PRODUCTION MACHINES

Identification of natural frequencies of machine tools during milling: comparison of the experimental modal analysis and the operational modal analysis

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Abstract

Modal parameters (natural frequencies, mode shapes and modal damping) help to understand the dynamic behaviour of complex systems like machine tools. There are several approaches for finding the modal parameters. The Experimental Modal Analysis (EMA) has proven to be effective at standstill of a machine tool. The excitation, realized with impulse hammer or shaker, and excited responses at several locations are measured. Alternatively, the Operational Modal Analysis (OMA) can be deployed for finding the modal parameters during operation. Here, responses to excitation resulting from operation are only measured. The modal parameters are mathematically identified from the measured signals in both cases but with different methods. This paper discusses, to what extent both approaches (EMA and OMA) can lead to plausible identification of natural frequencies of a machine tool during milling. Concerning the EMA, attention is paid to capturing the excitation. Process forces can be assumed to be the most significant excitation. However, there are other excitation sources beside the process forces (e.g. drives, hydraulic and pneumatic aggregates), which are considered by this assumption to be a part of disturbances with consequence for the identification of the modal parameters. Regarding the OMA, attention is paid to the fact that the excitation is assumed to be broadband like the white noise. Unfortunately, this assumption does not match the characteristics of a real excitation. This paper contains the identification of natural frequencies of a machine tool during milling within both approaches. The achieved results are compared and discussed.

Keywords Machine tool · Dynamics · Experimental modal analysis · Operational modal analysis

1 Introduction

The dynamic behaviour of a machine tool, i.e., the response (vibration) of a machine tool to mechanical excitations, takes an influence on its four properties (the working accuracy, the performance, the reliability and the environmental behaviour) [11]. The sources of the mechanical excitation can be external (e.g., neighbouring machines) or internal (e.g., cutting process, movements of NC-axes and imbalances of rotating components). The dynamic behviour is largely determined by the mechanical structure and the drives of the machine.

In general, the aim is always to shift existing limits, e.g., to increase the depth of cut, to improve workpiece quality, to reduce noise pollution and to increase the life time of machine components and cutting tools. All these outcomes are affected not only by the machine tool itself but also by the used tools, fixtures, clamping devices, the workpiece and the way of operation. Furthermore, the dynamic behaviour can depend on the actual NC position in the working space. It is obvious that the complexity is huge when existing limits should be shifted. In order to be able to manage such complexity, mathematical models resulting from a system identification are deployed. The experimental identification of a system depends on the currently acting boundary conditions, under which the investigation takes place, on the current state and healthy of the system. In case of machine tools, a significant difference between identification performed at standstill and during operation can exist,

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as referred in [19, 22, 26]. The difference can be caused by the process damping [1, 25], changing inertial masses due to the workpiece and tool weight, excitation by moving masses [12, 17], changed static preload in components with non-linear characteristics (like bearings) and gyroscopic moments [14]. The system identification is also important in stability assessment of cutting process. As referred in [3, 25], there is a potential for improvements in stability assessment that probably remains unused and can be partly linked to the mathematical model.

2 Modal analysis of machine tools

In machine tools, the modal analysis has been used for system identification when the dynamic behaviour is investigated [11]. The modal parameters (natural frequencies, modal damping and mode shapes) in combination with the visualisation of the mode shapes (usually by using a wireframe model) significantly helps to understand the complex dynamic behaviour. Consequently, improvements can be derived effectively [10].

2.1 Experimental modal analysis

When conducting the experimental modal analysis (EMA), the mechanical structure is excited with an auxiliary device, e.g., an impulse hammer or a shaker. The excitation force is measured together with responses of the structure to this excitation. The measured excitation and response signals are often used for the estimation of frequency response functions (FRF), from which the modal parameters can be identified by using curve-fitting methods [13]. This corresponds to the phase separation procedure of the EMA. There exist many estimators for FRF [13]. In this paper, the estimators H1 and H2 are implied [11].

In sake of simplicity, a single input and single output system is assumed for further explanation. The measured signal of the excitation (force $F_m(t)$) represents the input signal from the point of view of the system theory. The measured response signal (accelerations $\ddot{x}_m(t)$) stands for the output signal. Both, input and output signals, are subject to errors, depicted by noise of the input ($v_{in}(t)$) and the output ($v_{out}(t)$) in Fig. 1. $H(j\omega)$ represents the FRF between the input and the output and it is also a mathematical model of the dynamic behaviour of the system. Furthermore, this FRF may not reproduce the dynamic behaviour of the system perfectly. The difference between the real system behaviour and the modelled one is called the process noise $w(t)$. This difference can be caused by assumptions being made at modelling. The estimator functions H1 and H2 are calculated by using the power spectral density (PSD) of the measured signals [13]. If the noise
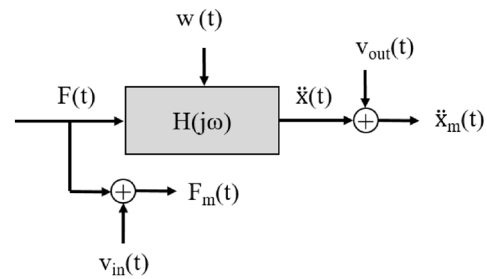

Fig. 1 Principal scheme for performing EMA

of the input signal can be neglected, the H1 estimator is recommended to be used. In this case, the averaged cross-PSD $\overline{S}_{FX}(j\omega)$ between the input and the output signal is set in relation to the averaged auto-PSD $\overline{S}_{FF}(\omega)$ of the input signal according to

$$H^{H1}(j\omega) = \frac{\overline{S}_{FX}(j\omega)}{\overline{S}_{FF}(\omega)} \tag{1}$$

On the other hand, if the noise of the output signal can be neglected and the noise of the input signal has to be considered, the H2 estimator should be used for computing the FRF.

$$H^{H2}(j\omega) = \frac{\overline{S}_{XX}(\omega)}{\overline{S}_{FX}(j\omega)} \tag{2}$$

The scheme from Fig. 1 can be generalized to a multiple input and multiple output (MIMO) system, with m inputs and n outputs. In such case, a matrix ($n \times m$) of FRF $H^{\text{MIMO}}(j\omega)$ can be estimated according to

$$H^{\text{MIMO}}(j\omega) = x(j\omega)x(j\omega)^{\text{H}}\left(f(j\omega)f(j\omega)^{\text{H}}\right)^{-1} \tag{3}$$

where x and f denote the output vector of dimension $n \times 1$ and the input vector of dimension $m \times 1$, respectively.

EMA assumes a stable linear time-invariant (LTI) system and clear causality between the input and the output. In order to meet these assumptions as much as possible, machine tools are investigated at standstill. Conducting EMA during milling let come up new challenges related to these assumptions. A challenge, which is specific for EMA, is the causality. It can be assumed that the process forces are the most significant excitation source in the machine tool and the measurement of these forces represents the captured input signal. Nevertheless, the process forces are not the only excitation source. There are other excitation sources like the drives of NC axes, chip conveyor, lubrication units, coolant pumps, various ventilators, hydraulic and pneumatic devices etc. All these excitations are not considered by FRF for the process forces.
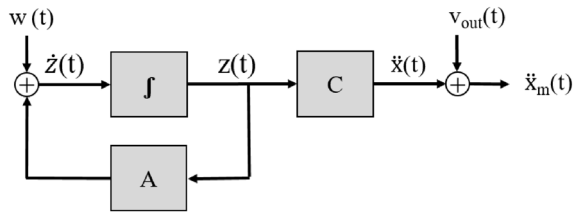
Fig. 2 Principal scheme for performing OMA when SSI is applied

Therefore, the process noise $w(t)$ can become significant. In the evaluation, this fact can appear as a noise of the input or the output depending on the estimator.

2.2 Operational modal analysis

Alternatively, the modal parameters can be identified by using the operational modal analysis (OMA) [5]. In such case, acceleration responses $\ddot{x}_m(t)$ are only considered for the identification, as shown in Fig. 2. These can also be affected by the output noise $v_{out}(t)$. The excitation remains unknown. However, it is assumed that the process noise $w(t)$ acts as excitation source and has the characteristics of white noise and it is distributed over the investigated structure so that all modes are excited uniformly. Moreover, the process noise is statistically distributed according to the normal distribution.

Beside the explained inputs and outputs, the system description includes the states $z(t)$ of the system, the system matrix $\mathbf{A}$ and the output matrix $\mathbf{C}$. The dynamic behaviour of the system can be described with the forward stochastic model, as follows

$$\dot{z}(t) = \mathbf{A}z(t) + w(t)$$
$$x_m(t) = \mathbf{C}z(t) + v_{out}(t) \tag{4}$$

OMA aims at finding the system matrix $\mathbf{A}$, from which the modal parameters can be computed through the eigendecomposition [21]. The finding the system matrix $\mathbf{A}$ is based on the Stochastic Subspace Identification (SSI) [16, 18].

OMA originates from the investigation of very large structures (buildings, ships, aircraft), which are very difficult to excite adequately by using auxiliary devices [21, 23]. In all these cases, the excitation results from ambient conditions such as wind, water waves or ground vibrations. OMA has also been applied in machine tools [24].

The challenge with the causality in the context to EMA, which was explained in the previous subsection, has no relevance in the case of OMA, since OMA assumes all excitation sources to be a part of the process noise. Contrary, there is another challenge being linked to the excitation, since the common excitation sources in machine tools do not fulfil the assumption related to white noise excitation of the OMA, as stated above.

3 Procedure

As each approach has a drawback related to the fundamental assumptions, the theoretical discussion in the previous section does not clearly provide a suggestion, which approach should be used when a machine tool is investigated during milling. Therefore, the goal of this paper is to present some practical aspects that can help to make the right choice. For this purpose, natural frequencies of a machine tool during milling are identified within both approaches. The natural frequencies belong to global modal parameters. Thus, they are essential for successfully performed modal analysis, in general. In the paper, there is only one experimental setup for both approaches and both approaches process the same signals, as shown in Fig. 3.

The investigation of the dynamic behaviour of a machine tool during milling is linked to a few issues. The first big issue is the observability, which is needed for both approaches (EMA and OMA). In the context of the identification of modal parameters of a machine tool, this means that responses measured with accelerometers include information of all modes being of interest. Assuming that the milling process is the most significant excitation source, it has to be ensured that the milling process causes a broadband excitation to excite all those mode shapes. A milling process with constant cutting speed is always linked to a multiple harmonic excitation (frequencies are the multiple of the tool speed). Concerning OMA, the excitation should also fulfil the white noise assumption. Therefore, the milling process has to be modified to achieve a broadband excitation [4, 6, 9, 16]. The modification being applied in this paper is explained more in
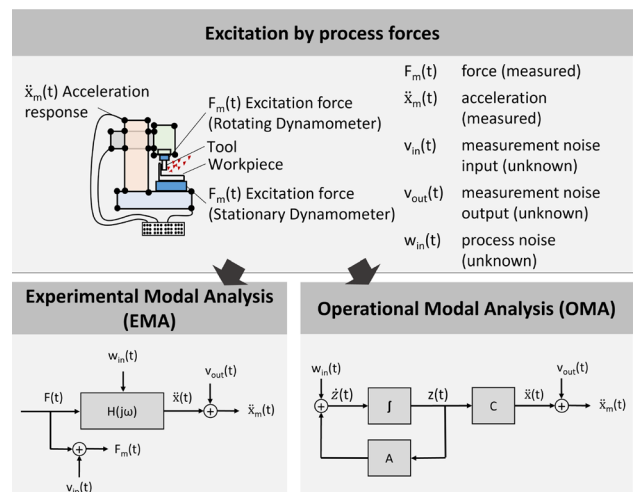

Fig. 3 Principal procedure for comparing EMA to OMA being pursued in the paper

detail in Sect. 4.2. The modification of the milling process implies a controllability of the excitation.

The next issue consists in the assumption of the time-invariance due to the fact that the dynamic behaviour of a machine tool depends on the tool position in general. Considering the varying tool position during milling, the dynamic behaviour of a machine tool is not time-invariant any more. In [8], a method for a quick assessment of the time-invariance of the dynamic behaviour is suggested. Based on this, a tool path with time-invariant dynamic behaviour can be planned, as referred in [20].

The last issue, being addressed in this paper, is related to the causality as already discussed in Sect. 2.1.

Concerning EMA, there is a need to measure the process forces. In general, such measurement takes an influence on the dynamic behaviour of the investigated machine. Since the measurement setup is identical for both approaches, this influence does not affect the comparison of EMA to OMA here. In general, the measurement of the process forces can be affected by the location and by the type of the measuring device. Thus the measurement of the process forces during milling is investigated with two types of dynamometers in this paper: (1) a multicomponent platform dynamometer being installed between the workpiece and the machine table (further referred as SD); (2) a rotating cutting force dynamometer being installed between the tool and the spindle of the machine tool (further referred as RD). These two types of dynamometers are often deployed for measurement of process forces in a machine tool.

4 Experimental setup

All investigations are carried out on a three-axis machining centre of medium size. A workpiece with the dimensions 300×20×35 mm (L×W×H) is processed, as shown in Fig. 4. The excitation caused by the process forces is measured with
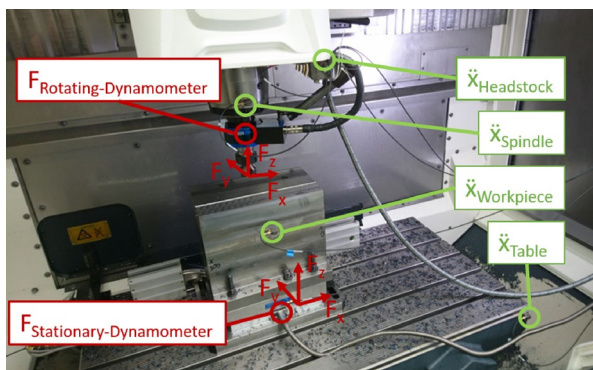
both dynamometers (SD: Kistler 9255B and RD: Kistler RCD 9170A) simultaneously. The responses to the excitation are measured with triaxial accelerometers at various locations on the machine tool (see Fig. 4).

4.1 Measurement of the excitation during milling

The measurement with RD or SD is affected by their installation. This is visible in the limited frequency range of FRF, which are considered for identification of modal parameters. In order to be able to set an appropriate frequency range, FRF of each dynamometer are evaluated. Here, FRF between forces measured with a dynamometer and input forces from impulse hammer are computed, as shown in Fig. 5. The evaluable frequency range corresponds to the frequency range with constant magnitude in FRF of a dynamometer.

These FRF are shown for SD in Fig. 6 and for RD in Fig. 7. The excitation in both cases is performed with an impulse hammer in x, y and z directions successively. Due to the short pulse duration, this excitation can be regarded as constant up to approx. 1200 Hz with amplitude drop less than 3 dB.

It can be seen that FRF of SD shows an extremely large amplitude gain (particularly for x direction) approximately starting at frequency of 180 Hz. Thus, SD is suitable for
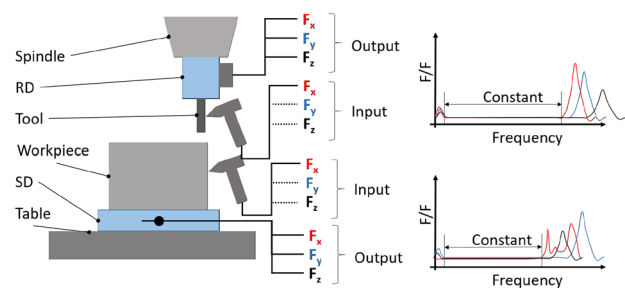

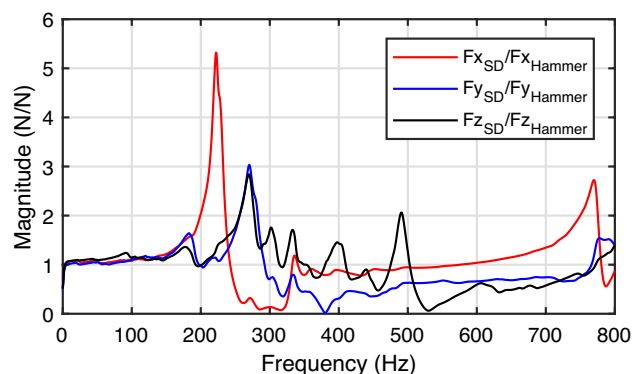Fig. 5 Measurement procedure for estimating frequency response function of RD and SD

Fig. 4 Installation of the rotating dynamometer (RD), the stationary dynamometer (SD) and accelerometers in the machine tool

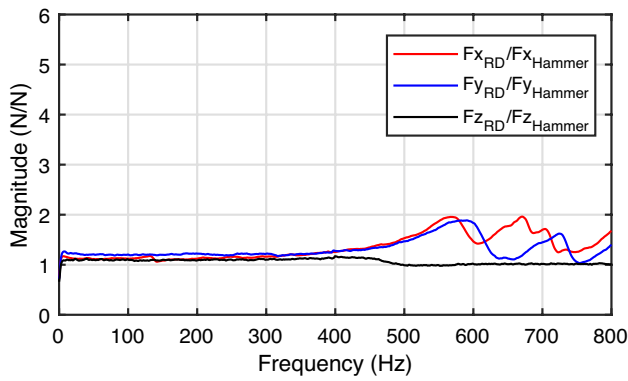Fig. 6 Frequency response function of installed SD—Kistler 9225

Fig. 7 Frequency response function of installed RD—Kistler RCD 9170A

measurement of the excitation in a narrow frequency range, i.e., from 0 to 180 Hz. This is in contrast to the data sheet, in which the resonance frequencies higher than 1 kHz are stated. The cause for the strongly reduction of the usable frequency range is the fact that SD does not measure the process forces directly but the reaction forces between the workpiece and the machine table, which are affected by the inertial forces of the workpiece. For instance, the large peak at approx. 220 Hz corresponds to a mode shape of the machine table.

In case of RD, an increase in the magnitude of the FRF is visible from approx. 460 Hz. Thus, the usable frequency range for further investigations with RD is defined from 0 to 400 Hz. According to the state of the art, this frequency range could be extended with corrections, e.g., as suggested in [15]. However, the frequency range from 0 to 400 Hz is considered to be sufficient for the further work, so that measurements only with RD are further processed in this paper.

4.2 Modification of the cutting process

As explained above the cutting process has to be modified in order to achieve a broadband excitation of the machine tool. For this purpose, the spindle speed is varied at a constant feed rate. This leads to chip thickness modulation that generates a broad frequency spectrum of process forces, which cause a broad band excitation of the machine. In this paper, a spindle speed variation according to a sinus function, $n = 3000 + \hat{n}\sin(2\pi f_n t)$, is used. This strategy is presented in previous papers [6, 7]. The spindle speed varies with an amplitude of $\hat{n} = 2400$ min^{-1} and with the frequency of $f_n = 0.5$ Hz. The milling is performed with a milling cutter with 4 inserts and diameter of 40 mm. The feed rate is constant at $v_f = 300$ mm/min. Considering the workpiece length of 300 mm and the constant feed rate, the time period per one milling path amounts to 60 s. This time period defines the signal length being available for the signal processing

per one milling path. The resulting frequency spectrum of the process forces, measured with RD, is depicted in Fig. 8. The frequency spectra of the process forces resulting from the modified cutting process can be described as broadband. However, they are not uniform over the whole frequency range unlike the white noise. Thus, the mode shapes are not excited uniformly, as assumed for OMA, which would affect their identification.

In general, the process forces excites a machine tool in three directions at the spindle as well as at the table according to the third Newton's law of motion. This implies that the theory of the MIMO system should be applied in case of the EMA. The estimation of the FRF matrix $\boldsymbol{H}^{\mathrm{MIMO}}(\mathrm{j}\omega)$ by using Eq. (3) is only possible for uncorrelated excitation forces. Considering the location of the excitation, the excitation forces are correlated due to the third Newton's law of motion. In case of directions of the excitation forces, there exists partly correlation, as shown in Fig. 9. In this figure, coherence functions between various directions of the process forces are evaluated to reveal the level of correlation over the frequency axis. There are ranges, especially in the frequency range less than 80 Hz, with a strong correlation between all directions. In contrary, the coherence value is very low for frequencies higher than 150 Hz. Eventually,
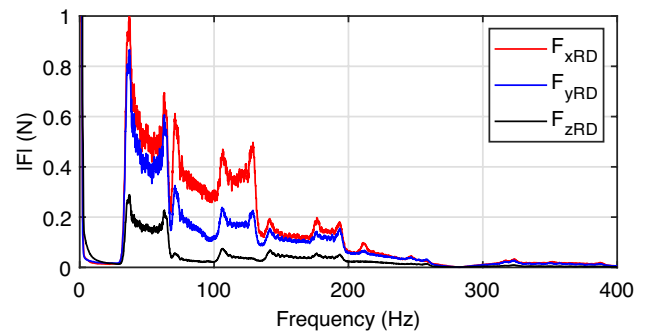

Fig. 8 Frequency spectra of process forces of modified cutting process
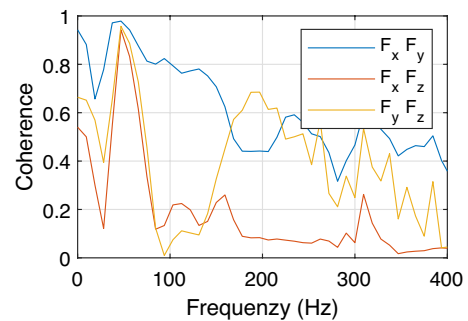

Fig. 9 Coherence of the measured process forces

the excitation is not uncorrelated neither for location or for directions which can be linked with numerical issues at estimating the FRF matrix of the MIMO system. For this reason, the theory for the MIMO system is not pursued further in this paper. The assumption of single input system for the EMA of a machine tool during milling implies some restrictions in the interpretation of the results. The computation with the modal parameters would always lead to response of the system for relative excitation, i.e., between the spindle and the table, and the vector of the resulting excitation force should be oriented identically as the vector of the measured resulting process force. However, any of these restrictions does not affect the estimation of the natural frequencies.

5 Identification of natural frequencies

5.1 Experimental modal analysis

The identification of modal parameters according to EMA usually starts with the estimation of FRF. In order to be able to perform averaging of PSD, a couple of measured signals are needed. For this purpose, the whole signal length of 60 s is equally divided into 60 signal segments each of the length of 1 s. Such signal segment length corresponds to the half of the period of the sinus function for the spindle speed

variation. This implies that this signal length contains the whole range of the spindle speed variation.

For illustration, FRF between the excitation by the process forces, measured with RD, and responses, measured with accelerometers at the headstock, which were estimated according to H1 and H2, are shown in Fig. 10. The grey lines depict all individual estimations of FRF and the black line depicts the estimation with averaged PSD. Here, it is obvious that an estimation being based on the averaged PSD features a low noise level than the grey lines. However, it can be seen that the scatter of the estimated FRF is high. Moreover, there is a large difference between the two estimators (H1 and H2), which indicates a large portion of the process noise. This is caused by the assumption that the cutting process represents the only excitation source in the machine, as explained above. If one estimator has to be selected, the estimation H1 should be preferred, since the force measurement is affected less than the measurement of responses (the RD is located near to the process). FRF of the same structure estimated with H1 but excited with shaker at standstill are shown in Fig. 11. Even a simple visual comparison between the FRF estimated with H1 from signals captured during milling and FRF estimated for shaker excitation indicates a quite large difference in the shape of the functions. Thus, the identification of natural frequencies by using the FRF estimated from signals captured during milling cannot be successful
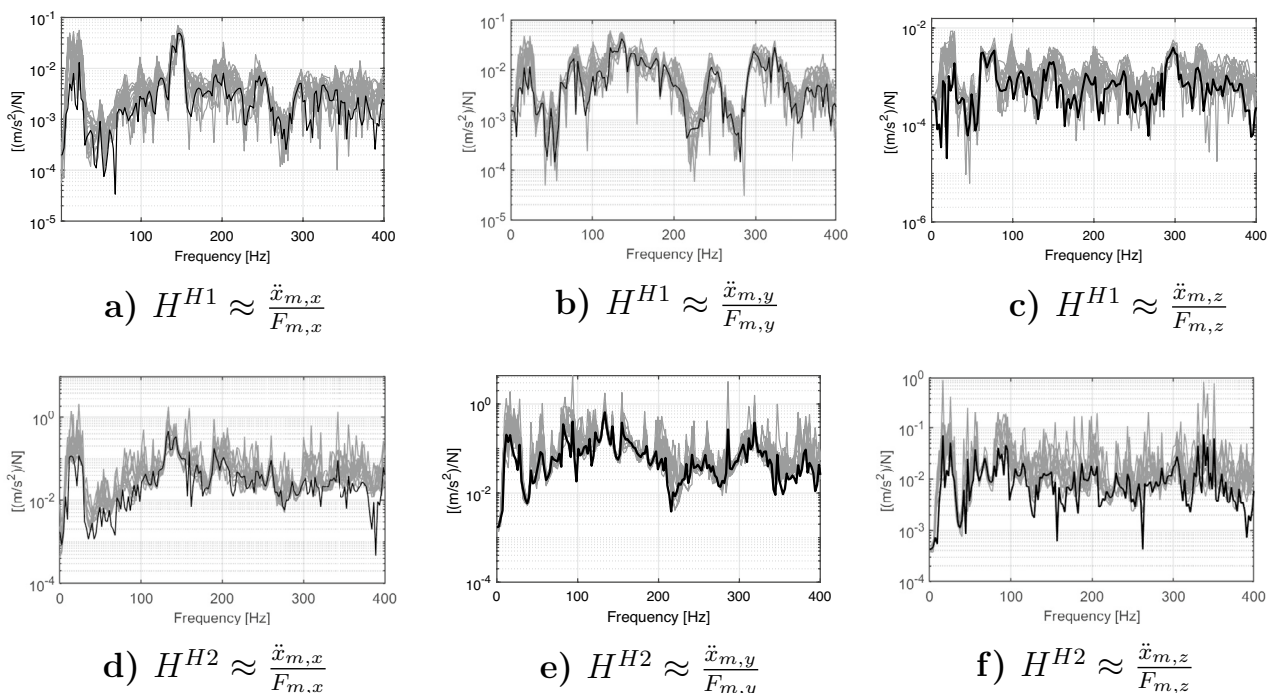

a) $H^{H1} \approx \dfrac{\ddot{x}_{m,x}}{F_{m,x}}$ b) $H^{H1} \approx \dfrac{\ddot{x}_{m,y}}{F_{m,y}}$ c) $H^{H1} \approx \dfrac{\ddot{x}_{m,z}}{F_{m,z}}$

d) $H^{H2} \approx \dfrac{\ddot{x}_{m,x}}{F_{m,x}}$ e) $H^{H2} \approx \dfrac{\ddot{x}_{m,y}}{F_{m,y}}$ f) $H^{H2} \approx \dfrac{\ddot{x}_{m,z}}{F_{m,z}}$

Fig. 10 FRF estimated according to H1 and H2 for RD and responses measured with the accelerometer at the headstock during milling: Gray lines—FRF for individual estimates; Bold black line—FRF based on the averaged PSD
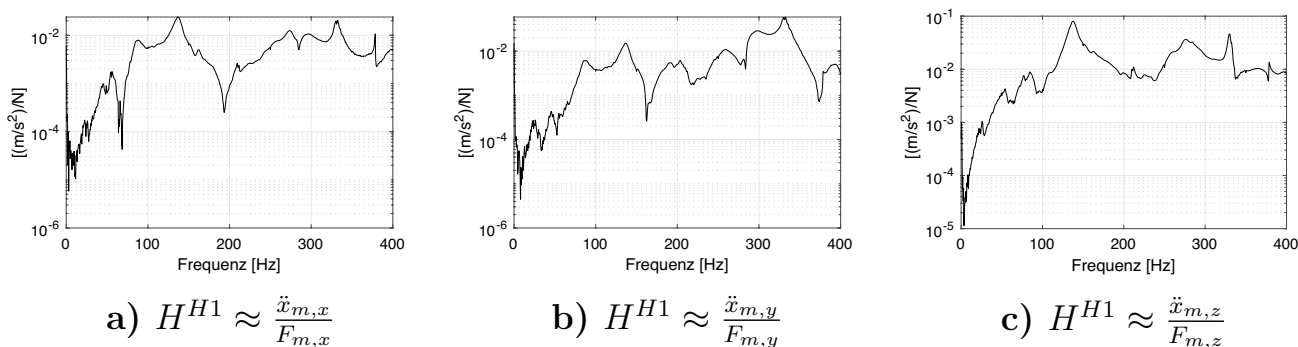
a) $H^{H1} \approx \dfrac{\ddot{x}_{m,x}}{F_{m,x}}$ b) $H^{H1} \approx \dfrac{\ddot{x}_{m,y}}{F_{m,y}}$ c) $H^{H1} \approx \dfrac{\ddot{x}_{m,z}}{F_{m,z}}$

Fig. 11 Estimated FRF for shaker excitation at the headstock (as reference)

which is demonstrated in the remaining paragraphs of this subsection.

The modal parameters are identified with the Least-squares complex exponential method [26] from FRF estimated according to H1 and H2. The stability criteria for finding the eigenvalues are set to 1% for frequency and 0.8% for the damping ratio. The stability diagrams are presented in Fig. 12. Here, the black line represents the Complex mode indicator function (CMIF) [2]. The red markers stand for stable modes. Unlike the H2 estimation, there are clear peaks in the CMIF indicating possible eigenvalues for the H1 estimation.

The stability diagram tends to be overestimated due to the chosen high model order. Thus, narrow limits for the stability criteria are set as written in the previous paragraph. Despite the high model order, just few reasonable eigenvalues with natural frequencies at 80, 135, 235 and 280 Hz could be found, which correspond to already known natural frequencies of the investigated machine. It can be seen in Fig. 12a that the stable diagram contains many stable eigenvalues. The reasonable selection of the four eigenvalues could be only performed with support of the CMIF. Unfortunately, this is not the case of the H2 estimation, as can be seen in Fig. 12b. Here, even with the help of the CMIF, any eigenvalue could not be reasonable selected and selection of all stable eigenvalues would lead to a strongly overestimated model.

5.2 Operational modal analysis

Concerning the identification of the modal parameters within OMA, acceleration responses measured during milling are only processed. All signals to be evaluated have the same length of 60 s as in the case of EMA. In analogy to EMA, stability diagrams are also used to detect the eigenvalues. However, these diagrams are established with the SSI method in the time domain [16, 18]. The stability criterion are set to 5% for the frequency and 5% for the damping
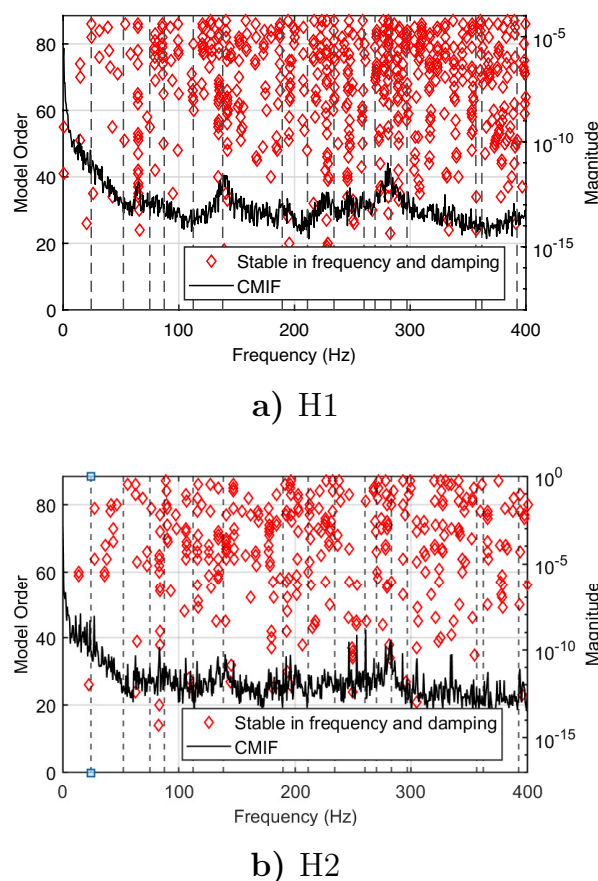

a) H1

b) H2

Fig. 12 Stabilisation diagram for identification of natural frequencies within EMA during milling (as reference, the vertical black dash lines depict natural frequencies, which were identified within EMA at standstill with shaker excitiation)

ratio, i.e., the limits are not so strength as in case of EMA. Despite the wider stability criteria, stable eigenvalues can be clearly detected, see Fig. 13. In this figure, various stability diagrams for responses of various components are shown. Here, the detected eigenvalue with a frequency at 0 Hz is so
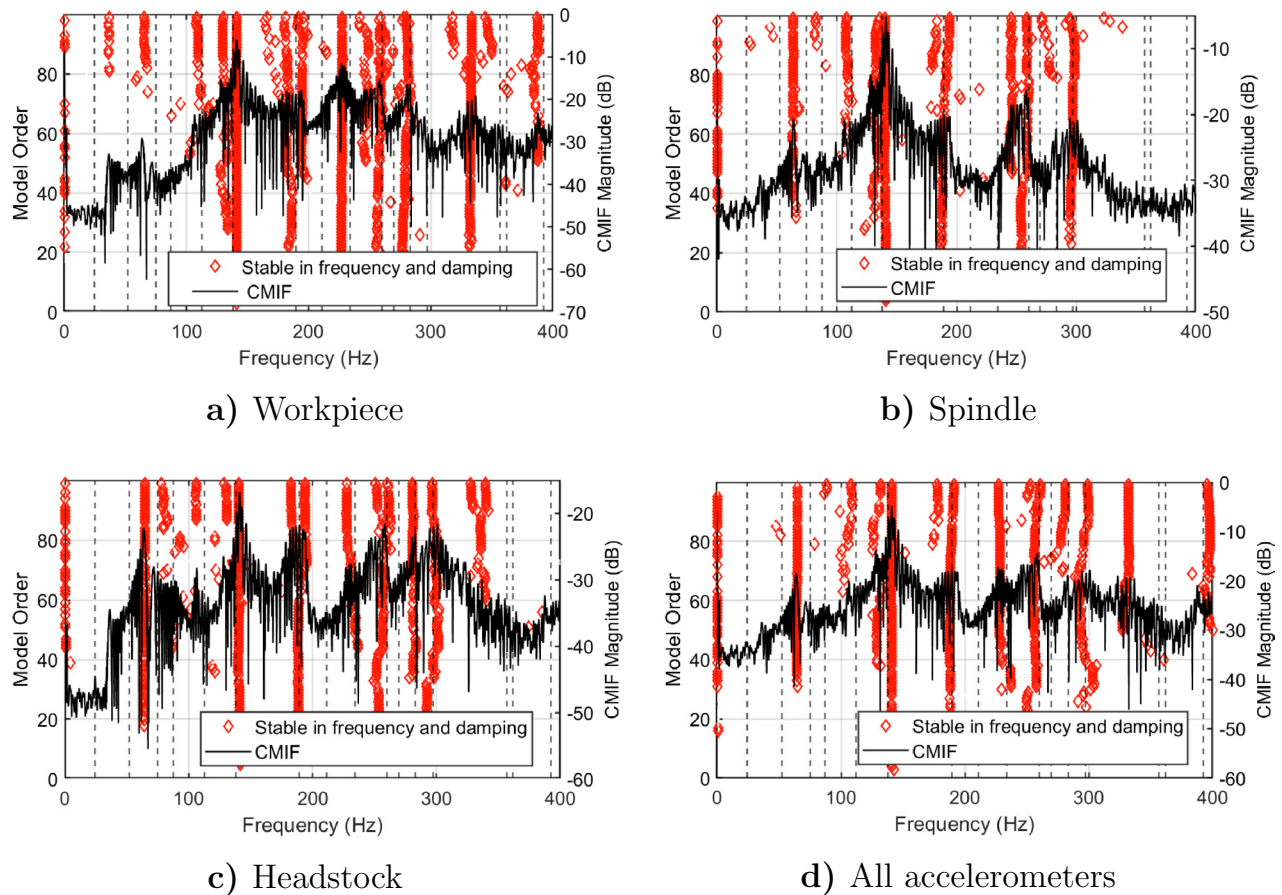
a) Workpiece

b) Spindle

c) Headstock

d) All accelerometers

Fig. 13 Stabilization diagrams for identification of modal parameters within OMA (as reference, the vertical black dash lines depict natural frequencies, which were identified within EMA at standstill with shaker excitiation)

called mathematical mode, which has not a physical meaning, since the experimental setup does not allow identification of any rigid body mode shapes. The peaks of the CMIF in each stable diagram let indicate the natural frequencies, which correspond to the stable eigenvalues.

5.3 Discussion

The results of EMA with H1 estimation shows an overestimation of the number of natural frequencies. However, it was possible to select some reasonable eigenvalues after considering CMIF. In contrary, it was not possible to select reasonable eigenvalues in the case of EMA with H2 estimation despite considering CMIF. Concluding, when EMA during milling were performed, only 4 natural frequencies could be identified reliably. For comparison, there were 16 natural frequencies identified within EMA at standstill, which are depicted in Fig. 12 by vertical dash lines. The poor stability at identification of natural frequencies as well as the low number of identified natural frequencies within EMA during milling indicate that this approach is not appropriate

for identification of natural frequencies of a machine tool during milling when the cutting process is assumed to be the only excitation source. It must be noted at this point that the identified natural frequencies during milling does not have to be coincident with the natural frequencies identified at standstill in general. A difference between these two values, which mostly lies in the range of a few percent, is possible. Moreover, it should be mentioned that the assumption of causality, which is crucial for the identification within EMA, could not be fulfilled due to many others excitation sources in the machine during milling.

Concerning OMA, it is noticeable that the detection of stable eigenvalues could be achieved. Here, the identifications of eigenvalues were performed for each machine component being captured (Workpiece, Spindle, Headstock) separately. Furthermore, all signals of all components were also used for the identification of eigenvalues (see Fig. 13d). Firstly, it can be seen that the stability at identification is clear and the eigenvalues could have been identified even without considering CMIF. Nevertheless, CMIF were also considered within OMA. In general, it is always meaningful

to use all information being available when modal parameters are identified. It is evident that natural frequencies differ depending on evaluated acceleration signals (Workpiece, Spindle, Headstock, All accelerometers). This effect is logical, since there can be mode shapes that affect few or just one machine component. In such case, the corresponding natural frequency can be identified from the signal. It must be noted that the identification with signals from all accelerometers did not reveal all the natural frequencies. The reason for that should be searched in the numerical sensitivity of the used SSI method. Here, mode shapes with large amplitudes put mode shapes with low amplitudes in shadow. In this case, it seems to be more effective to perform the identification for each machine component with following synthesizing the identified eigenvalues according to the same criterion being defined for the stability assessment. In such way, 15 natural frequencies could be identified within OMA. The results also show that the frequency range from 30 to 400 Hz could be sufficiently excited by the cutting forces after the modification of the cutting process (see Fig. 8).

6 Conclusion and outlook

The paper deals with the issue concerning the identification of natural frequencies of a machine tool during milling. It is the state of the art that there is a difference in modal parameters being identified at standstill or during operation. A simple transfer of the approach for EMA at standstill to EMA during operation is not possible as shown in this paper. Here, the excitation by the milling process is measured with rotating dynamometer in the near of the tool and with a platform dynamometer being installed between workpiece and machine table. It is shown that only the rotating dynamomemter is suitable for the measurement of the excitation in this paper, since the inertial forces of the workpiece limit the useful frequency range of the platform dynamometer significantly. In general, performing modal analysis is linked to assumptions regarding the causality, the stability and the linear time-invariant system. The fulfilment of these assumptions is a fundamental issue for modal analysis during milling. In the paper, the causality is addressed. The deficient causality leads to scattered FRF with subsequent effect on the identification of natural frequencies in the case of EMA. We obtained eigenvalues with poor stability for H1 and H2 estimators. The selection of the natural frequencies was only possible by additionaly considering the CMIF. In the case of H2 estimator, it was not possible to select any natural frequency. Contrary, the issue of causality is not relevant for OMA, since OMA considers every excitation to the process noise, which is further considered to be the excitation source. In this case, we obtained stable eigenvalues. Nevertheless, OMA assumes that all mode shapes

are excited uniformly and the excitation is characterized by the white noise. Anyone of these assumptions could not be fulfilled by the excitation through the modified milling process. Nevertheless, this fact does not affect the finding the eigenvalues but the mode shapes, which were not evaluated in the paper.

As this paper shows, OMA has a better potential for identifying the natural frequencies during milling. Therefore, the research work focuses on the treatment the two assumptions of OMA for the excitation in the future, so that the non-uniform excitation of the mode shapes can be compensated within the evaluation.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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