Chapter 14
Guided Analysis Tools for Highly Efficient Impact Testing and Modal Parameter Estimation

Bart Peeters, Simone Manzato, and Mattia Dal Borgo

Abstract Impact testing is a widely used technique for measuring structural Frequency Response Functions (FRFs). Even though this testing methodology is already a few decades old and reached a very high level of maturity, modern industrial testing requirements and the continuous drive for increased efficiency, necessitated a (r)evolution in the way impact testing is performed and the "best" hits are selected for obtaining optimal-quality FRFs in a minimal amount of time with minimal involvement of human resources. This paper will highlight the new Smart Hit Selection (SHS) method that, in a fully automated way, assists the user in obtaining optimal measurement results. The methodology will be explained and illustrated by means of a measurement campaign.

The goal of impact testing is to understand the structural dynamics behaviour of a physical structure. After acquiring FRFs, often Experimental Modal Analysis (EMA) is applied to estimate the eigenfrequencies, damping ratios and mode shapes to gain additional quantified insights in the tested structure. As a second part of this paper, an innovative Hybrid AI method, incorporated in the EMA process, will be highlighted. Hybrid AI represents a significant advance in the field of artificial intelligence by bridging two distinct approaches: machine learning-based and rule-based methods. In the specific method discussed here, unsupervised learning is combined with domain expertise captured in rules. The Hybrid AI method has been designed to automatically estimate the modal parameters with the same level of quality as an expert in the modal analysis field would do. The innovative technology will be illustrated using FRF data obtained by SHS.

Keywords Impact testing · Experimental modal analysis

Smart Hit Selection (SHS)

Impact testing is a widely used technique to measure FRFs of a structure or component. Often a roving hammer approach is adopted in which the operator sequentially excites the structure at all locations of interest. A few fixed accelerometers are recording the structural responses due to impact excitation. At each location, multiple hits are applied and the data from multiple hits is "averaged" to reduce noise and bias errors on the FRFs. Not all hits are suited to be considered for the FRF calculations. Example of mishits are the following: too low force is applied resulting in noisy measurements; too high force is applied resulting in overload; impact is not applied at the right location or in the right direction; an acquisition is erroneously triggered e.g. by accidentally touching an object with the hammer. Also, in case of a highly resonating structure, it is sometimes difficult to avoid double or multiple impacts: the operator will hit unintentionally the structure multiple times. This is not necessarily problematic and such measurements do not have to be excluded a priori, but it may lead to higher noise levels as the force spectrum of a double/multiple impact will exhibit oscillating behaviour: some frequencies are better excited than others.

For all these reasons, it is important that the right hits are selected, i.e. the hits that are consistently applied at the same location and in the same direction and have a high signal-to-noise ratio (SNR). A manual, interactive process can be used, but this will considerably slow down the measurement campaign. Therefore, a fully automated, user-guided process has been developed called "Smart Hit Selection" (SHS). The main idea of SHS is to select the hits that are most similar to each other, assuming that these have been applied closest to the target location (Figure 1). Different metrics can be used to express such "similarity" and in the research leading to SHS, multiple metrics have been investigated such as correlation between

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instantaneous FRFs, coherence improvement ratio, correlation between instantaneous and averaged FRFs. However, it was found that the following 2 metrics lead to the highest overall coherence (and thus FRF quality) of the selected hits:

- "Pairwise similarity": a metric expressing the "similarity" between 2 instantaneous FRFs across a certain frequency range. Examples of such metric are presented in [1][2]. In the SHS method, the following is used:

$$S(H^{(1)}, H^{(2)}) = \frac{\left|H^{(1)} + H^{(2)}\right|^2}{2(\left|H^{(1)}\right|^2 + \left|H^{(2)}\right|^2)} \tag{1}$$

  where $H^{(i)}$ is the i^{th} instantaneous (based on a single hit) FRF.

- "Pairwise coherence": the classical coherence between input (force) $u\,(t)\,,\ U(\omega)$, and output (acceleration, typically) $y\,(t)\,,\ Y(\omega)$, based on 2 averages (2 hits) only:

$$\gamma_{yu}^2 = \frac{|S_{yu}|^2}{S_{yy}S_{uu}}\ ,\quad S_{yu} = \frac{1}{2}\sum_{i=1}^{2} Y^{(i)}U^{(i)^*} \tag{2}$$

Both metrics have a value between 0 and 1 for each spectral line. They are averaged across the frequency range of interest to obtain a single number quality indicator.

In the SHS method, the selected metric is calculated for all pairs of hits for all sensors. When applied in online mode, each additional hit will trigger immediately new metric calculations. The metric is compared to a user-defined target value and all hits above or equal to the target are retained as good hits. If the number of retained hits is lower than the minimum value of required hits, the best hits are selected up to this minimum number. At least 2 good hits are required, but it is recommended to set the minimum value of required hits a bit higher to have enough statistical confidence in the averaged FRF.

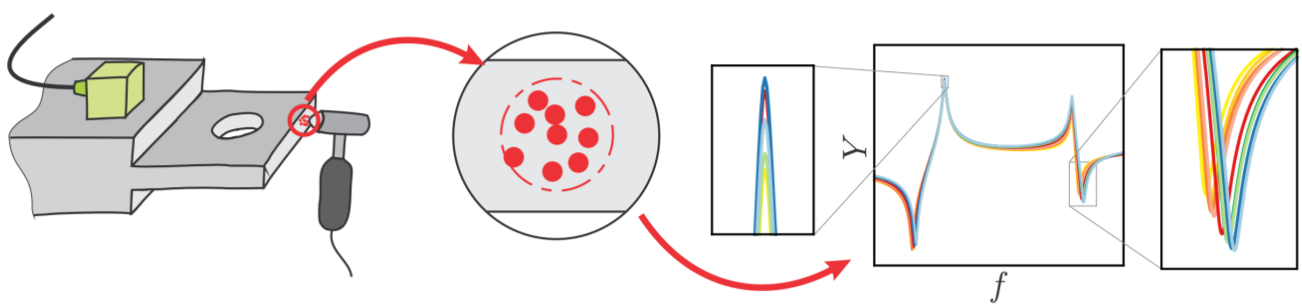

Fig. 1 Impact testing: it is challenging to always hit at the same location and in the same direction. Changes in location and orientation will lead to changes in the acquired FRF. SHS assists the user in selecting the hits that are most similar to each other, leading to high quality FRFs and high coherences

The SHS concepts are illustrated using data from a simple metal plate (Figure 2, Left). In Figure 3 and Figure 4, two hits at the same location are compared to each other (Figure 2, Right). The 1^{st} hit is a good, single-impact hit, but with rather low excitation level, resulting in noisy data at higher frequencies. The 2^{nd} hit is actually a double or even multiple-impact hit, but with a high excitation level, resulting in a good SNR even at high frequencies.

From Figure 3, it can be observed that the pairwise similarity is much noisier than the pairwise coherence. This is caused by the 1^{st} hit which also shows a very noisy instantaneous FRF (Figure 4). The pairwise coherence is much less affected by the noisy hit (just like the averaged FRF is less affected – see Figure 4): lower-level signals contribute less to the averaged FRF (H1 estimator), which is not true for the instantaneous FRFs. This is also the reason why H1 estimators are used for averaging rather than simply taking the average of all instantaneous FRFs.

It should be noted that for other hit pairs, and in general, not so big differences are observed between both criteria: pairwise similarity and pairwise coherence, and both can be used with confidence to obtain the best hits.

In Figure 5, the benefits of SHS are made clear: there is a clear quality improvement when running SHS and retaining the 3 or 5 best hits compared to using all hits. The SHS method is able to improve the coherence considerably, leading to higher quality FRFs. Benefits of "Smart Hit Selection" include [3]:

- The operator can focus on testing, the algorithm will discard bad hits;

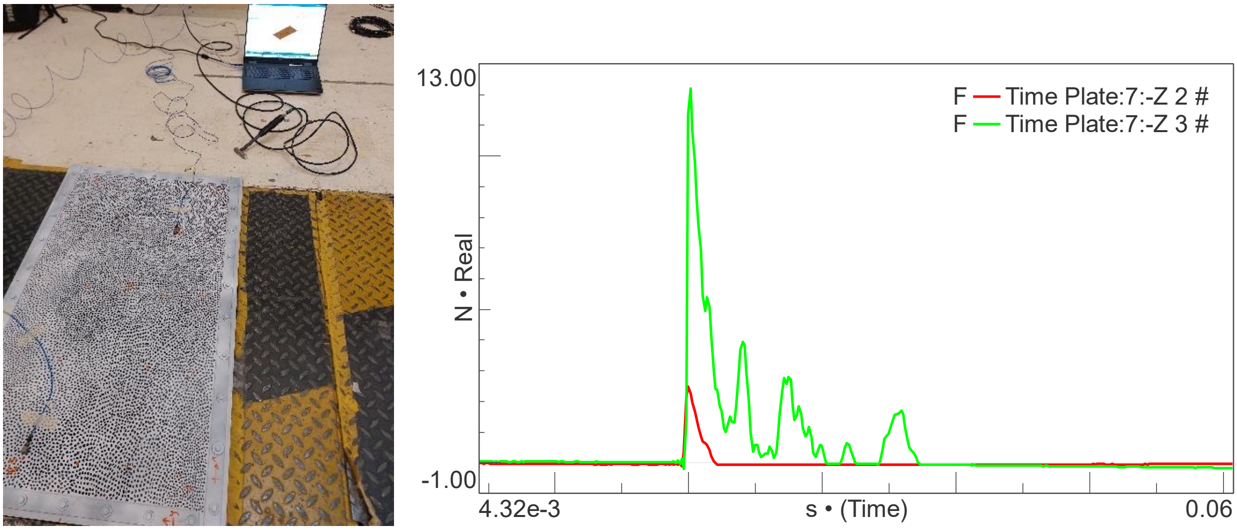

Fig. 2 (Left) Plate used to illustrate the SHS method. Plate is fuzzily supported, and roving hammer excitation has been applied in a rectangular grid. Two fixed accelerometers are capturing the plate response. (Right) Plate is highly resonating resulting in quite some double / multiple-impact hits as illustrated by the force measurements in time domain. A low-level single hit is shown together with a higher-level multiple-impact hit

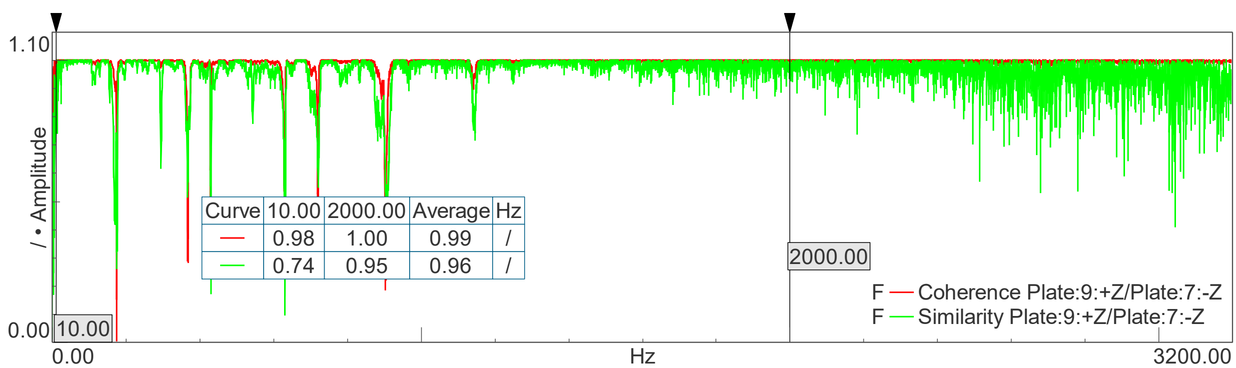

Fig. 3 Pairwise coherence and pairwise similarity of the same 2 hits

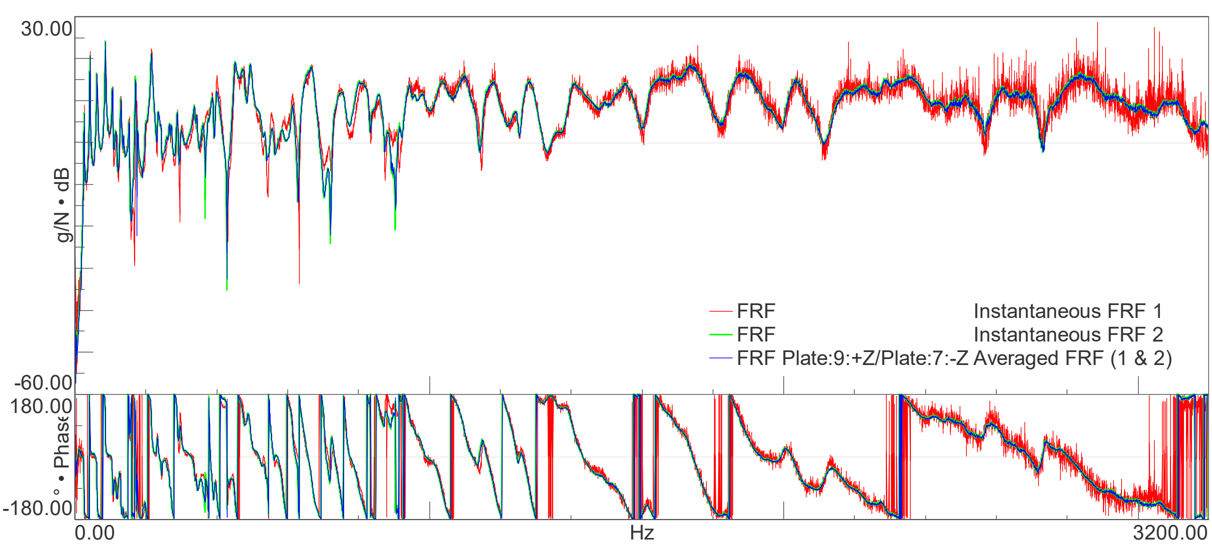

Fig. 4 Two instantaneous FRFs and the averaged (H1 estimator) FRF based on 2 hits

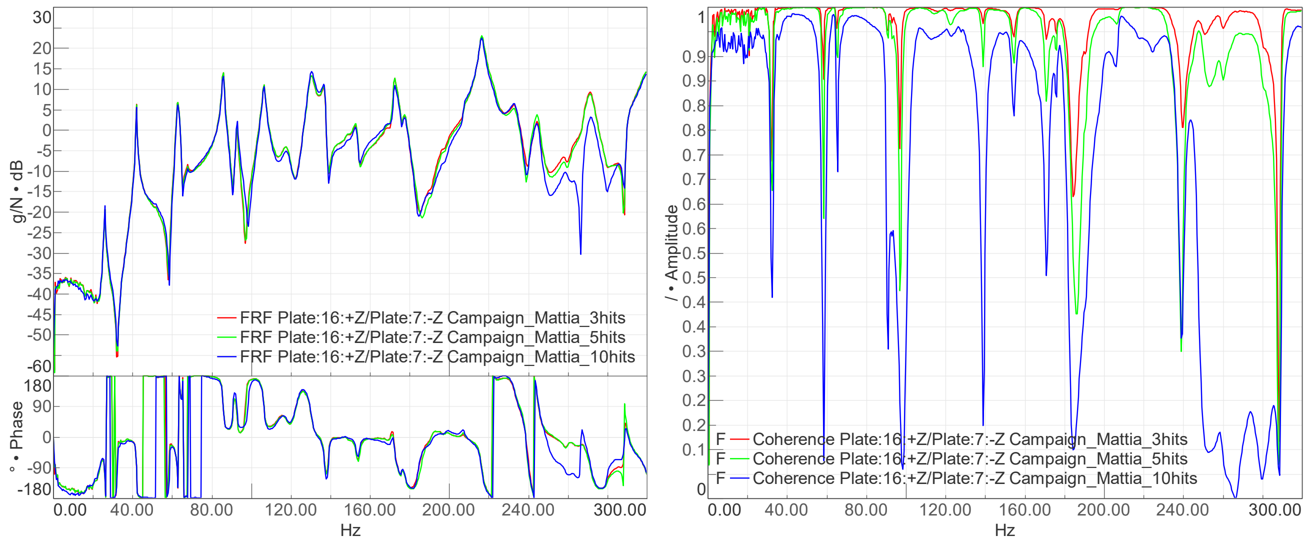

Fig. 5 (Left) FRFs obtained using SHS: all 10 hits, 5 best hits, 3 best hits; (Right) corresponding coherences

- There is less/no need to manually scan all data after the test;
- Highest quality FRFs are obtained from the available impacts;
- SHS can be applied online during the test and/or offline after the test. Parameters of the method (selected metric, frequency range, target value, ...) can be modified at any moment, allowing to tune the method to the particularities of the tested structure and inherent measurement quality.

The application of AI in the modal analysis process

Experimental Modal Analysis is the process of estimating structural modes (eigenfrequencies, damping ratios, and mode shapes) based on vibration measurements in either controlled experimental or operational conditions, respectively. This happens by so-called curve-fitting techniques where a modal model is fitted to the measurement data.

When trying to estimate the modal parameters from sometimes noisy data, it is generally a good idea to over-specify the model order considerably, i.e. to try to fit high-order models that contain much more modes than present in the data. Afterwards the true physical modes are separated from the spurious numerical ones by interpreting a so-called stabilisation diagram (Figure 6). The poles corresponding to a certain model order are compared to the poles of a one-order-lower model. If their differences are within pre-set limits, the pole is labelled as a stable one. The spurious numerical poles will not stabilise very well during this process and can be sorted out of the modal parameter data set more easily.

Nevertheless, the interpretation of stabilisation diagrams may be intimidating for the non-expert and the selection of the “right” poles can be a time-consuming and error-prone process. Therefore, the automation of pole selection in modal analysis is important to accurately process complex datasets without user-dependent interaction and with repeatability. Such automated modal analysis method was recently proposed in [5]: a so-called Hybrid AI method was developed using a Machine Learning (ML) density-based clustering technique, combined with domain knowledge of modal parameter selection. In contrast to other clustering algorithms, density-based clustering techniques have the capability of automatically neglecting spurious data points, which can be a useful capability for the analysis of poles in stabilization diagrams. More specifically, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) has been selected as the clustering algorithm: it organizes points based on their density in the feature space, typically evaluated using a distance function [6]. Unlike many clustering methods, DBSCAN does not require a predefined number of clusters as a hyperparameter. Instead, it relies on two key hyperparameters: (1) epsilon distance (ε), which defines the neighborhood around a point, and (2) minimum points ($MinPts$) needed within that neighborhood to form a cluster.

To improve the effectiveness and as an integral part of the proposed Hybrid AI method, cluster verification steps are applied after DBSCAN, again without requiring any user interaction. The following verification steps, based on expert knowledge cast in rules, are performed:

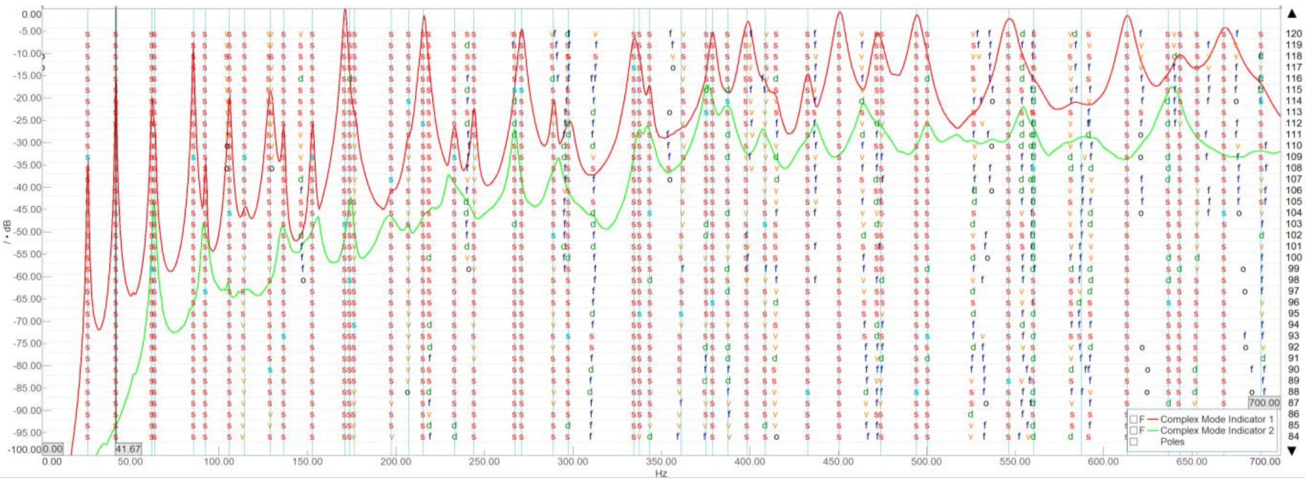

Fig. 6 Typical stabilisation diagram, allowing to select stable poles despite over-fitting. The FRF data from the plate introduced in previous section (Figure 2, Left) is used

- It may be necessary to join multiple clusters together that belong to the same physical pole but may have been separated by DBSCAN, due to high damping ratio differences.
- In case of very high model orders and complex data, sometimes too many clusters are obtained with representative poles that contribute very little to the measured data. Such low-contributing poles will be labelled as "numerical poles" and not retained in the final set of "physical poles".

The complete Hybrid AI method is represented in Figure 7. More details can be found in [5]. The result of the method applied to the stabilization diagram of Figure 6 is provided in Figure 8, where the different clusters are indicated and a single representative physical pole per cluster is selected. A view on the "dashboard" containing the full modal parameter estimation process within Simcenter Testlab Neo Modal Analysis is shown in Figure 9.

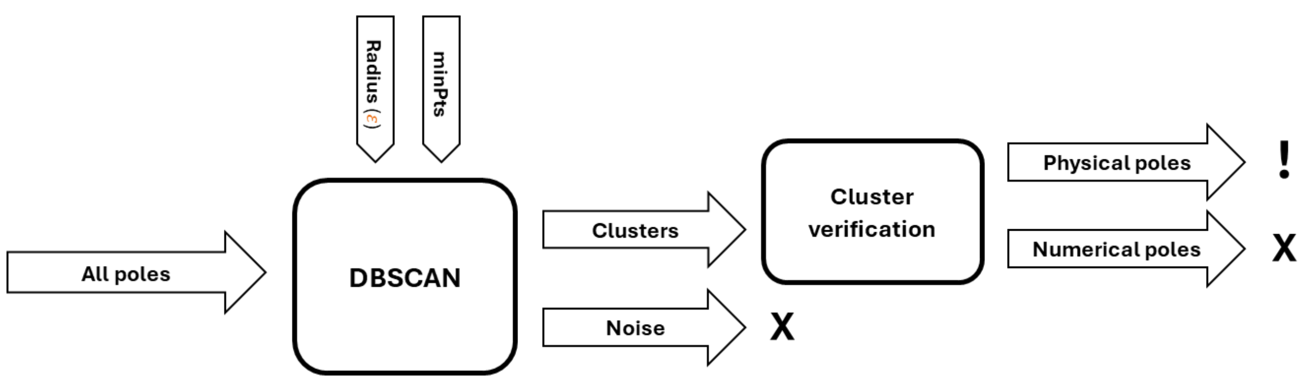

Fig. 7 Hybrid AI scheme adopted for automatic modal analysis: unsupervised learning (DBSCAN clustering) is combined with domain expertise (cluster verification)

Conclusions

This paper presented guided analysis tools for:

- highly efficient impact testing;
- AI-assisted modal parameter estimation.

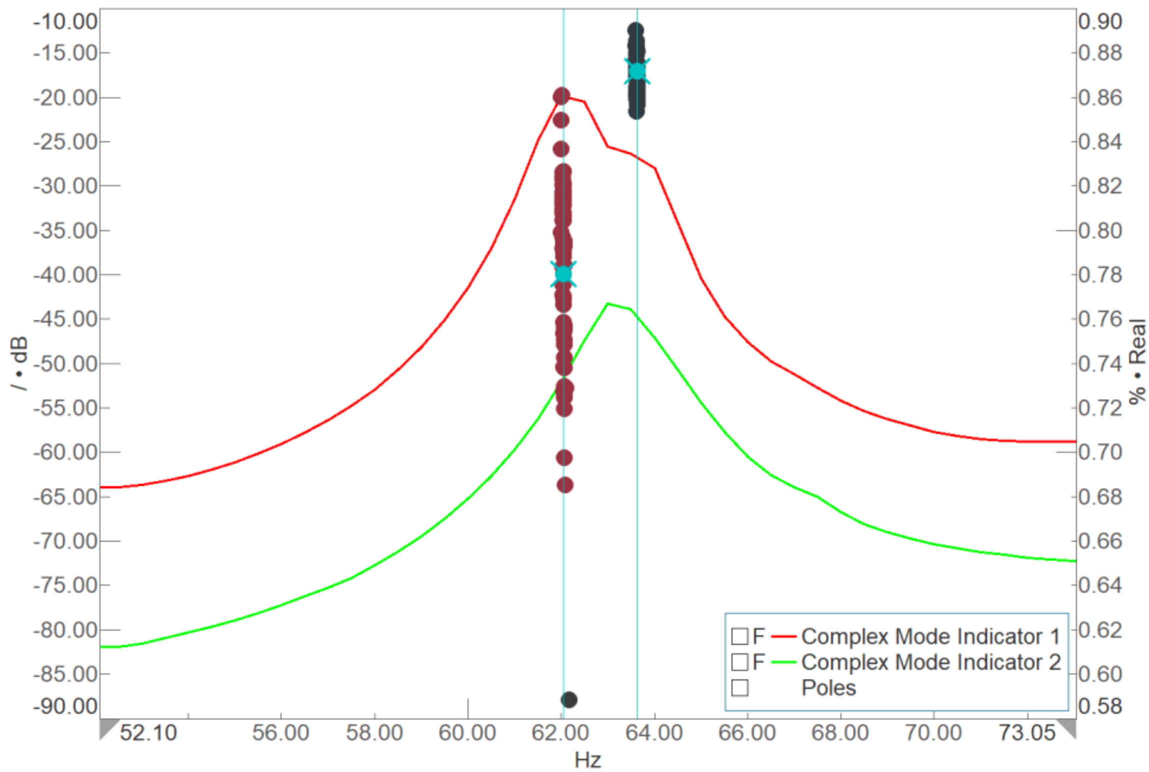

Fig. 8 Cluster representation of the stabilisation diagram from Figure 6, with poles selected by the Hybrid AI method, zooming in at 2 close poles

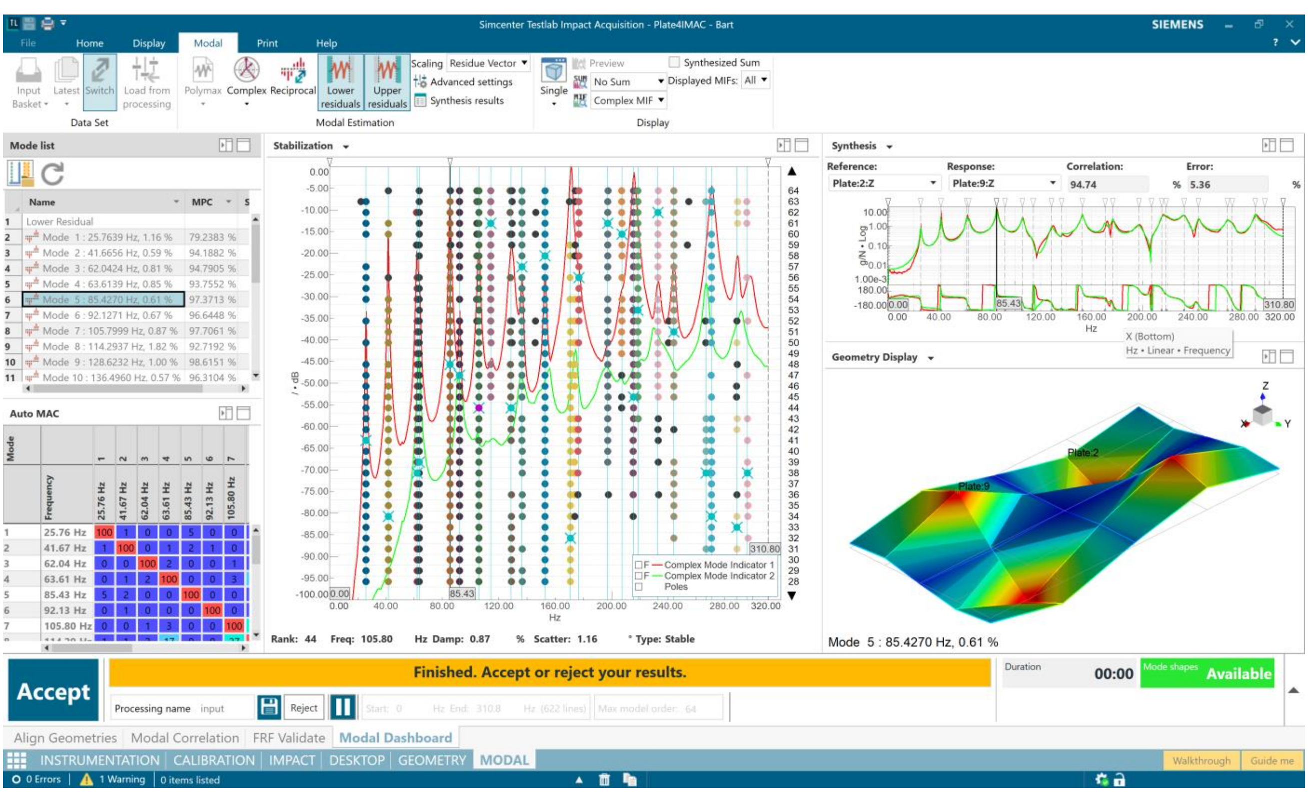

Fig. 9 Simcenter Testlab Neo Modal Analysis with embedded AI

Both methods aim to considerably facilitate the work of the experimentalist. The Smart Hit Selection (SHS) method allows the operator to focus on acquiring data in a highly efficient way, while SHS takes care of selecting the best hits resulting in optimal-quality FRFs and coherences, eliminating measurement errors and reducing noise propagation. AI-assisted modal parameter estimation combines advanced density-based clustering techniques with domain knowledge-driven mode validation. This integrated solution streamlines the time-intensive steps of experimental modal analysis, providing reliable and repeatable expert-level results with minimal user intervention.

References

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