Chapter 6
Making Modal Analysis Easy and More Reliable – Challenging Ai-Based Algorithms with the Barc Example

Tim Kamper, Denis Beljan, Patrick Hüskens, and Haiko Brücher

Abstract Though modal analysis is a common tool to evaluate the dynamic properties of a structure, there are still many individual decisions to be made during the process which are often based on experience and make it difficult for occasional users to gain reliable and correct results.

The paper presents how on different steps of the process experience-based decisions can be supported and replaced by automated evaluations to make modal analysis accessible to less experienced users. In addition to traditional methods such as the Least-Squares Complex Frequency-domain (LSCF) estimator the presented approach takes advantage of more innovative methods such as a neural network to reduce experience-based decisions and increase reliability.

The advantage of the presented approach is shown based on the example of a Box Assembly with Removable Component (BARC). BARC is known as a challenge structure for approaches for the evaluation of dynamic properties. In the study two groups of users are exposed to perform a modal analysis of the BARC. The groups are selected as heterogeneous groups with different levels of experience in modal analysis. The first group performs the modal analysis based on classic algorithms and methods whereas the second group is supported by AI based technology.

Keywords Modal Analysis · Optimal Driving Point · AI

Introduction

Modal analysis is a widely used method to analyze the dynamic properties of structures. It is used for a variety of tasks such as troubleshooting, validation of numerical models and the parametrization of numerical models. Due to its various use cases the user group of modal analysis is very heterogeneous with different background-knowledge and experience. Unfortunately, the process of modal analysis, that starts the planning of the measurements and ends with the postprocessing of the results requires a lot of decisions based on the experience of the user. Thus, it is difficult to judge on the reliability of the results of modal analysis and the whole process is hardly reproducible. Furthermore, wrong decisions at an early step of the process can often only be discovered in the very end of the process, if at all. This is particularly painful, as the process of modal analysis can be a quite time-consuming task.

This paper focuses on the evaluation of different methods that are designed to contribute to an easier process of modal analysis that delivers more reliable results.

Figure 1 gives an overview of the process steps of modal analysis with the corresponding decisions that are necessary to be made by the individual user. All these decisions have an impact on the completeness and the quality of the results, such as number of extracted mode shapes, accuracy of the fitted frequency response functions (FRF) and of the detected mode shapes. Before the user can start the experimental data acquisition, the test must be designed properly. During the test design phase, the used data acquisition method and hardware must be chosen (shaker excitation, impact testing with roving hammer/accelerometer, laser vibrometer, etc.). Choosing the right geometric resolution of measurement points enables capturing local shape characteristics. The selection of correct number and positions of good reference degrees of freedom (DOFs) is crucial, as it results in satisfactory signal-to-noise-ratio (SNR) and deflection magnitudes for all modes within the desired frequency range, enabling the detection of all corresponding eigenfrequencies during postprocessing. Furthermore, the number of reference DOFs may be kept down by a good selection. This leads to less equipment needed and less data to

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Alexandra Karlicek et al. (eds.), *Dynamic Environments Testing, Vol. 7*, Conference Proceedings of the Society for Experimental Mechanics Series, https://doi.org/10.13052/97887-438-0152-8_6

be acquired and processed. During the step of data acquisition, the user must configure settings for the frequency response functions (FRFs) like the time to be recorded, block size, windowing of excitation and/or response. Sensor ranges must be adapted to induce a good SNR without overloading. Depending on the structure, there is a bad reproducibility at some measurement points (i.e. non-linear behavior) and in the case of impact testing, the user might be confronted with double hits. Once the data acquisition is complete, the modal parameters can be extracted in the next step wherein the curve fitting method must be selected. The next experience driven decision is to further parameterize the curve fitting method itself. The method outputs pole candidates which then must be grouped, selected and extracted by the user. Finally, the modal parameters consisting of mode shapes with corresponding eigenfrequencies, and damping values form the modal model which can be evaluated in the postprocessing step.

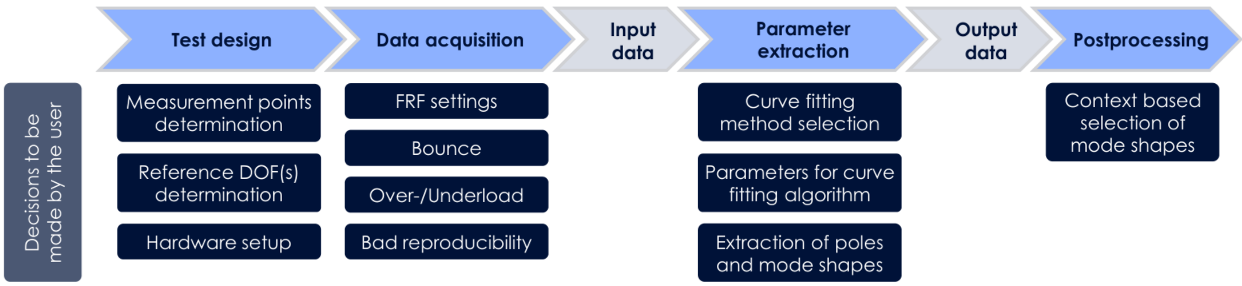

Fig. 1 Process of experimental modal analysis and steps that require user interaction, affecting result completeness and quality.

This paper focuses on the validation of solutions for two different steps in the process of modal analysis: The initial step of test design for the modal analysis and the step of parameter extraction where the user must provide input parameters for the curve fitting algorithm. Both steps and the corresponding decisions to be made by the user will be described in the following sections. Moreover, the suggested solution approaches based on AI will be discussed.

To validate the suggested solution approaches a study with participants that have different experience levels regarding modal analysis was performed. The study demonstrated the advantages of the suggested approaches and will be discussed in the last section of this paper.

Identified Problems and Solution Approaches

Test design: Reference DOFs identification

In the step of test design, the user must decide among other on the correct number and positions of reference DOFs. The correct number and positions of reference DOFs is important to make sure that every eigenfrequency present in the frequency range of interest can be detected. This is particularly critical because a missing eigenfrequency, and thus an incomplete modal model, can hardly be detected by the user.

The importance of the correct choice of reference DOFs can be illustrated by the simplified examples given in Figure 2, where the first modes of two simple oscillating structures are depicted. If the reference DOF is placed at the position marked in red, the respective mode cannot be detected because the reference DOF is placed in a node of the mode shape.

Placing the reference DOF at or near a node of the mode shape is not suitable for introducing energy into the structure to excite the specific frequency if used as an excitation DOF, nor for detecting a vibrational amplitude if used as a measurement DOF.

Using simple examples like they are given in Figure 2 the decision on the number and positions of reference DOF is simple and straight forward. But for real, complex structures with a lot of modes this decision is not easy and cannot be made without any previous thoughts and analyses.

For the identification of the number and positions of reference DOFs different methods exist. They can be divided into two groups by the fact whether a numerical model is needed to get insights into the dynamic properties of the structure or not.

- Methods based on numerical simulations: Based on the modal deformation derived from numerical simulations it is possible to decide on the number and positions of reference DOFs [1, 2]. In [3] a method was introduced which works based on a non-validated numerical model in a fully automated manner.

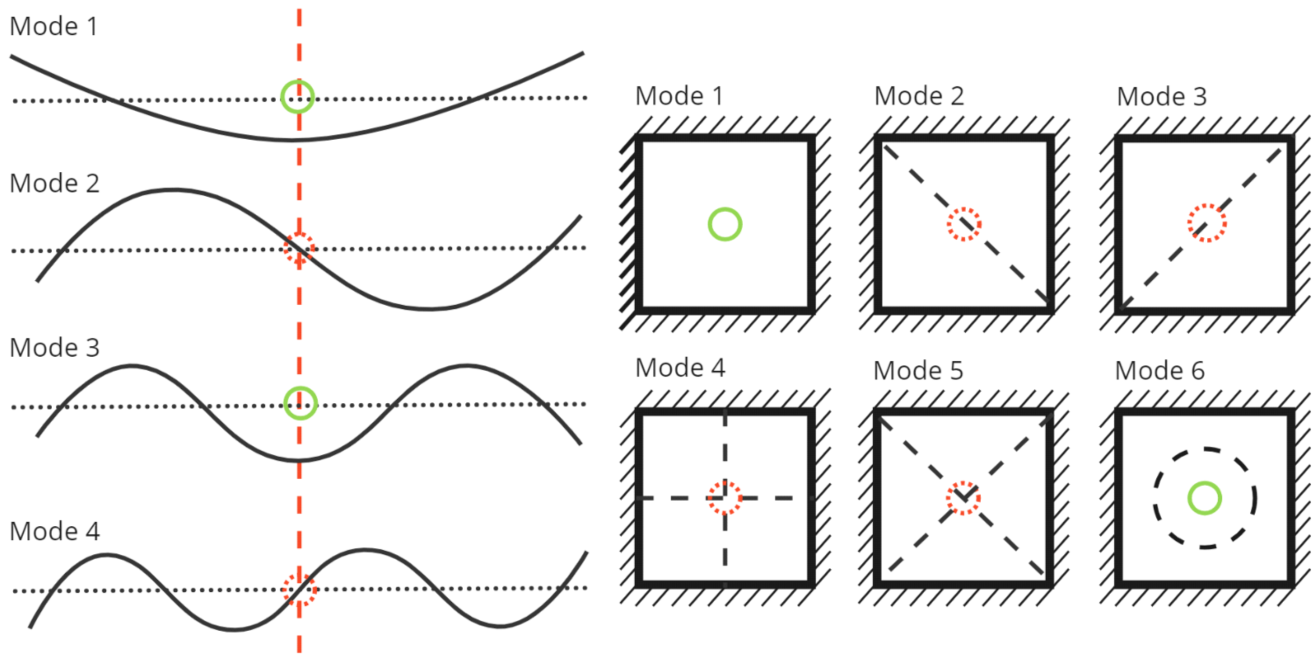

Fig. 2 Examples for the importance of a good choice of the reference DOF (red circle: mode cannot be detected, green circle: mode can be detected) [4].

- Methods based on tests: When there is no numerical model available the decision on the optimal number and positions of reference DOFs is much more difficult. Since there is no prior knowledge of the structure available the decision must be made based on measurements. The simplest and most common approach is the visual inspection of a few driving point measurements (DPM) at different potential reference DOFs. To perform a driving point measurement, an accelerometer is placed at one potential reference DOF and the structure is excited as close to this point as possible using an impact hammer. By visual inspection of the measured DPM and based on his or her individual experience the user must decide what are the modal properties of the structure under test and which of the potential reference DOFs is suited best to detect all the modes of interest. For simple structures with a limited number of frequencies in the frequency band of interest, this method may work, but it is hardly reproducible, and the effort raises with the complexity of the structure.

In this study we focus on the validation of a method which was introduced in [4] and allows to identify the optimal number and positions of reference DOFs without prior knowledge or experience based on measurements in an automated manner. In the following a brief description of the method will be given. For more details, please refer to the corresponding paper [4].

Figure 3 gives an overview of the steps in the process of the test based prestudy.

Before the start of the prestudy the frequency range of interest must be defined. The study then aims to find the optimal number and positions of reference DOFs to achieve a complete modal model containing all the modes in the respective range of interest. The prestudy relies on driving point measurements at potential reference DOFs. Since no prior knowledge is available, with every DPM added to the prestudy the knowledge of the dynamic properties and hence the eigenfrequencies to be detected increases. One core element of the prestudy is the automated detection of poles for every driving point measurement which is done with the help of a neural network. The following step is the processing of the detected poles for the whole dataset. This step can be separated into three subtasks:

- First all the poles detected in different DPMs are captured in one group.
- In a second subtask the dynamic properties of the structure (eigenfrequencies, damping) known so far are derived from the group of poles.
- In the third subtask it is analyzed which pole is suitable to detect which frequency.

The outcome of the step of processing the detected poles for the whole dataset is a list of the DOFs which were tested until the current state including the information which DOF is suitable to detect which eigenfrequency. This list is then used

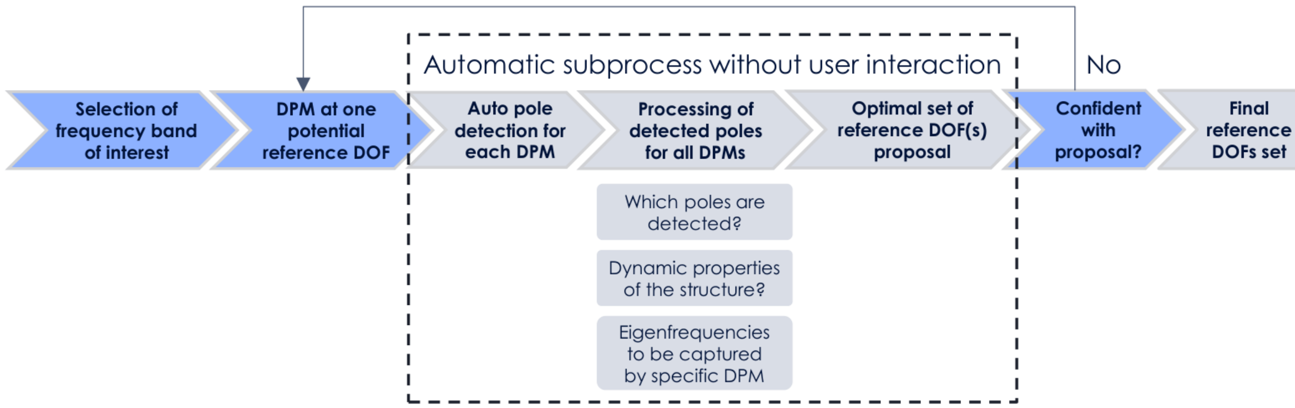

Fig. 3 Process of test based prestudy.

in a final step to generate a suggestion of the minimal number of reference DOFs which are needed to make sure that every eigenfrequency can be detected in the consecutive modal analysis. The user than can decide whether he/she is confident with the suggestion. If not an additional DPM must be measured and be fed to the algorithm and the process starts all over again. It is important to notice that besides the conduction of the driving point measurement the whole process works in an automated manner to relieve the user. Since no prior knowledge of the structure is available, the algorithm learns about the structure during the conduction of the prestudy and with every measurement taken, the knowledge about the dynamic properties of the structure is more and more complete. Since there is no reference against which to compare the identified eigenfrequencies, there is no hard criteria for the end of the study. Instead, the study can be regarded as complete, when the number of identified modes and the number and positions of suggested reference DOFs does not change for a few iterations.

Depending on the chosen method for modal analysis (roving excitation or roving accelerometer) the identified reference DOFs are then declared as excitation DOFs or measurement DOFs and the next steps according to Figure 1 can be tackled.

Input data: Parameterization of parameter extraction

For the step of parameter extraction displayed in Figure 1 different curve fitting algorithms have been developed in the past. The curve fitting algorithms aim to extract the modal properties of the structure from the measured data. The Least Squares Complex Frequency Method (LSCF-Method) [5] is currently one of the most common methods and is widely used throughout the modal analysis community. The LSCF-Method needs to be parameterized by the user to identify all poles existent in the dataset. A wrong choice of parameters leads to incomplete results or results of poor quality. Since the LSCF-Method iteratively attempts to fit a mathematical model of increasing order to the measured data, the highest requested order must be defined by the user. If the highest order is too low, then the LSCF-Method tends to miss poles and consequently the derived modal model is incomplete, leading to the disadvantages discussed above. If the highest order is too high, then the LSCF-Method tends to identify spurious poles which confuse the user and mess up the further analysis of the problem. Furthermore, a too high model order leads to an unnecessarily increased computational effort. The recommended modal order is linked to the number of expected poles in the dataset and the user decides based on his or her experience often in an iterative manner what model order to set as an input parameter for the LSCF. To make this step more reproducible, more reliable and faster in [6] a neural network was introduced which is capable to estimate the number of poles based on measured transfer functions which serve as the input data for the extraction of modal parameters.

Since this paper focuses on the validation of the benefit of the approach for users of modal analysis, at this point only a short description will be given. For more details, please refer to the corresponding paper [6].

The network architecture chosen to perform the task of pole estimation is a convolutional neural network based on convolutional layers. Figure 4 shows the architecture which is, based on its shape also called a U-Net. The left part is known as the encoder, where the neural network reduces the spatial information of the input while extracting the features. The right part is called the decoder, where the feature information is mapped back onto the original spatial representation. In this case the input is a transfer function (FRF) with a fixed number of frequency steps in the format of real part and imaginary part. The output is a vector of the same length as the input and for every frequency step the probability is given that the FRF has a pole at this specific frequency step. From the output of the neural network for all the FRF measured for the respective modal analysis the requested maximal model order is derived and given to the LSCF as an input parameter.

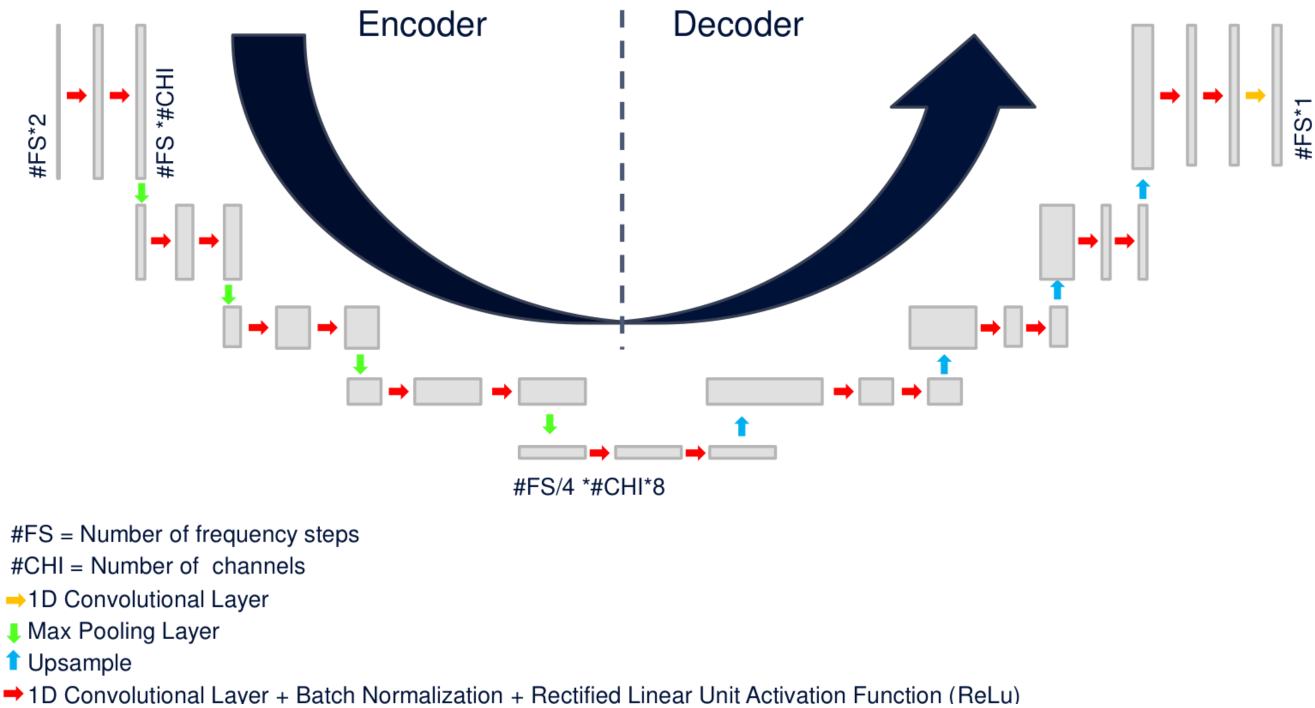

Fig. 4 Network architecture [6].

For the training of the neural network aprox. 700000 datasets with known number and positions of poles where necessary. This is almost impossible to achieve with data from real measurements. This is why the training of the neural network is based on synthesized FRF, which can be produced in an unlimited number with known modal content.

For the synthesis of the FRF an equation known from the curve fitting was used [7]:

$$H_{pq}(\omega) = \sum_{r=1}^{N_m} \left(\frac{A_{pqr}}{j\omega - \lambda_r} + \frac{A^*_{pqr}}{j\omega - \lambda^*_r} \right) \tag{1}$$

In equation 1 the FRF from DOF p to DOF q in dependency of the angular frequency ω is represented by H_{pq}. λ_r and $\lambda_r{}^*$ represent a pole and its conjugate complex value while N_m denotes the number of poles. A_{pqr} and $A_{pqr}{}^*$ denote the residue and its complex conjugate and can be calculated according to equation 2:

$$A_{pqr} = \frac{1}{j2\omega_{dr} m_r} \psi_{pr} \psi_{qr} \tag{2}$$

In equation 2 ψ_{qr} and ψ_{pr} denote the shape coefficients, ω_{dr} is the damped angular eigenfrequency, and m_r represents the vibrational mass of the specific mode.

With the help of the neural network, the step of parameter extraction can be performed significantly faster and is much less error prone.

Validation of Added Value

To validate the added value of the two solution approaches discussed above a study with 19 participants with different background knowledge regarding modal analysis was conducted. The participants were divided into two groups, one had the task to perform a modal analysis without these solution approaches and the other group had the task to perform a modal analysis with the help of these solution approaches. Figure 5 gives an overview of the experience level of the participants in the different groups regarding experimental modal analysis (EMA). It demonstrates that both groups include participants that have never conducted an EMA on their own and have only theoretical knowledge of the process as well as participants who classify themselves as very experienced users.

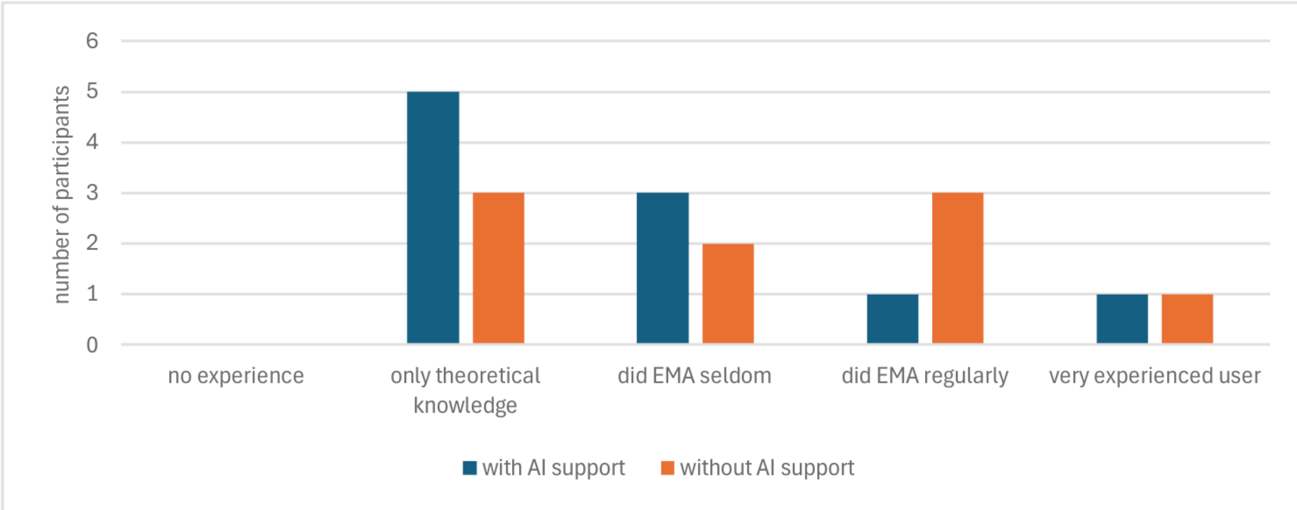

Fig. 5 Experience level of the participants of the study regarding experimental modal analysis (EMA).

From the 19 participants 17 where students, research assistants and professors from the RWTH Aachen University, the University of Applied Sciences Aachen, and the University of Applied Sciences Dortmund. Two participants where employes of HEAD acoustics GmbH.

The object under investigation is the Box Assembly with Removable Component (BARC) structure (see Figure 6). It was designed in 2018 facing the "Boundary Condition for Component Qualification" round robin test setup challenge [8]. Since then, the BARC structure is well known by structural dynamics experts in the American region as it was subject of several investigations and studies, i.e. [9, 10]. It has two main parts, the box and the removable component, which may be coupled either by bolted joints or glue. The box is a symmetric square profile which is cut off in the upper center. The component consists of two pieces of a C-channel, which are connected to a beam in an asymmetric manner. Both main parts are made of aluminum. The simplicity of the parts allows for easy and cost-effective reconstruction. Furthermore, it allows for easy numerical model setup. Due to the asymmetry of the assembled BARC structure, the mode shapes are not easy to predict intuitively even by experts, what makes the selection of appropriate reference points a complicated and potentially time-consuming task.

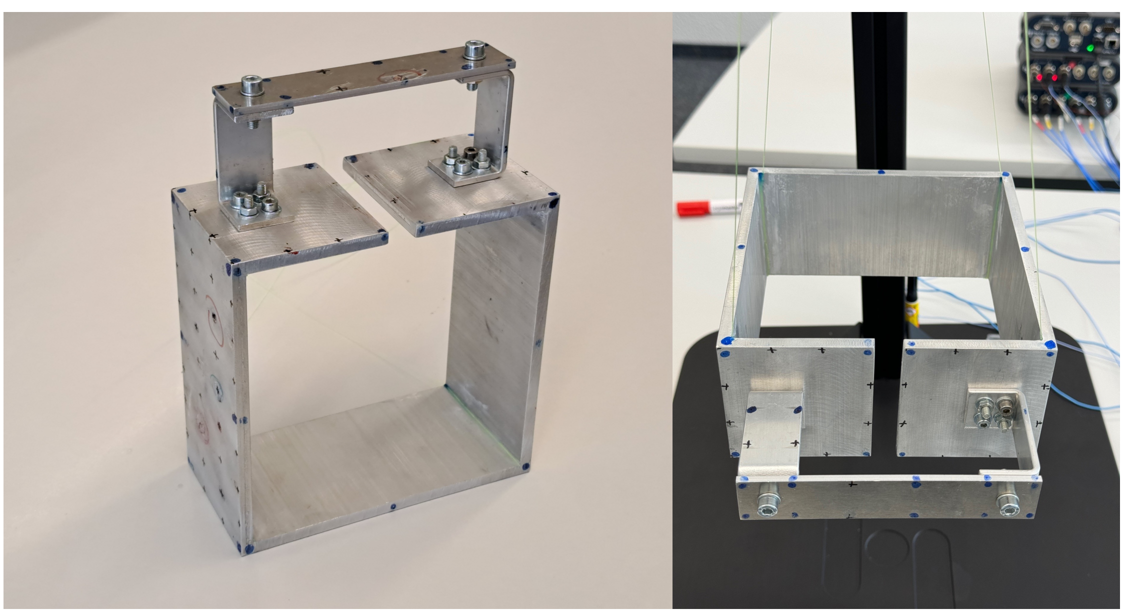

Fig. 6 DUT (left) and suspension of the DUT (right).

To make the study fair and comparable, different measures were taken in advance:

- The DUT was suspended by four threads attached to the corners of the box (see Figure 6). This suspension was kept equal for all participants.
- The method of roving excitation was used throughout the experiments to minimize the effect of mass loading
- The experiments were conducted under the guidance of a supervisor who has experience in both: experimental modal analysis as well as the software in use.
- Same geometrical resolution of excitation points.
  - The positions of the excitation points were predefined by the supervisor.
- All participants used the same type of hardware (e.g. impact hammer, hammer tip, acceleration sensors, frontend).
- The boundary conditions (e.g. frequency range of interest, sampling rate, windowing) were predefined by the supervisor and kept equal throughout the experiments.
- The supervisor gave a short introduction to every participant on the importance of reference point identification and the relevance of the model size for the step of parameter extraction.
- Every participant conducted the EMA separately at a different time. The results of the EMA where not shared with the participants during the ongoing study. Neither a statement regarding the correctness of the results was given.
- The supervisor kept track of time and allowed a maximum of 30 minutes for the choice of reference points as well as a maximum of 30 minutes for the curve fitting.
- The impact measurements itself were conducted by the supervisor to ensure only the approaches discussed above contribute to the results of the participants.

To establish a reference against which to compare the results of the respective participant's modal analysis, the BARC structure was analyzed thoroughly with the help of experimental and numerical modal analysis.

To validate the completeness of the received modal models their similarity to the reference model was analyzed using the Modal Assurance Criterion (MAC)-Matrix. The MAC value is a measure to compare the eigenvectors and thus the mode shapes of different modal models [11]. It takes values between 1 and 0. While a MAC value of 1 means the compared shapes are identical, a value close to 0 means the shapes have no similarity. Thus, the MAC value can be used to verify that the modal model is comparable to the reference model and contains all the desired modes.

Figure 7 displays the results of the conducted study: while all participants in the group which was allowed to use AI support where able to achieve a complete modal model in the frequency range of interest regardless of their individual experience in the field of modal analysis, the majority of participants was not able to achieve a complete modal model without the support of the AI driven tools introduced in the previous chapters. In this study a complete modal model is defined as a modal model which contains all the modes in the respective frequency range but no additional modes which have no physical meaning.

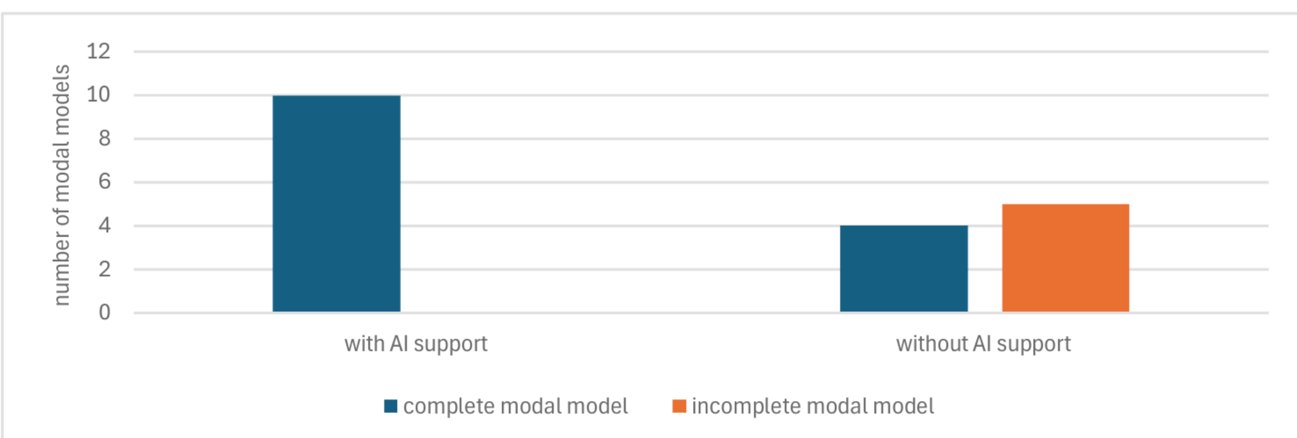

Fig. 7 Number of complete modal models for the groups with and without AI support.

Figure 8 focuses on the group which was not supported by AI approaches and displays the number of complete and incomplete modal models versus the experience level of the participants. Like one would assume, the more experience the participant has the bigger is the probability that he/she can achieve a complete modal model. On the other hand, users with

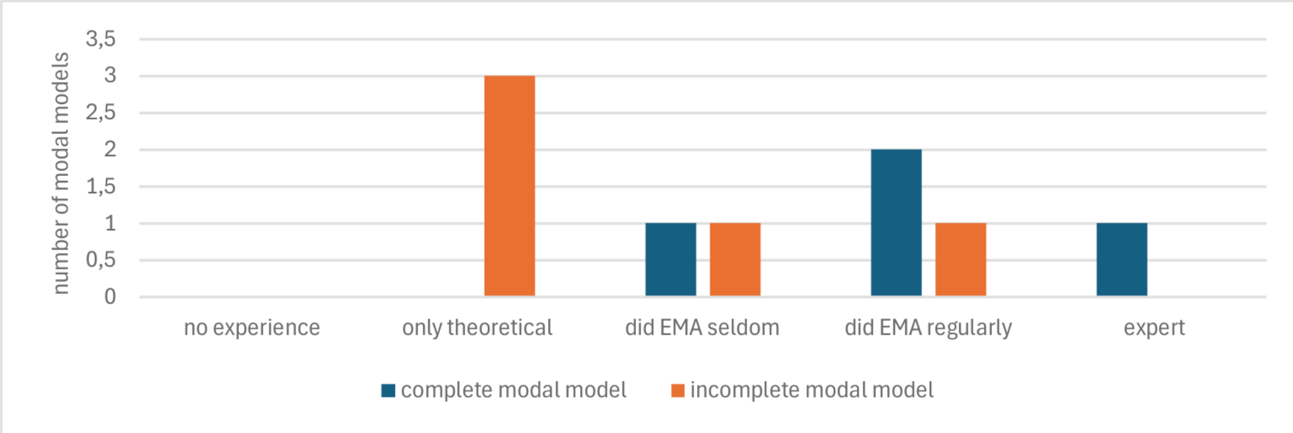

Fig. 8 Results of the study with focus on the group of participants without AI-support.

only theoretical knowledge of the modal analysis had no chance to achieve a complete modal model without the solution approaches presented in this paper. This evaluation is plausible and supports the general result of the study.

Two more remarkable outcomes of the study:

- Two participants using the AI support managed to finalize the step of parameter extraction and curve fitting in the timespan of just one minute. This shows that with the parametrization of the LSCF via the neural network parameter extraction is possible very fast and almost automated.
- The average confidence with the resulting modal model was similar for both, the supported as well es the unsupported participants. The participants were asked to rate their confidence with the results they gained from 1 to 10 with 10 marking the highest confidence and 1 the lowest. The fact, that both groups have a similar average confidence of approx. 7, strengthens the point, which was made in the beginning, that possible mistakes in the process of modal analysis which affect the completeness of the modal model are hard to detect. Without a reference against which to compare these mistakes even might be unrevealed, except that the modal model derived is not suitable to solve the problem it was intended to solve.

Conclusion

In this paper two of many difficulties in the process of modal analysis are addressed: The test design step, where number and positions of reference DOFs must be defined and the step of parameter extraction where the extraction algorithm needs to be parametrized. Both steps are highly dependent on the user's knowledge and experience making it hard for users with less expertise or occasional users to gain reliable end reproducible results of high quality. But even users with more experience in modal analysis tend to spend a lot of thoughts and time on these steps. To solve this issue two approaches are discussed which were introduced in [4, 6] and assist the user among other with the help of AI to gain reliable results independently from their individual experience.

The added value of the two approaches was validated by a study on the example of the BARC structure. For the study two groups of participants performed a modal analysis of the BARC structure one without any support and the other was allowed to benefit from the AI supported approaches introduced in this paper. The study proves that these approaches help users of modal analysis to gain reliable results fast and independent from their individual experience even though no prior knowledge of the structure (e.g. numerical model) is available. This marks another important step towards an easy and reliable process of modal analysis.

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