subjected to a Fast Fourier Transform (FFT). The FFT is performed with a sliding time window, taking into account the conflicting aims of time and frequency resolution. In training and applying the model, each time step is considered as a separate data point, in combination with the cutting conditions applying at that point in time. The force spectrum in each direction is used directly as a multi-dimensional input and output vector respectively, whereas the measured acceleration spectrum in each direction is integrated twice to obtain a displacement spectrum. In order to consider the effect of machine pose, the position of the feed axes is used as an additional input to the machine model.

3.3 Implementation of sub-models

Each sub-model (process model and machine model) constitutes a supervised learning task. Given the aim of predicting vibration amplitudes within a continuous range, regression is required. According to studies on a wide range of tasks, suitable machine learning algorithms include random forests, ANN, and SVMs [24]. The process model has a low-dimensional input and high-dimensional output, whereas the inputs and outputs of the machine model are both high-dimensional. In this respect, the required models show similarities to generative models and autoencoders respectively, suggesting a neural network may be suitable. On the other hand, the problem may be converted into multiple models with a single output, each corresponding to the amplitude of force or displacement in a given frequency band. An alternative approach consists in using the frequency as an additional input, thus representing the entire spectrum within a single model with a single output and successively applying the model to individual frequency bands. The latter approach has the advantage of allowing a flexible frequency resolution, which may be used to focus on the most relevant frequency bands (e.g. frequencies with significant amplitudes in a given process).

4 Deployment, transfer and update of models

The present approach is designed to be applied to multiple processes and machines, and adapt to changes in machine behaviour. Therefore a strategy is required for the initial training of models, their transfer to further machines and processes, and model updates based on new data.

4.1 Algorithm selection and hyperparameter tuning

As described above, several algorithms appear to be suitable for the implementation of the sub-models, and each algorithm provides hyperparameters that must be determined. To enable generalisation and transfer, these choices should not be made based on data from only one machine or one process. A dataset should be constituted that is representative for the group of machines and processes to which the approach is to be applied (e.g. all machining centres within a factory, or all machining centres produced by a particular machine vendor). Ideally, this wide ranging set of data is acquired from real production. However, this data isn't generally available, therefore it may be preferable to train with simulated data based on existing methods and validate with measured data.

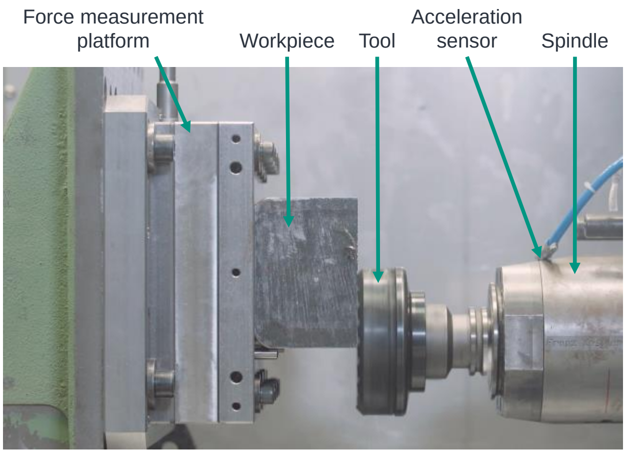

Fig. 4. Experimental setup for initial modelling of cutting processes

4.2 Initial training of sub-models

In general, a dynamic measurement of process forces is impractical in industrial production. If a valid machine model is available, this can be used to train the models of processes that are performed using this machine. Conversely, if process models are available for processes that collectively provide a sufficiently broad excitation spectrum, these can be used to train the machine model based on data gathered during these processes. If neither sub-model is available, force measurement must be performed for one machine. This may be based on a direct force measurement (Fig. 4) or an indirect measurement relying on available signals such as motor currents. After this initial effort, further machines may be modelled as described in the next section.

4.3 Transfer of models and model update

Machines of the same type do not present identical vibration behaviour, however the similar stiffness and mass distribution lead to similar natural frequencies. In order to exploit the similarity between machines of the same type, it is proposed to use pre-trained machine models from similar machines where available, and adapt them by continuing training with data from the specific machine, thus achieving a form of transfer learning. Likewise, it is proposed to transfer process models from processes where the workpiece material and tool type are similar.

During manufacturing operations, the data required for training the models is collected continuously. Periodically, the collected data is reviewed with respect to the accuracy of the existing model and the suitability of the data for training (e.g. broad excitation spectrum). Based on these criteria, the update of a sub-model may be triggered. In this case, the sub-model in question is trained using the newly collected data, while the weights of the other sub-models are frozen. When updating process models, data from multiple machines should be used if available.

5 Conclusions

In this contribution, an overall concept is presented for predicting vibrations in machine tools, consisting of two sub-models: a process model and a machine model. Both the final output (displacement spectrum) and the data transmitted from the process model to the machine model (force spectrum) are represented in the frequency domain. By relying on data acquired during regular manufacturing operation, the approach has the potential to enable a more widespread use of vibration prediction in process planning for machining.

Additional data is required to evaluate the models in detail and select optimal implementations of the sub-models. Further work may also focus on extending the model to consider the influence of self-excited chatter and vibrations not directly caused by the cutting force.

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