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Concept for Individual and Lifetime-Adaptive Modeling of the Dynamic Behavior of Machine Tools

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Abstract: The increasing demand for personalized products and the lack of skilled workers, intensified by demographic change, are major challenges for the manufacturing industry in Europe. An important framework for addressing these issues is a digital twin that represents the dynamic behavior of machine tools to support the remaining skilled workers and optimize processes in virtual space. Existing methods for modeling the dynamic behavior of machine tools rely on the use of expert knowledge and require a significant amount of manual effort. In this paper, a concept is proposed for individualized and lifetime-adaptive modeling of the dynamic behavior of machine tools with the focus on the machine's tool center point. Therefore, existing and proven algorithms are combined and applied to this use case. Additionally, it eliminates the need for detailed information about the machine's kinematic structure and utilizes automated data collection, which reduces the dependence on expert knowledge. In preliminary tests, the algorithm for the initial model setup shows a fit of 99.88% on simulation data. The introduced re-fit approach for online parameter actualization is promising, as in preliminary tests, an accuracy of 95.23% could be reached.

Keywords: machine tool; digital twin; dynamics; simulation; lifecycle

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1. Introduction

Machine tools are used to manufacture high-precision products. The trend towards individualization and an aging society in Europe creates new challenges for production [1]. As part of the megatrend of individualization, more and more product variants are required from production. At the same time, the quantities per variant are decreasing [1]. Skilled workers have extensive knowledge of their machines [2] and can therefore make an important contribution to meeting these requirements. However, a major problem in Europe is the shortage of skilled workers, which is exacerbated by demographic change [3]. To meet the challenges of increasing production demands and skilled labor shortages, intelligent systems and machines are needed to support the few remaining skilled workers. An important framework for addressing these issues is a digital twin that represents the dynamic behavior of a machine tool. This can be used, for example, in combination with a process model for preliminary process optimization in virtual space.

Different approaches exist to characterize the dynamic behavior of machine tools. There are approaches that derive models from modal analysis and other approaches that estimate the parameters of already existing models to match real-world behavior. Even modeling through machine learning algorithms is possible. In the sections below, all approaches are presented. Finally, the drawbacks are discussed and the requirements for a new concept are derived.

1.1. Estimation of Modal Parameters

The most prominent way to characterize the dynamic behavior of a machine tool is to conduct a modal analysis. The frequency response function (FRF) can be calculated and modal parameters can be obtained by applying multi degree of freedom (MDOF) fitting algorithms, such as Non-Linear Least Squares or the Rational Fraction Polynomial methods [4]. Contemporary approaches, such as the Complex Frequency-domain Least-Squares method, offer improved performance in handling closely spaced modes during the identification process [5].

There are different approaches to modal analysis. The essential way to conduct modal analysis is by applying force excitation either through impact hammer or shaker excitation while the machine tool remains stationary. By measuring the input force and the system's response (e.g., the displacement or acceleration) the FRF can be obtained. However, the dynamic behavior of a machine tool under real operating conditions slightly differs from the results that are obtained by impact hammer or shaker tests. Therefore, alternative ways to conduct modal analysis have emerged to better reflect the dynamic behavior of a machine tool under real cutting conditions [6].

In industrial applications, it can sometimes be difficult to measure the process forces when performing modal analysis during milling. Therefore, output-only methods have emerged that simulate the process force. Or, as with Operational Modal Analysis (OMA), ignore the process force and focus solely on the system response [6]. However, OMA methods are often limited to white noise, such as force excitation. This results in difficulties when estimating modal parameters under real process conditions such as milling forces, which do not represent a white-noise signal. Therefore, Devriendt and Guillaume [7] propose the Transmissibility Function-based Operational Modal Analysis (TOMA), where the form of the force excitation does not matter. The force excitation signal just has to be able to excite the structure in the frequency range of interest. The system response has to be measured at two different points and the force must be applied at two other points on the structure. A transmissibility function is calculated by using the vibration spectra of the two different points where the system response is measured. Here, it is important to note that it is assumed that the mode shapes show a linear behavior between both measuring points. The transmissibility function allows one to calculate the natural frequencies of the system. However, the TOMA is not suitable for machine tool applications. This is because machine tools are only excited at one point during operation, the Tool Center Point (TCP). In order to make the method practicable for these applications, Liu and Altintas [8] performed a mode shape compensation of the TOMA. As a result, only one force excitation point is needed. In order to achieve mode shape compensation, the mode shape is assumed to be linear along the structure. Mode shapes used for the compensation of the transmissibility function are obtained through a classic modal analysis. Since the modal parameters of machine tools are pose-dependent, the method cannot be used when the axes of a machine tool are moving. Liu et al. [9] built a mode shape database by conducting classical modal analysis at different points in the workspace of the machine tool. Between the measuring points, they use linear interpolation. The mode shape compensation TOMA proposed by Liu and Altintas [8] is then conducted with the mode shapes from the pre-built database at the respective point of the machine tool workspace.

There are methods which take the input force from the simulation rather than measuring it. Ostad Ali Akbari et al. [10] estimate the FRF at the tool tip by using in-process data and receptance coupling. The cutting forces are simulated at different spindle speeds by using a two Degrees-of-Freedom (DoF) milling model. The system response is measured by a non-contact displacement sensor mounted at the spindle flange. In order to get the FRF at the tool tip, the Receptance Coupling Substructure Analysis (RCSA) proposed by Schmitz et al. [11,12] is applied. The coupling parameters between the machine tool–spindle substructure and the tool holder–tool substructure are estimated using optimization. Altun, Çalıskan and Özsahin 2023 [13] identify the FRF of the workpiece–fixture system by using a similar approach. The cutting forces are simulated using a two DoF milling model. Two acceleration sensors mounted on the workpiece measure the system's response. In contrast to Ostad Ali Akbari et al. [10], the milling force coefficients are unknown. Instead, they estimate the milling force coefficients by using a least-squares algorithm. After the estimation of the cutting force coefficients, the milling forces can be used alongside the measurements of the acceleration sensors to calculate the FRF.

Also, methods exist where the force excitation is measured during the milling process. Iglesias et al. [14] propose a method where a sweep milling force is used to excite the machine tool. Interrupted cuts are performed, during which the spindle speed is steadily varied to create a frequency sweep over the frequency area of interest. The excitation forces are measured with a dynamometric tool holder. The system's response is measured with three accelerometers mounted on the spindle head. As expected, the obtained FRFs through sweep milling force excitation differ slightly from the FRFs obtained through impact hammer excitation. However, the calculated stability lobes obtained through the sweep milling force FRF show a better match to the real cutting limits than the ones calculated from the FRF obtained through the impact hammer testing.

1.2. Estimation of Parameters for Existing Models

Other ways to determine the dynamic behavior of a machine tool can be conducted if a parametric model exists and the parameters need to be identified.

Methods such as those proposed by Zollo et al. [15] employ direct approaches to deduce the equation of motion (EOM) for a multi-body model. The resolution for stiffness parameters involves simplifying and linearizing the EOM, followed by employing linear regression techniques.

Ellinger et al. [16] conducted a Global Sensitivity Analysis (GSA) to obtain a dimensionality reduction of models, such as a position-flexible multi-body system model. Only the model parameters that significantly influence the model's behavior are retained for the following parameter estimation. In this way, the dimensionality problem is mitigated. In subsequent research, Ellinger and Zaeh [17] used the GSA in combination with an iterative approach to estimate the parameters of complex models of machine tool structures. The parameter optimization is conducted by minimizing the difference between the measured behavior of the machine tool and the simulated behavior of its model. Here, the challenge is to manage local optima and a sparse high-dimensional input space. However, for the method to work, parameter boundaries must be narrowly defined. If this is not the case, it performs poorly. In addition, high computing resources are required.

1.3. Machine Learning Approaches to Model the Dynamic Behavior

In addition to physical modeling, it is also possible to model systems with deep neural networks. Barton and Fleischer [18] propose a concept that uses operational data to reduce the modeling effort through machine learning. The proposed approach comprises two sub-models: a process model and a machine model, both represented in the frequency domain. For regression tasks in machine learning, suitable algorithms include Random Forests, Artificial Neural Networks, and Support Vector Machines. To train the models, it is necessary to have a dataset that is representative of the machines and processes to which the approach is applied.

Modeling dynamic behavior through machine learning has also been demonstrated in other disciplines, such as civil engineering. Wu and Jahanshahi [19] showed that deep convolutional neural networks can be used to accurately predict the acceleration response at the roof of a building modeled as a MDOF system given the ground motion as input. However, with this approach, no modal parameters can be estimated, as is the case with all the presented machine learning approaches.

1.4. Review of the State-of-the-Art Methods

In Sections 1.1–1.3, several approaches to the characterization of the dynamic behavior of machine tools have been presented. The challenges and drawbacks of these methods are discussed in the following section. Finally, the requirements for a new concept are derived.

Methods that incorporate a force simulation model into modal analysis require the force model to closely resemble real-world behavior [10,13]. Also, either the parameters of the tool system and workpiece must be known [10] or the milling force model has to be adjusted, if different tools are used [13].

Methods that conduct modal analysis under operating conditions often require specific toolpaths or force excitation to be executed [13,14]. Therefore, this makes these methods not practicable to observe the dynamic behavior of machine tools in industry.

It can be shown that modal parameters are dependent on the axis positions of machine tools [13]. However, this is often not considered or not investigated in proposed methods [7,8,10,14,18].

Although TOMA methods mitigate the problems of both the need for force simulation and the need for a specific force excitation, not all modal parameters can be estimated [9]. In fact, only natural frequencies and damping ratios can be estimated. The mode shapes cannot be estimated.

Methods to identify the parameters of existing models require user expertise and are not fully automated, making them impractical for non-experts [15,17,20]. Furthermore, they often require digital models of the machine components. Additionally, the quality of these models directly affects the quality of the final simulation results [16,17].

Approaches that use machine learning technologies show good results in modeling a system's dynamic behavior. However, they require extensive training data and are fixed to use cases they are trained for [18,19].

In conclusion, current approaches need extensive expert knowledge for data collection and model creation. Going forward, the data needed for modeling must be captured automatically by each machine. The model itself must also be built independently by each machine using these data. In addition, there should be no need for detailed information about the kinematic structure of the machine, such as CAD data or other prior information. The influence of the position dependency of the axis positions must be taken into account to ensure realistic modeling. Also, due to manufacturing tolerances, variations in dynamic behavior can occur between machine tools of the same series. Furthermore, over the life of a machine tool, factors such as component wear cause an increasing discrepancy between the original model of the machine and its actual operating behavior [2]. Corresponding models must therefore be individual and lifetime-adaptive models of the machine's dynamic behavior. In order to meet these requirements, a novel concept is presented. The concept consists of a combination of existing and already proven algorithms and their application to the presented use case. Furthermore, the presented algorithms could be easily applied to a wide range of machine kinematics.

2. Materials and Methods

As presented in Section 1.4, the current methods for modeling the dynamic behavior of machine tools often require expert knowledge as well as comprehensive manual effort. This makes it especially impractical for industrial use if the dynamic behavior is to be captured throughout the entire lifetime of a machine tool. In order to ensure industrial applicability, both the data acquisition and the subsequent model setup should be fully automated. This provides the foundation for updating the model over the lifetime of a machine tool without manual effort. It also paves the way for modeling machines individually, since the dynamic behavior of machine tools produced in the same series differs slightly. The presented concept aims to fulfil these requirements by modeling the dynamic behavior of the machine tool as a linear time-invariant (LTI) system. Here, the focus is to investigate the dynamic behavior of the machine tool's TCP. Figure 1 illustrates the methodology of the approach presented in this paper. First, the machine tool's a priori FRF is autonomously measured at various positions within the workspace (Section 2.1). The transfer function of the a priori LTI model is then estimated by solving a least-squares problem (Section 2.2). The interpolation between the measuring points within the machine tool's workspace is carried out according to Baumann et al. [21]. Using operational data, a local re-fit of the dynamic behavior of the LTI model is performed to match the lifetime-changing behavior of the machine tool (Section 2.3). This re-fit is carried out continuously throughout the machine tool's lifetime to model changes.

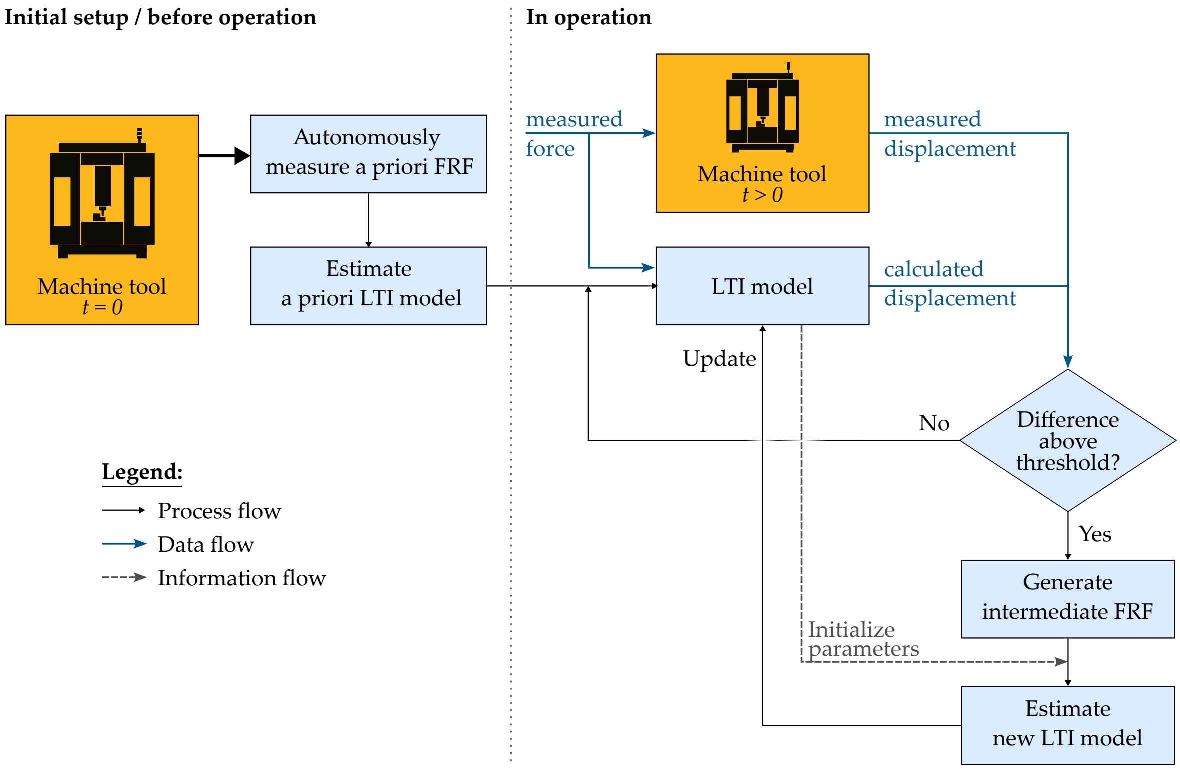

Figure 1. Methodology of the approach for modeling the dynamic behavior. The initial setup of the machine tool LTI model is performed at $t = 0$ (Section 2.2). During the machine tool's lifetime $t > 0$, its dynamic behavior changes and the update procedure is conducted (Section 2.3).

2.1. Autonomous Frequency Response Measurement

The primary objective here is to investigate the dynamic behavior of the machine tool's TCP. Therefore, a measurement setup is implemented with a triaxial accelerometer positioned on the spindle housing in close proximity to the rotating part of the spindle. This sensor measures the system's response. Through double integration, the displacement of the spindle is determined. The force excitation is simultaneously measured using a dynamometric spindle sensor. In future work, it is planned to incorporate an alternative, more cost-efficient system that enables a measurement without interrupting the machine tool's stiffness, and therefore, better replicates the dynamic behavior. In addition to the force and acceleration measurements, the axis positions are taken from the machine control system. This is necessary because the dynamic behavior of the machine tool is dependent on the axis positions.

The initialization of the LTI model (Section 2.2) involves a FRF measurement, facilitated by force excitation at various points in the workspace of the machine tool. This approach takes care of the position-dependent nature of modal parameters. To streamline this often time-consuming task for practical implementation, an ongoing project aims to develop a specialized tool. This tool is designed to automate the FRF measurement, ensuring efficiency and consistency in the acquisition of dynamic behavioral data across the machine tool's workspace. This involves measuring the force excitation (input) and the system response. The `modalfrf` function in the Matlab® Signal Processing Toolbox is then used to compute the FRF, a key element in establishing the LTI model.

Table 1 shows the measurement setup used for the initial model estimation (Section 2.2) and for the model update (Section 2.3).

Table 1. Data acquisition for initial model estimation (before operation) and for model update (in operation).

	Initial Setup / Before Operation	In Operation
Force excitation	Specialized tool for autonomous impact testing	Process forces during milling of a workpiece
Measurement of force	Dynamometric spindle sensor	
Measurement of displacement	Triaxial accelerometer *	
Measurement of axis positions	Machine control system	

* Through double integration, the displacement of the spindle is determined.

2.2. Estimation of the a Priori Model of the Machine Tool

The detailed procedure for estimating the a priori LTI model for each measured point in the workspace of the machine tool is shown in Figure 2. First, the number of poles of the measured FRF is determined by evaluating the output of the Matlab® Signal Processing Toolbox (Version 23.2 R2023b) function `modalsd`. This function computes the natural frequencies of the measured FRF that are stable between successive model orders. The transfer function of the a priori LTI model is then estimated by using the Matlab® System Identification Toolbox (Version 23.2 R2023b) algorithm `tfest`.

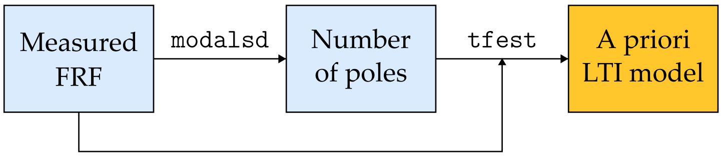

Figure 2. Procedure for estimating the transfer function of the a priori LTI model.

The inputs of the `tfest` algorithm are the measured FRF $F(\omega_k)$ at frequency points $\omega_k,\ k = 1,\ldots,N_f$, as well as the number of poles and a frequency-dependent weight factor $W(\omega_k)$. The factor $W(\omega_k)$ provides the ability to weight certain frequencies in the optimization. The resulting LTI model obtained by the `tfest` algorithm consists of a time-discrete transfer function of the following shape:

$$H(z^{-1}) = \frac{a_0 + a_1 z^{-1} + \cdots + a_n z^{-n}}{1 + b_1 z^{-1} + \cdots + b_m z^{-m}} \tag{1}$$

In order to obtain this transfer function, the following least-squares problem is solved by performing S-K iterations [22–24]:

$$\min_{H(\omega)} \sum_{k=1}^{N_f} |W(\omega_k)(H(\omega_k) - F(\omega_k))|^2 \tag{2}$$

where $H(\omega)$ is the estimated transfer function in frequency space.

2.3. Updating Model Parameters Using Operating Data

To keep the built LTI model up to date throughout the machine's lifetime, an update algorithm is required that uses operational measurement data. With the transfer function (Equation (1)) of the a priori LTI model, it is possible to calculate the estimated displacement $\hat{y}$ given a measured force input u at time step k:

$$\hat{y}[k] = a_0 u[k] + \cdots + a_n u[k-n] - b_1 \hat{y}[k-1] - \cdots - b_m \hat{y}[k-m] \tag{3}$$

A least-squares problem is established by comparing the estimated displacement $\hat{y}$ to the measured displacement y.

Under operating conditions, the milling force does not excite the machine tool structure in all the frequencies of the interested frequency range to be modeled. Therefore, determining a complete FRF for updating the LTI system, as presented in Section 2.2, is not possible. However, as machine tool components wear unevenly, the entire FRF does not change significantly, but only part of it. Thus, the existing LTI system can be used in combination with the newly measured data for a local re-fit procedure. A detailed description of the update process for the parameters of the LTI systems is provided below. The right-hand side of Figure 1 illustrates this update process.

First, the measured force is used as an input for the LTI model to calculate the expected displacement $\hat{y}$ according to Equation (3). Then, the deviation between the measured displacement y and the calculated displacement $\hat{y}$ is calculated. If the difference is above a threshold value, the update process is started.

The starting point for the initial update is the initially measured FRF and the transfer function of the a priori LTI model (Section 2.2). During the initial update, the parameters of the LTI model are updated to match the behavior of the machine tool under operating conditions. Once the initial update of the LTI model to the operating behavior has been made, further updates of the model are carried out based on the model and the FRF of the respective previous update step. This allows for the dynamic behavior to be continuously monitored.

During the operation of the machine tool, the force and displacement are measured and the Power-Spectral-Density (PSD) of the measured data is calculated. The ratio of the displacement PSD and the force PSD is then calculated to obtain data points for an intermediate FRF. These data points are combined with the FRF from the previous update step. The data points of the FRF from the previous update step are replaced with the new data points from the measured operating data at the same frequencies. This results in an intermediate FRF that contains steps at the points where the new data points were inserted. Figure 3 shows the FRF obtained in a previous time step and the newly measured data points.

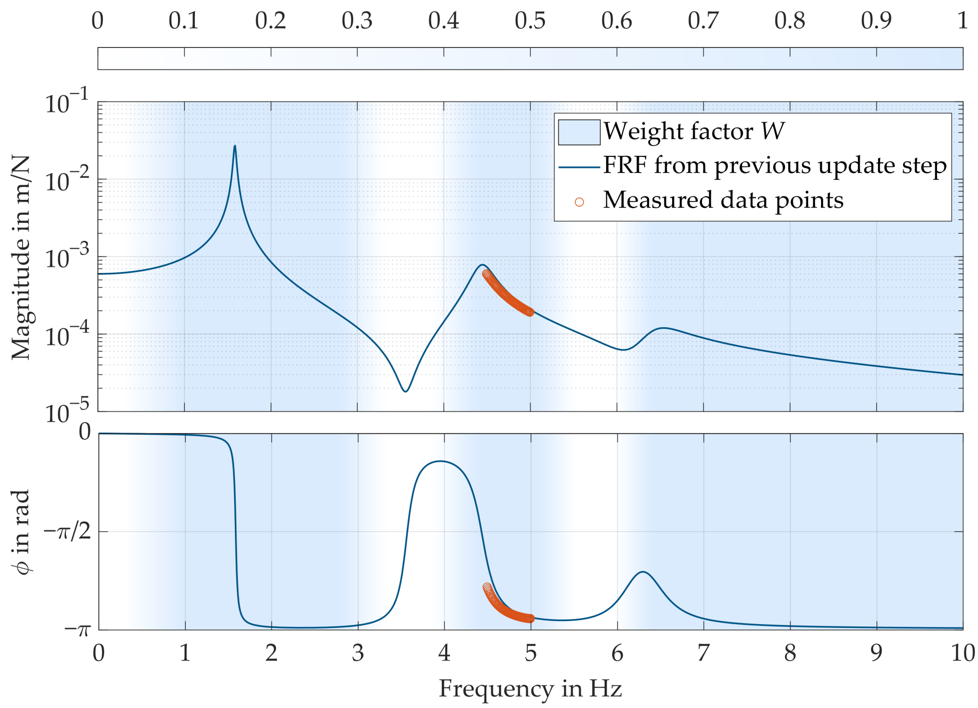

Figure 3. Comparison of the FRF obtained from the previous update step and the newly measured data points used for construction of the intermediate FRF. Also, the concept for constructing the frequency-dependent weight factor $W(\omega_k)$ is shown.

The `tfest` algorithm is applied to this intermediate FRF in a comparable way to the estimation of the a priori LTI model. But this time, the algorithm is initialized by using the parameters for numerator and denominator from the previous update step. Here, it must be noted that, when performing the initial update to match the behavior of the a priori model to operating conditions, the algorithm is initialized with the parameters from the a priori LTI model. As there are steps in the intermediate FRF, the frequency-dependent weighting factor $W(\omega_k)$ (Equation (2)) is also defined preliminary to the optimization. As shown in Figure 3 the factor is set to one at the frequencies where the newly measured data points are inserted and where the values of the previous FRF are maintained. An uncertainty range around the measured data points and at the frequency 0 Hz is defined. There, the frequency-dependent weight factor is selected to be less than one. The uncertainty range could be determined by examining the influence of the eigenmodes that could be identified as significantly different from the current LTI model based on the measured data. The frequency-dependent values for $W(\omega_k)$ are selected such that the new data points that generate the step in the intermediate FRF are smoothly faded in. Figure 3 illustrates how $W(\omega_k)$ could look like. The exact construction of the frequency-dependent weighting factor $W(\omega_k)$ is investigated in further research.

The update process of the LTI model described above is carried out by using operating data only for the point in the machine tool's workspace at which they were measured. However, changes in machine tool components also affect the observed dynamic behavior at other points in the workspace. For this reason, we propose an interpolation of the transfer function, so that surrounding positions are also updated. The interpolation to obtain this position update is performed with descending weighting on the surrounding points. The exact weighting of the position update is also part of future research.

3. Results

The main focus of this paper is the introduction of a concept for the individual and lifetime-adaptive modeling of the dynamic behavior of machine tools. Initial tests have been conducted in virtual space to get a first impression of the application of the concept explained in Sections 2.1–2.3 and to validate its capabilities. In this section, the results of these preliminary tests are presented. For this purpose, a simplified three-DoF model was used as a reference model within the simulation, as shown in Figure 4. It is important to note that this three-DoF model does not represent an actual machine tool. However, this model should be sufficient enough for testing the algorithm under controlled conditions.

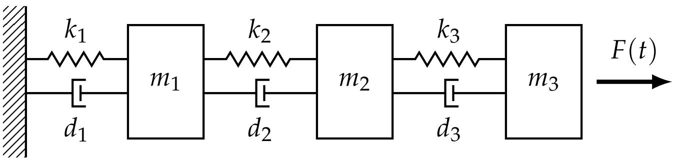

Figure 4. The three-DoF model used for the simulation to obtain an FRF validation.

3.1. Estimation of the a Priori Model of the Machine Tool

First, the FRF has to be simulated. This is performed by exciting mass m_3 with a chirp signal that contains frequencies that are in the frequency range of interest. By simulating the displacement of m_3, the response of the system is obtained.

With the simulated FRF, the natural frequencies for successive model orders are determined by the `modalsd` algorithm. The results of this algorithm are saved into a matrix. The number of poles is determined by evaluating the number of natural frequencies that differ only slightly across the different model orders. In the presented example, we obtain three poles. But, as every pole of a system has a corresponding complex conjugate, six poles are considered for the `tfest` algorithm. After setting up the frequency-dependent weight factor $W(\omega_k)$ (Equation (2)), the `tfest` algorithm is able to estimate a time-discrete transfer function of the a priori LTI model. In the case of the simulation of the three DoF system, we choose $W(\omega_k) = 1, \; k = 1, \ldots, N_f$ to be constant across all frequencies. For a sample time of $T_s = 0.01$ s, the resulting transfer function consists of eleven free coefficients and can be expressed as follows:

$$H(z^{-1}) = \frac{0.9874z^{-1} - 3.715z^{-2} + 5.424z^{-3} - 3.635z^{-4} + 0.9461z^{-5}}{1 - 5.704z^{-1} + 13.78z^{-2} - 18.06z^{-3} + 13.54z^{-4} - 5.504z^{-5} + 0.9485z^{-6}} \times 10^{-5} \quad (4)$$

Figure 5 shows that a good fit of the estimated transfer function to the simulated FRF is reached. In order to obtain an accurate quantification of the accuracy of the estimated transfer function, the fit is calculated by using the complex FRF values of the simulated data F and the estimated data H [25]:

$$\text{fit} = \left(1 - \frac{\|F - H\|}{\|F - \text{mean}(F)\|}\right) \times 100\% \quad (5)$$

For the three DoF example presented above, we calculate a fit of 99.88%.

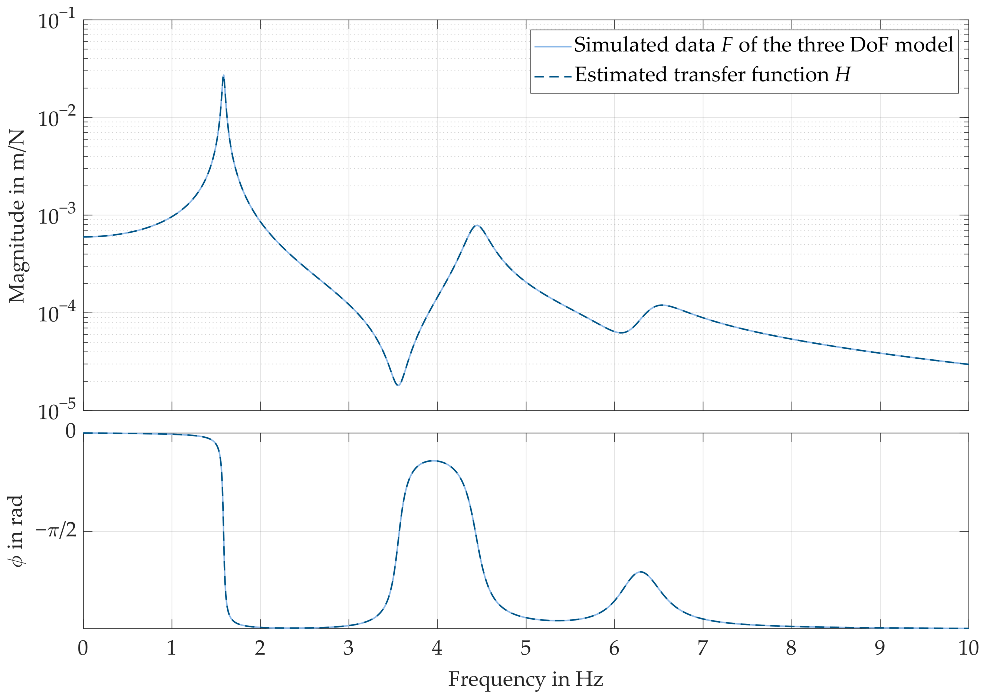

Figure 5. Comparison of the simulated FRF of the three-DoF model (Figure 4) and the FRF obtained through estimation.

3.2. Updating Model Parameters Using Operating Data

Once the a priori model of the machine has been built, the machine behavior may change during the operation of the machine tool. This section illustrates how the updated process described in Section 2.3 could be performed in practice. Here, the same three-DoF model, as discussed in Section 3.1, is used. In order to induce a change in its dynamic behavior, the stiffness parameter k_1 is intentionally reduced by ten percent.

To validate the update process, the model is excited with real measured milling forces, as shown in Figure 6, because simulated milling forces may not fully capture the complexities present in real-world scenarios. This allows one to validate the updating process in a more realistic scenario. The displacement of mass m_3, representing the system's response, is simulated. To identify the frequencies where the system is significantly excited by these milling forces, the displacement PSD is calculated as shown in Figure 7. A threshold value is set and the frequencies that exceed this threshold value are determined. In this example, this threshold is set to 10^{-9}. It is important to note that the choice of the threshold value plays a key role in determining the frequencies, as it directly affects the subsequent construction of the intermediate FRF. Once the frequencies have been determined, the measured data points to be inserted into the intermediate FRF are calculated. This is performed by calculating the Fourier transform of the measured force and displacement at the determined frequencies.

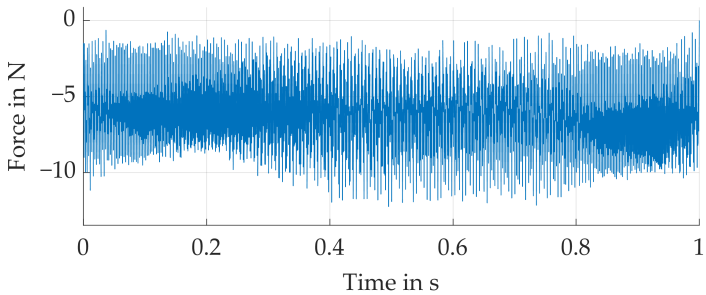

Figure 6. Milling force excitation used for simulation of the *In operation*-phase of the proposed concept introduced in Section 2.3.

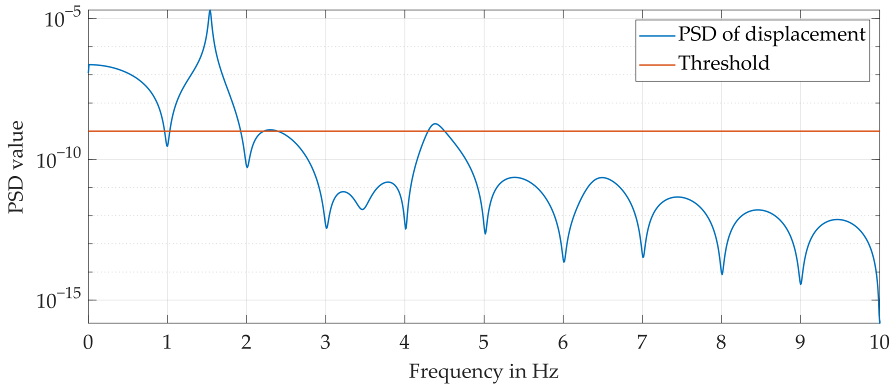

Figure 7. Simulated PSD of the displacement of mass m_3 and the selected threshold for the selection of the measured data points to be used in the intermediate FRF. All points at frequencies where the PSD is above the selected threshold 10^{-9} are selected as measured data points for the use in the intermediate FRF.

Next, the intermediate FRF is constructed. The data points of the previously determined FRF in Section 3.1 are substituted with the newly calculated data points from the measurement. Figure 8a shows the calculated data points from the measurement at the frequencies identified by using the PSD threshold. Figure 8b shows the intermediate FRF with the already inserted measured data points and the resulting steps in the FRF.

With the intermediate FRF established, the `tfest` algorithm is applied to update the parameters of the a priori LTI system determined in Section 3.1. The algorithm is initialized with parameter values from section Section 3.1, and the weight factor $W(\omega_k)$ is determined. Here, a weight factor of one is selected at all frequencies where the measured data points are inserted. Between these frequencies, the weight factor is set to zero. Choosing a non-zero weight factor between these points could cause the algorithm to misinterpret the steps in the intermediate FRF (Section 2.3) as a pole. At a distance from the last inserted measured data point, the weight factor returns to one as the influence of the eigenmode decreases in this region.

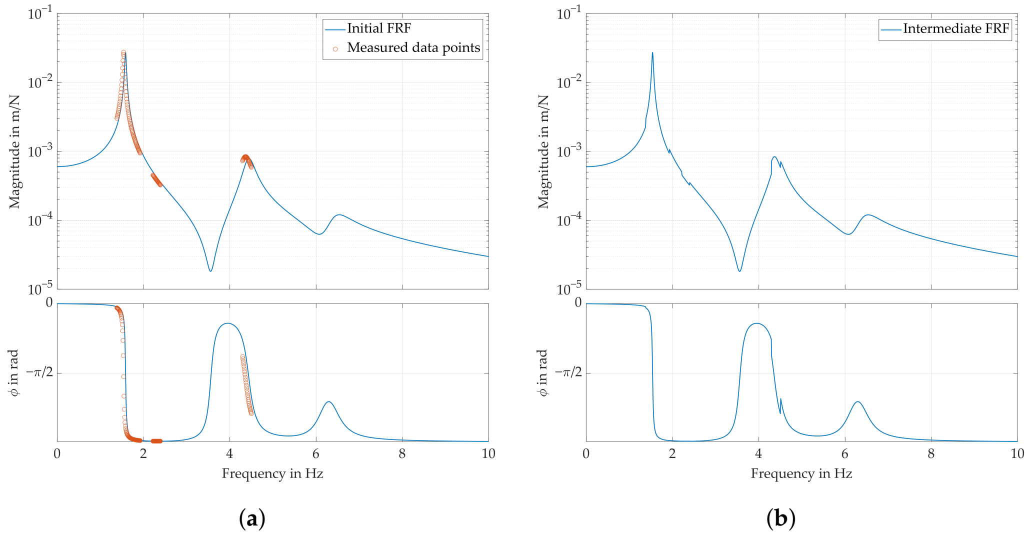

Figure 8. (**a**) Initial FRF obtained in Section 3.1 and the selected measured data points for the use in (**b**) the intermediate FRF.

Figure 9 displays the result of the parameter update, showing the FRF of the updated transfer function. In addition, the weight factor is visually represented by color coding the frequency ranges. For comparison, a complete FRF of the system with the stiffness parameter k_1 changed by 10% was simulated (theoretical FRF at $t > 0$). The FRF of the updated transfer function shows a fit to the theoretical FRF at $t > 0$ of 95.23%. Better results could be achieved by further optimizing the weighting factor $W(\omega_k)$ in future research.

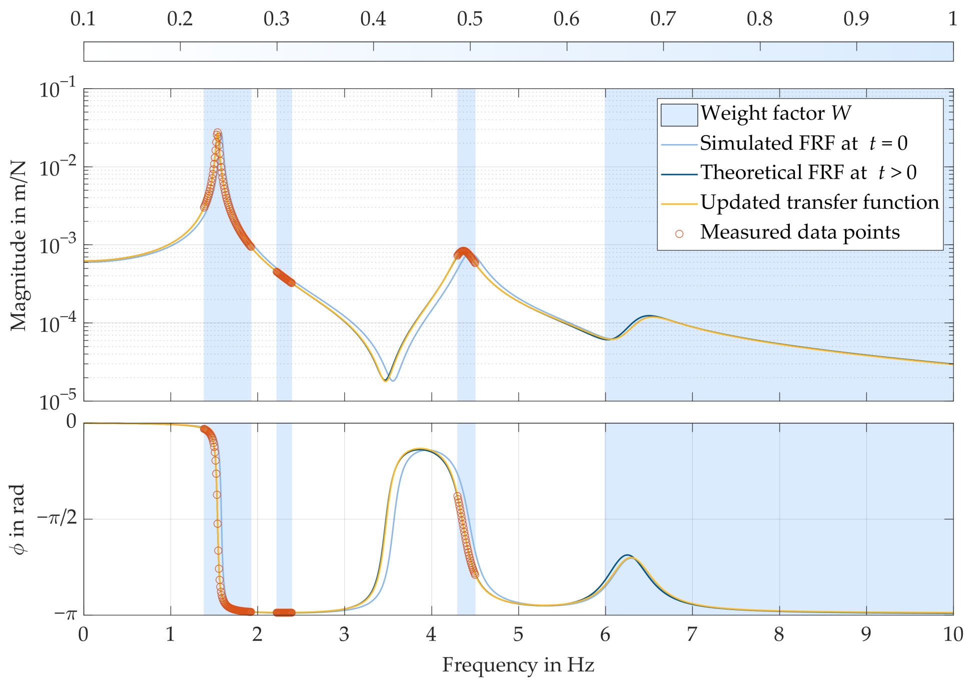

Figure 9. Result of the parameter update process. The FRF of the updated transfer function shows a fit to the theoretical FRF at $t > 0$ of 95.23%.

4. Discussion

The estimation of the a priori LTI model using `modalsd` and `tfest` shows promising results for simple systems. However, it is important to review the capabilities of this approach for real system behavior. These more complex cases can present challenges that are not apparent in simpler ones such as the presented three-DoF model. High modal density can be an example of such challenges.

Furthermore, it is crucial to investigate the reliability and effectiveness of the concept for the parameter update. It is necessary to validate this approach by demonstrating its functionality and its ability to match the dynamic behavior of the updated LTI model to the behavior observed in the real world.

Also, the proposed update interpolation at various points in the machine tool's workspace could lead to insufficient modeling.

In addition, the proposed concept relies on the reliability of the automatic measurement of force and acceleration. As a result, this automatic measurement is critical for the concept to work as intended.

In the following, we also evaluate the advantages and disadvantages of the proposed concept compared to the state of the art, focusing on the following key aspects:

4.1. Computational Efficiency

Compared to methods like Ellinger's [16,17], which require extensive optimizations, our approach has a significantly faster computation time. The reason for this is that the parameter space is smaller, and the expected displacement is calculated analytically instead of performing a time-consuming numerical simulation. In fact, we achieve results within seconds, improving the real-time applicability.

4.2. Model Independence and Accuracy

The presented approach does not rely on the accuracy of a manually constructed model. As opposed to relying on precise parameter selection, as proposed by Ellinger [16,17], the presented approach captures all effects and considers flexible bodies and axes. However, the presented approach limits the optimization efforts in understanding component-specific vibrations due to the lack of insight into the machine structure.

4.3. Direct Force Measurement

Measuring force directly, as opposed to simulating [10,13], eliminates the inaccuracies associated with simulating force. However, there are additional challenges, such as measurement uncertainties and increased sensor requirements, which have an impact on the measurement quality, costs and installation space.

4.4. Autonomous Measurement

The presented approach has the potential for autonomous operation without requiring user expertise. However, thoughtful design considerations for the excitation tool are needed to ensure that the quality of autonomous measurements meets certain standards.

4.5. Lifetime Applicability

The proposed concept is suitable for continuous use throughout the lifetime of the machine. In contrast to the re-fit approach presented in this work, the other methods require the entire process to be restarted, which involves a considerable amount of time and effort.

4.6. Versatility across Machines

Ideally, even with more complex cinematic systems, the presented approach should be easily transferable to a wide variety of machine tools. For the transferability to work, it is necessary to install the necessary measurement technology. The acceleration sensor is unproblematic, but the force measurement unit is not. An ongoing project is working on a solution that is as easy to retrofit as possible.

In summary, our proposed concept excels in several aspects, including computational efficiency, model independence and lifetime applicability. While there are challenges such as increased sensor requirements and retrofitting for transferability to different types of machines, our approach represents a promising leap forward in the direction of autonomous and versatile machine diagnosis.

5. Conclusions and Outlook

In this contribution, a concept is proposed for the individual and lifetime-adaptive modeling of the dynamic behavior of machine tools. The proposed concept consists of the following elements:

- A measurement setup that enables the autonomous measurement of the frequency response at different positions in the machine tool workspace.
- A modeling approach that models the machine tool as a LTI system.
- An estimation procedure that estimates the transfer function of the LTI model.
- A concept for the lifetime accompanying update of the LTI model.

The approach for estimating the transfer function of an a priori LTI model of the machine tool shows promising results for simple systems. In preliminary tests conducted in virtual space using a simplified model, a fit of 99.88% could be reached. The concept for updating the parameters of the LTI model introduces a new approach into the lifetime-adaptive observation of the dynamic behavior of machine tools. In preliminary tests performed in virtual space where one stiffness value was reduced by ten percent, a fit of 95.23% was obtained between the FRF of the updated transfer function and the theoretically correct FRF of the simulated model. However, better results could be obtained by further optimizing the weighting factor $W(\omega_k)$ used for the re-fit process. The exact construction of the frequency-dependent weighting factor $W(\omega_k)$ is investigated in further research.

In future work, also, an alternative, more cost-efficient system that enables a measurement without interrupting the machine tool's stiffness is developed. To streamline the often time-consuming task for the practical implementation of FRF measurement, an ongoing project aims to develop a specialized tool. In addition, the capabilities of the LTI transfer function estimation approach will be verified using real machine tool data. Further investigations will be carried out to explore the practical implementation of the transfer function update procedure as well as the interpolation of the position update.

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Abbreviations

The following abbreviations are used in this manuscript:

DoF	Degrees of Freedom
EOM	Equation of motion
FRF	Frequency response function
LTI	Linear time-invariant
MDOF	Multi-degree-of-freedom
OMA	Operational Modal Analysis
PSD	Power Spectral Density
RCSA	Receptance Coupling Substructure Analysis
TCP	Tool Center Point
TOMA	Transmissibility Function-based Operational Modal Analysis

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