Computational Model Updating of Axis Symmetric Systems

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Abstract

This paper addresses the application of computational model updating to axis symmetric systems like aero engine components. These systems usually exhibit repeated (in reality nearly identical) eigenfrequencies. The corresponding eigenvectors have the same shape but are rotated against each other about the axis of symmetry by a certain angle. The absolute orientation of the analytical eigenvectors with respect to the axis of symmetry is arbitrary and depends on the employed computation method. Thus, an identical orientation of both the test eigenvectors and the analytical eigenvectors is usually not the case. This complicates especially the automatic correlation of the eigenvectors and the utilization of the important eigenvector information in the computational model updating process. For a real life problem different possibilities for treating eigenvectors in computational model updating of axis symmetric systems are presented.

1 Introduction

To assess the fidelity of Finite Element models, test data, e.g. from an experimental modal analysis, may be utilized. If the deviations between test and analysis are unacceptable, the idealization of the investigated elastomechanical system must be reviewed. Because of the number of uncertain model parameters usually being very high for industrial applications, an appropriate 'manual' update based on engineering skills will most likely fail. Here, computational model updating techniques must be applied which allow for a simultaneous update of multiple model parameters.

In this paper the application of computational model updating is discussed for systems that exhibit axis symmetry, which can frequently be found for instance in aero engines. Here, (in practical application nearly) repeated roots occur. The corresponding eigenvectors are only defined with respect to their shape and their angular position to each other. However, the eigenvectors can appear rotated by an arbitrary angle about the axis of symmetry.

For practical applications the orientation of the eigenvectors from test and analysis is usually different, posing problems with respect to the utilization of eigenvector information for computational model updating (pairing / eigenvector residual). The simplest way to deal with this is to neglect the eigenvector information. Yet, to benefit the computational model updating process, the eigenvector information should be made available.

One way to make use of the eigenvector information is to modify the model manually or computationally such, that proper orientation of test and analysis eigenvectors is obtained. This may, however, require some amount of effort. Another, easier, way is to adequately condition (i.e. transform) either test or analysis eigenvectors to compensate for mismatches. This issue is especially addressed in the paper.

The presented techniques are demonstrated by means of a practical application from the aero engine industry. The discussed results were obtained within the framework of the European Union project for cost effective rotordynamics engineering solutions (CERES).

2 Theory

2.1 Update of Physical Parameters

The foundation for updating physical stiffness, mass, and damping parameters is a parameterization of the system matrices according to equations (1) (see also [1], [2]):

$$\mathbf{K} = \mathbf{K}_A + \sum \alpha_i \mathbf{K}_i \quad , \quad i = 1 \ldots n_\alpha \tag{1a}$$

$$\mathbf{M} = \mathbf{M}_A + \sum \beta_j \mathbf{M}_j \quad , \quad j = 1 \ldots n_\beta \tag{1b}$$

$$\mathbf{D} = \mathbf{D}_A + \sum \gamma_k \mathbf{D}_k \quad , \quad k = 1 \ldots n_\gamma \tag{1c}$$

with: $\mathbf{K}_A$, $\mathbf{M}_A$, $\mathbf{D}_A$ initial stiffness, mass, and damping matrices

$\mathbf{p} = [\alpha_i \, \beta_j \, \gamma_k]$ vector of unknown design parameters

$\mathbf{K}_i$, $\mathbf{M}_j$, $\mathbf{D}_k$ given substructure matrices defining location and type of model uncertainties

This parameterization allows for the local adjustment of uncertain model regions. By utilizing equations (1) and appropriate residuals, which consider different test/analysis deviations, the following objective function can be derived:

$$J(\mathbf{p}) = \Delta\mathbf{z}^T \mathbf{W} \Delta\mathbf{z} + \mathbf{p}^T \mathbf{W}_p \mathbf{p} \rightarrow \min \tag{2}$$

with: $\Delta\mathbf{z}$ residual vector

$\mathbf{W}$, $\mathbf{W}_p$ weighting matrices

The minimization of the objective function (2) yields the desired design parameters $\mathbf{p}$. The second term on the right hand side of equation (2) is used for constraining the parameter variation. The weighting matrix must be carefully selected, as for $\mathbf{W}_p >> \mathbf{0}$ no parameter changes will occur (see also [1]).

The residuals $\Delta\mathbf{z} = \mathbf{z}_T - \mathbf{z}(\mathbf{p})$ ($\mathbf{z}_T$: test data vector, $\mathbf{z}(\mathbf{p})$: corresponding analytical data vector) are usually nonlinear functions of the design parameters. Thus, the minimization problem is also nonlinear and is to be solved iteratively. One solution is the application of the classical sensitivity approach (see [2]). Here, the analytical data vector is linearized at point 0 by means of a Taylor series expansion truncated after the linear term. Proceeding this way leads to:

$$\Delta\mathbf{z} = \Delta\mathbf{z}_0 - \mathbf{G}_0 \Delta\mathbf{p} \tag{3}$$

with: $\Delta\mathbf{p} = \mathbf{p} - \mathbf{p}_0$ design parameter changes

$\Delta\mathbf{z}_0 = \mathbf{z}_T - \mathbf{z}(\mathbf{p}_0)$ test/analysis deviations at linearization point 0

$\mathbf{G}_0 = \partial\mathbf{z}/\partial\mathbf{p}|_{p=p_0}$ sensitivity matrix at linearization point 0

$\mathbf{p}_0$ design parameters at linearization point 0

As long as the design parameters are not bounded the minimization problem (2) yields the linear problem (4). The latter is to be solved in each iteration step for the current linearization point:

$$(\mathbf{G}_0^T \mathbf{W}\, \mathbf{G}_0 + \mathbf{W}_p)\, \Delta \mathbf{p} = \mathbf{G}_0^T \mathbf{W}\, \Delta \mathbf{z}_0 \tag{4}$$

For $\mathbf{W}_p = \mathbf{0}$ equation (4) represents a standard weighted least squares approach. Of course, any other mathematical minimization technique can be applied for solving equation (2).

In contrast to the assembly of the analytic stiffness and mass matrix, the generation of the analytic damping matrix is usually a difficult task. For treating system damping in an update process modal damping parameters can be utilized alternatively. For further discussions on this topic it is referred to the literature (see for instance [1], [3]).

2.2 Eigenvalue and Eigenvector Residuals

Commonly, the eigenvalue and the eigenvector residuals are employed. Here, the analytical eigenvalues (squares of the eigenfrequencies) and eigenvectors are subtracted from the corresponding experimental results. The residual vector in this case becomes:

$$\Delta \mathbf{z}_0 = \begin{bmatrix} \boldsymbol{\lambda}_{Ti} - \boldsymbol{\lambda}_i \\ \cdots\cdots \\ \mathbf{x}_{Ti} - \mathbf{x}_i \end{bmatrix}_0 \quad , i = 1, \ldots, n \tag{5}$$

with: λ_{Ti}, λ_i — test/analysis vectors of eigenvalues

$\mathbf{x}_{Ti}, \mathbf{x}_i$ — test/analysis eigenvectors

The corresponding sensitivity matrix is given by equation (6). The calculation of the partial derivatives can be found for instance in references [1], [2].

$$\mathbf{G}_0 = \begin{bmatrix} \dfrac{\partial \boldsymbol{\lambda}_i}{\partial \mathbf{p}} \\ \cdots\cdots \\ \dfrac{\partial \mathbf{x}_i}{\partial \mathbf{p}} \end{bmatrix}_0 \quad , i = 1, \ldots, n \tag{6}$$

If real eigenvalues and eigenvectors are employed, the adjustment of damping parameters is not possible. The corresponding sensitivities equal zero since the real eigenvalues and eigenvectors depend solely on the stiffness and the mass parameters of the system.

2.3 Pairing of Eigenvalues and Eigenvectors

The pairing of analytical data and test data is accomplished by means of the MAC value of the eigenvectors:

$$\mathrm{MAC} := \frac{\left(\mathbf{x}_T^T\, \mathbf{x}\right)^2}{\left(\mathbf{x}_T^T\, \mathbf{x}_T\right)\left(\mathbf{x}^T\, \mathbf{x}\right)} \tag{7}$$

which states the linear dependency of two vectors $\mathbf{x}_T$, $\mathbf{x}$. A MAC value of one denotes that two vectors are collinear and a MAC value of zero indicates that two vectors are orthogonal.

Axis symmetric systems usually exhibit repeated (in reality nearly identical) roots. The corresponding eigenvectors are only defined with respect to their shape and their angular position to each other - the absolute orientation with respect to the axis of symmetry is arbitrary and depends on the employed computation method. Thus, an identical orientation of both, the test and the analytical eigenvectors, is usually not the case. This may cause a significant decrease of the MAC values of corresponding eigenvectors, which complicates or even prevents the utilization of the eigenvector information.

In these cases the following steps can be taken:

1) disregard of the eigenvector information and exclusive utilization of the eigenvalue information; eigenvector information will only be used to correlate (with limitations) corresponding test/analysis eigenvalues
2) 'manual' or computational remodeling of the Finite Element model to receive an equal orientation of the test/analysis eigenvectors
3) direct conditioning (transformation) of the analytical or experimental eigenvectors for compensating possible misalignments

Point 1) bears the disadvantage that the local eigenvector information cannot be used. This may deteriorate the convergence behavior of the update runs and may complicate the update of local regions, respectively. Point 2) is often very time consuming (for instance to exactly model/update local masses). Additionally, the method of choice varies depending on the investigated system. Point 3) usually requires only little efforts and is generally applicable. One possible realization is presented in the following section.

2.4 Eigenvector Transformation

The analytical modal analysis of axis symmetric systems primarily computes orthogonal pairs of eigenvectors exhibiting identical eigenvalues (repeated roots). The eigenvectors of corresponding pairs have the same shape but are rotated against each other by a certain angle. The total orientation of the eigenvectors with respect to the axis of symmetry is arbitrary, which means that any rotation of an eigenvector pair yields again a valid pair of eigenvectors.

For real systems the eigenvector orientation with respect to the axis of symmetry is usually fixed due to geometric tolerances (distortion of symmetry) and the corresponding eigenvalues are nearly identical (closely spaced). This can lead to very low MAC values for misaligned test/analysis eigenvectors, even if the visual coherence is obviously given.

For adjusting the orientation of test and analysis data, either the test or the analysis eigenvectors are to be rotated or transformed. One approach, as presented for instance in [4], proposes the rotation of the eigenvectors and/or their Fourier decomposition. However, this method requires equally spaced measurement positions about the circumference.

A more general method, which especially does not imply any limitations regarding the position of the measurement points, is illustrated below:

First, the repeated or closely spaced analytical eigenfrequencies are determined (for analytical results both eigenvalues of an eigenvector pair are usually given; for experimental data this is not necessarily the case). The assignment can be easily automated for instance by use of a selectable frequency bandwidth. This enables again a computational model updating without user interaction.

Next, the two test eigenvectors are determined, which can be correlated with a certain pair of analytical eigenvectors. This is accomplished by taking advantage of the fact, that each linear combination of the analytical eigenvectors of an eigenvector pair again yields a valid eigenvector. Ideally this means, that each corresponding test eigenvector can be considered as a linear combination of an eigenvector pair:

$$\mathbf{x}_{Ti} = \alpha_i\, \mathbf{x}_1 + \beta_i\, \mathbf{x}_2 \tag{8}$$

with: $\mathbf{x}_{Ti}$ test eigenvectors, i = 1…number of test eigenvectors

$\mathbf{x}_1, \mathbf{x}_2$ pair of analytical eigenvectors

α_i, β_i scalar factors

Due to the inevitable deviations between test and analysis the scalar factors α_i und β_i are practically determined in a least squares sense according to equation (9):

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = [\mathbf{x}_1 \quad \mathbf{x}_2]^+ \mathbf{x}_{Ti} \tag{9}$$

with: $[\mathbf{x}_1 \quad \mathbf{x}_2]^+$ pseudo-inverse of $[\mathbf{x}_1 \quad \mathbf{x}_2]$

Hence, for each test eigenvector a 'new' corresponding transformed analytical eigenvector can be computed utilizing the scalar factors determined via (9):

$$\mathbf{x}_{Ai} = \alpha_i\, \mathbf{x}_1 + \beta_i\, \mathbf{x}_2 \tag{10}$$

For all determinable pairs $\mathbf{x}_{Ti}$ and $\mathbf{x}_{Ai}$ the MAC values according to equation (7) are then calculated. The two test eigenvectors, which exhibit the largest MAC values with the transformed analytical eigenvectors, are finally considered as corresponding test eigenvectors. For practical applications it is advisable to solely use correlations above a certain MAC limit and within a certain frequency tolerance.

The determined transformed pair of eigenvectors according to equation (10) can already be used for further analyses like correlation. Yet, it should be mentioned that the two corresponding transformations do not have anything in common so far. For improving this situation the analytical eigenvector pair is finally transformed simultaneously onto the corresponding test eigenvector pair. This transformation is basically made by analogy to equation (8) to (10).

Additionally, the orthonormality of the analytical eigenvectors with respect to the mass matrix is enforced. A detailed description of the underlying method can be found in [5] (particular application of the eigenvector smoothing presented in [5]).

3 Example

For a real life example taken from the aerospace industry the discussed possibilities for treating eigenvectors within computational model updating of axis symmetric systems are presented in the following. The investigated system is a so called 'bypass duct' of an aero engine, which has been analyzed in the frame of the 'GROWTH' program of the European Commission in the research project CERES (Cost Effective Rotordynamics Engineering Solutions).

Figure 1 shows the Finite Element model of the bypass duct. It is a hybrid shell/beam model and consists of about 2000 elements and 3000 nodes. The boundary conditions are assumed to be free/free, as they can easily be realized in the test setup.

The investigated physical bypass duct is depicted in Figure 2. It possesses several attached masses, which are not explicitly considered in the Finite Element model. For this bypass duct an experimental model analysis in a free/free configuration was conducted by Rolls-Royce plc. in Bristol, England. The results state the foundation for the following model validation.

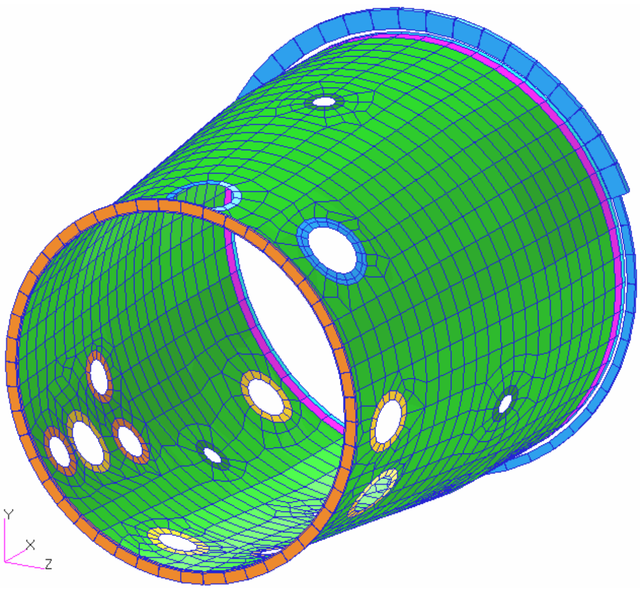

Figure 1: Finite Element model of the bypass duct

Figure 2: Investigated bypass duct (Rolls-Royce plc.)

The initial correlation for the first 20 eigenfrequencies and eigenvectors of the bypass duct is shown in Table 1 and Figure 3, respectively (EMA = experimental modal analysis, FEA = Finite Element analysis). The correlation considers only eigenfrequencies within a tolerance of 30 % and eigenvectors with a MAC value larger than 70 %. Please note that the numbering of the analytical eigenvectors starts at seven (one to six are rigid body eigenvectors of the free/free system).

Obviously, the correlation does not provide a satisfactory result. Especially the first two eigenvectors exhibit MAC values less than 60 %. A visual comparison of the shape of the first experimental eigenvector with the first elastic analytical eigenvector is shown in Figure 4. Both eigenvectors have the same shape but are rotated against each other by about 20°.

Nr.	**EMA Nr.**	**FEA Nr.**	**EMA Freq. [Hz]**	**FEA Freq. [Hz]**	**Freq. Dev. [%]**	**MAC [%]**
1	3	9	73,67	75,74	2,82	74,81
2	4	10	76,12	78,00	2,48	80,06
3	5	11	122,13	106,56	-12,75	83,19
4	6	12	127,41	106,80	-16,18	88,46
5	16	22	212,80	215,93	1,47	85,28
6	17	24	238,85	243,59	1,98	71,96

Table 1: Initial correlation

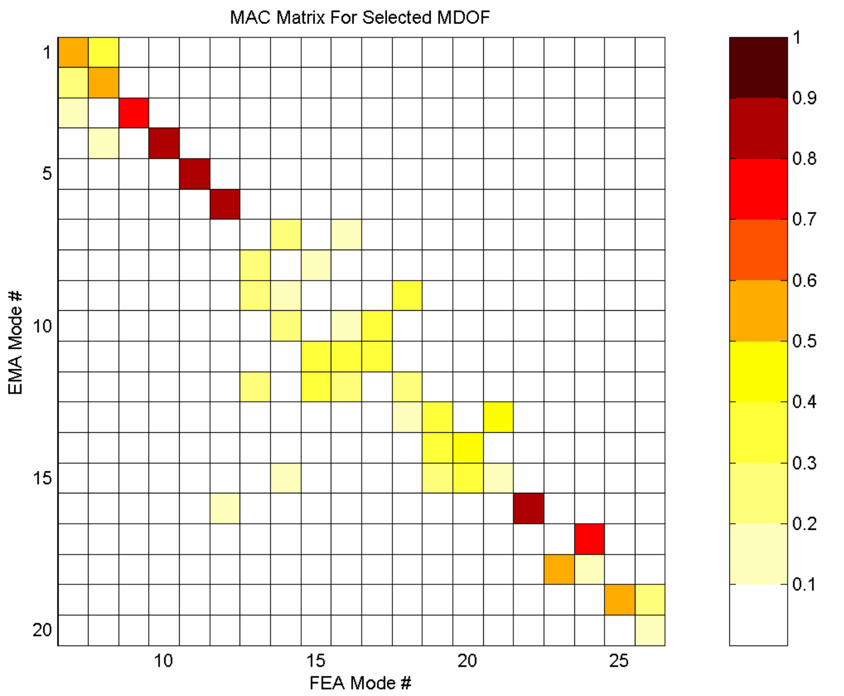

Figure 3: MAC matrix, initial configuration

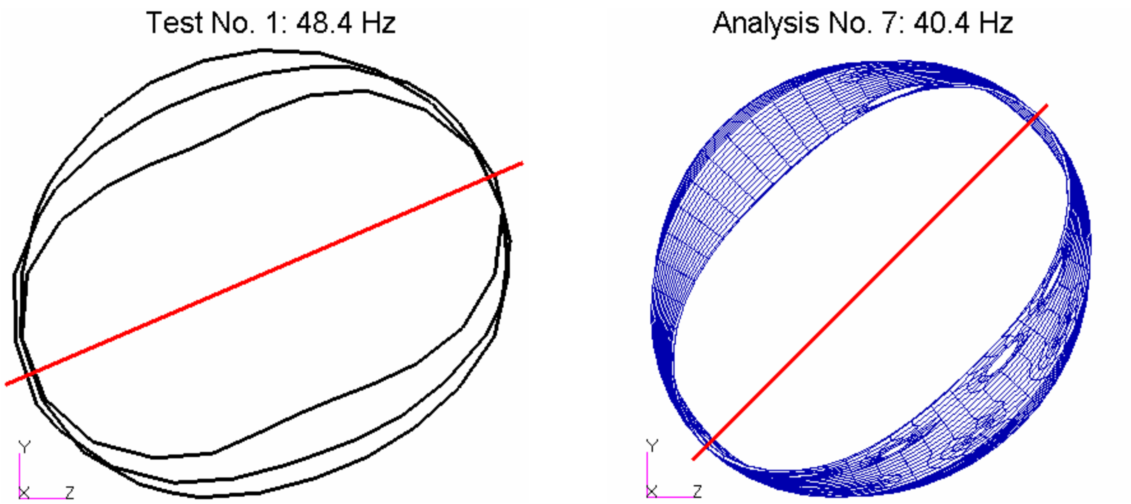

Figure 4: Comparison of first experimental with first analytical eigenvector

The correlation after applying the eigenvector transformation is given in Table 2 and Figure 5. Now, the number of correlated eigenfrequencies and eigenvectors is doubled and especially the first eigenvector shows a MAC value of about 90 %.

Nr.	EMA Nr.	FEA Nr.	EMA Freq. [Hz]	FEA Freq. [Hz]	Freq. Dev. [%]	MAC [%]
1	1	7	48,39	40,38	-16,57	89,19
2	2	8	48,77	40,64	-16,67	88,25
3	3	9	73,67	75,74	2,82	74,93
4	4	10	76,12	78,00	2,48	80,43
5	5	11	122,13	106,56	-12,75	84,65

Nr.	EMA Nr.	FEA Nr.	EMA Freq. [Hz]	FEA Freq. [Hz]	Freq. Dev. [%]	MAC [%]
6	6	12	127,41	106,80	-16,18	90,22
7	13	19	195,34	200,37	2,58	77,68
8	14	20	200,11	201,11	0,50	74,77
9	15	21	204,25	203,42	-0,41	79,29
10	16	22	212,80	215,93	1,47	85,28
11	17	23	238,85	242,67	1,60	78,08
12	18	24	239,31	243,59	1,79	73,69
13	19	25	286,76	297,30	3,68	76,34

Table 2: Correlation after applying the eigenvector transformation

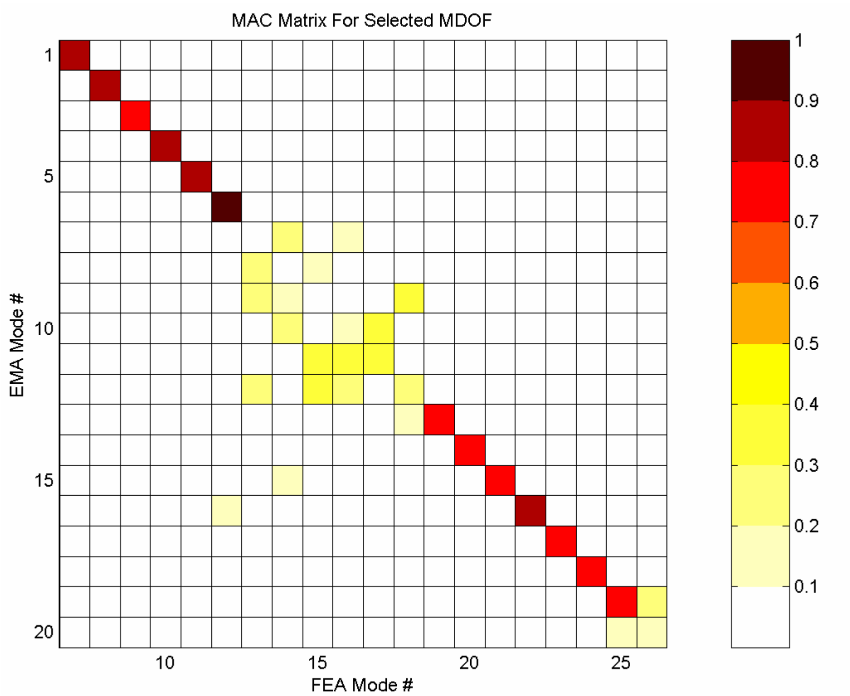

Figure 5: MAC matrix, after applying the eigenvector transformation

However, even after this considerable improvement of the correlation Figure 5 still exhibits a clear gap in the range between the seventh and the twelfth experimental eigenvector. The corresponding mode shapes show predominantly local deformations of the mantle surface of the bypass duct. The used Finite Element model is obviously not capable of representing these mode shapes, since the attached masses (see also Figure 2) are not explicitly modeled. Thus, this effect cannot be compensated by the eigenvector transformation.

The frequency deviations listed in Table 2 are not acceptable for some eigenvectors. Therefore, computational model updating will be performed investigating the different methods already described above: 1) Disregard of the eigenvector information and exclusive utilization of the eigenvalue information, 2) ‘manual’ or computational remodeling of the Finite Element model, and 3) direct conditioning of the analytical or the experimental eigenvectors. For all analyzed variants the dominant area moments of inertia of the front and the rear flange (two parameters) are considered for computational model updating.

3.1 Update without Eigenvector Information

The update without eigenvector information is carried out by solely using the eigenvectors for pairing the corresponding test and analysis eigenvalues. Only the upper block of equation (5) is used as the residual. Figure 6 shows the update progression over ten iteration steps. Convergence is achieved after about five iteration steps.

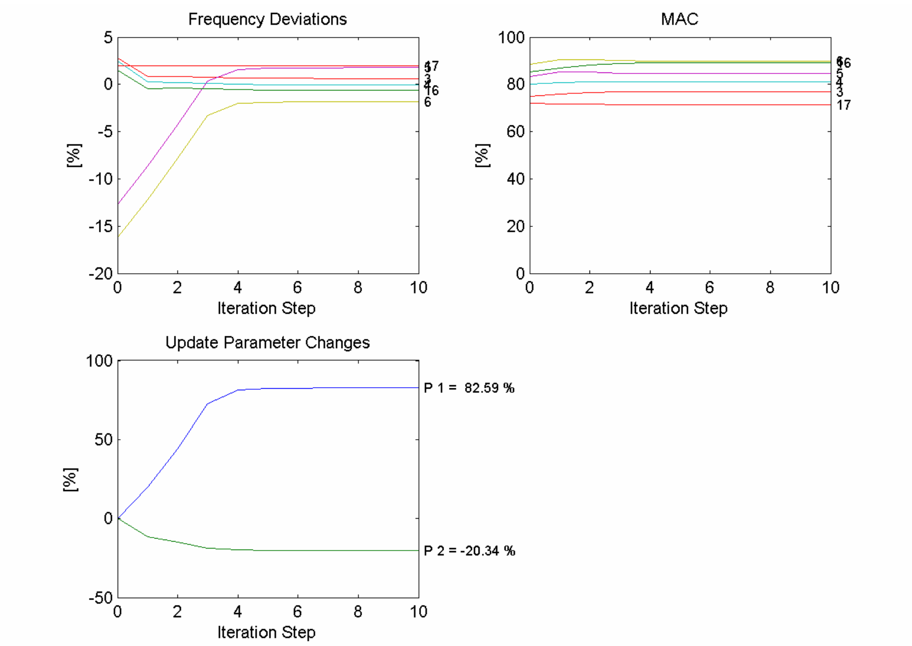

Figure 6: Update progression, eigenvector information neglected

For assuring comparability of the results the correlation after computational model updating will utilize the eigenvector transformation. The corresponding results are collected in Table 3 and Figure 7.

Nr.	EMA Nr.	FEA Nr.	EMA Freq. [Hz]	FEA Freq. [Hz]	Freq. Dev. [%]	MAC [%]
1	1	7	48,39	48,07	-0,66	90,98
2	2	8	48,77	48,38	-0,79	90,11
3	3	9	73,67	74,13	0,63	77,18
4	4	10	76,12	76,07	-0,07	81,35
5	5	11	122,13	124,29	1,76	86,10
6	6	12	127,41	125,02	-1,87	90,92
7	13	19	195,34	199,76	2,26	77,18
8	14	20	200,11	201,10	0,49	74,97
9	15	21	204,25	201,27	-1,46	81,08
10	16	22	212,80	211,52	-0,60	89,16
11	17	23	238,85	242,69	1,61	78,05
12	18	24	239,31	243,62	1,80	73,66

Table 3: Correlation after updating without eigenvector information

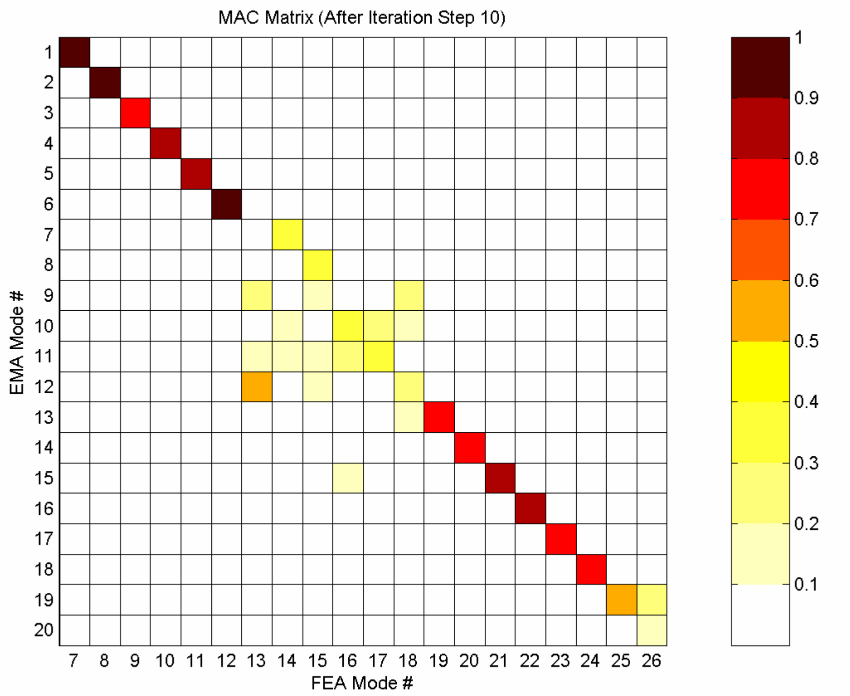

Figure 7: MAC matrix, after updating without eigenvector information

The computational model update yields an obvious reduction of the frequency deviations. For all paired eigenfrequencies the deviation lies below 3 %. The MAC values (using the eigenvector transformation) are only slightly improved by computational model updating.

3.2 Update after Modification of the Finite Element Model

In a first step the Finite Element model of the bypass duct is remodeled for minimizing misalignments between experimental and analytical eigenvectors. Since an explicit modeling of the attached masses is too time consuming, a different approach is favored making the following assumptions:

- uncertainties regarding the mass distribution of the bypass duct solely exist in the area of the mantle hole flanges
- the mantle holes can be grouped into four sets for computational model updating (small, intermediate 1, intermediate 2, and large; see also Figure 8)

By computationally model updating the flange densities in the area of the mantle holes a minimization of the eigenvector misalignment is reached. For the computational model updating only the eigenvector residual according to the lower block in equation (5) is utilized. Thus, a minimization of the eigenvalues is not forced at this time.

The correlation for the bypass duct after the remodeling step is exemplarily depicted in Figure 9 using the MAC matrix (MAC values computed without eigenvector transformation).

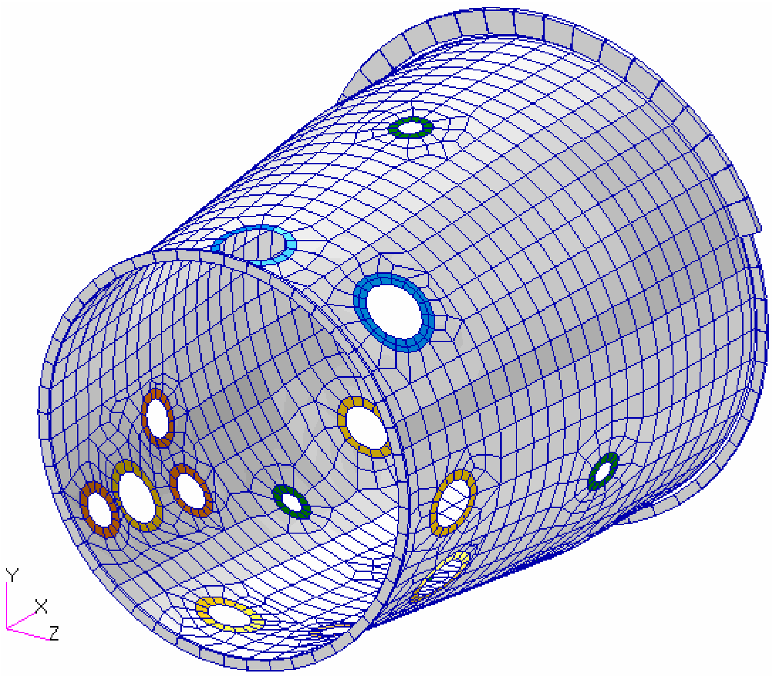

Figure 8: Mantle holes subdivided in four groups

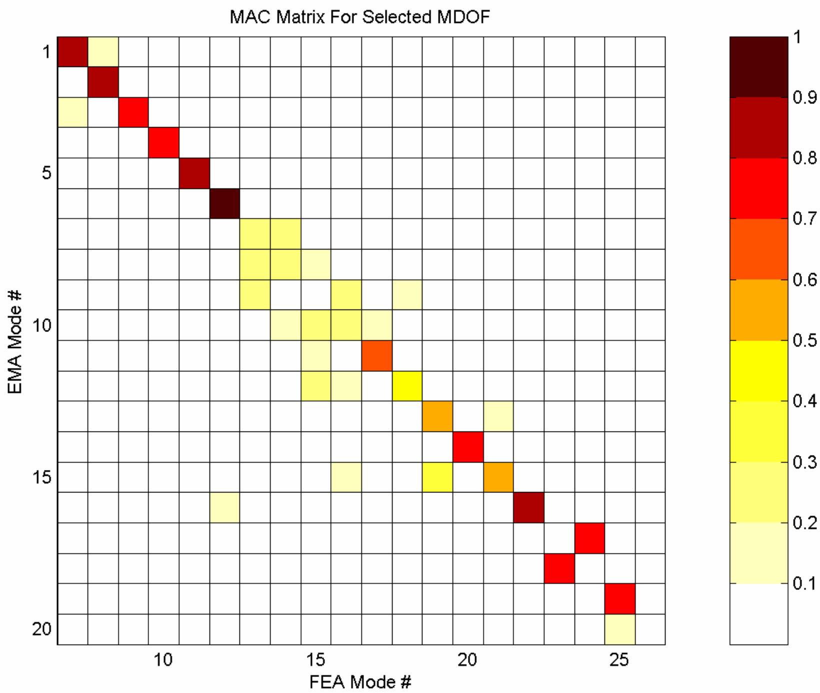

Figure 9: MAC matrix, after remodeling (without eigenvector transformation)

A comparison with Figure 3 shows an obvious reduction of the misalignment resulting in higher MAC values (after remodeling 11 instead of six eigenvectors can be paired with MAC values larger than 70 %).

Using the remodeled Finite Element model computational model updating is again performed disregarding the eigenvector transformation. It is assumed that the reduction of the misalignment is already sufficient. The progression of the model update is shown in Figure 10 for 10 iteration steps. The final parameter changes equal those depicted in Figure 6 without the eigenvector transformation.

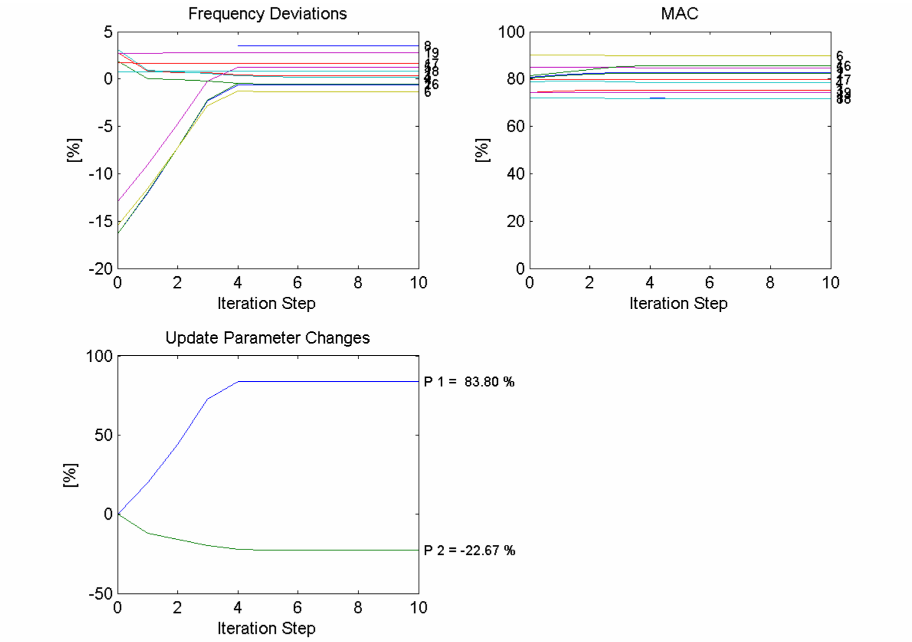

Figure 10: Update progression, modified Finite Element model

Table 4 and Figure 11 show the correlation after updating the modified Finite Element model. Again, the correlation after computational model updating is carried out with eigenvector transformation for ensuring comparability of the results.

Nr.	EMA Nr.	FEA Nr.	EMA Freq. [Hz]	FEA Freq. [Hz]	Freq. Dev. [%]	MAC [%]
1	1	7	48,39	48,09	-0,62	91,03
2	2	8	48,77	48,52	-0,51	90,18
3	3	9	73,67	73,92	0,34	77,35
4	4	10	76,12	76,27	0,20	81,23
5	5	11	122,13	123,64	1,24	86,67
6	6	12	127,41	125,74	-1,31	91,10
7	8	13	164,03	165,99	1,19	72,72
8	9	15	173,09	173,24	0,09	70,09
9	13	19	195,34	198,32	1,53	81,25
10	14	20	200,11	200,05	-0,03	77,38
11	15	21	204,25	201,86	-1,17	82,51
12	16	22	212,80	211,60	-0,56	85,50
13	17	23	238,85	241,23	1,00	79,32
14	18	24	239,31	242,86	1,48	72,68
15	19	25	286,76	294,64	2,75	74,30

Table 4: Correlation after updating the modified Finite Element model

Obviously, the computational model update yields again a clear reduction of the frequency deviations. For all paired eigenfrequencies the deviations are below 3 %. The MAC values (using the eigenvector transformation) are only slightly improved by computational model updating. However, the gap in the region between the seventh and the twelfth experimental eigenvector shows two additionally paired eigenvectors, which is most likely caused by the improved density distribution.

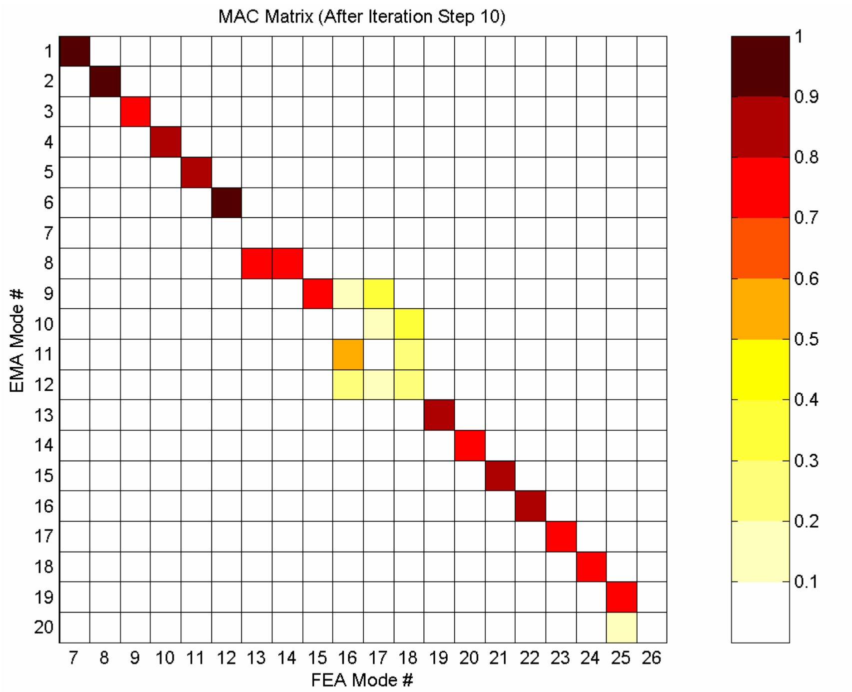

Figure 11: MAC matrix, after updating the modified Finite Element model

3.3 Update utilizing Eigenvector Transformation

The update progression using the eigenvector transformation is depicted in Figure 12 for 10 iteration steps. The employed model is again based on the initial model described in section 3.1. Convergence is reached after five iteration steps and the parameter changes are again similar to those in the other two update runs.

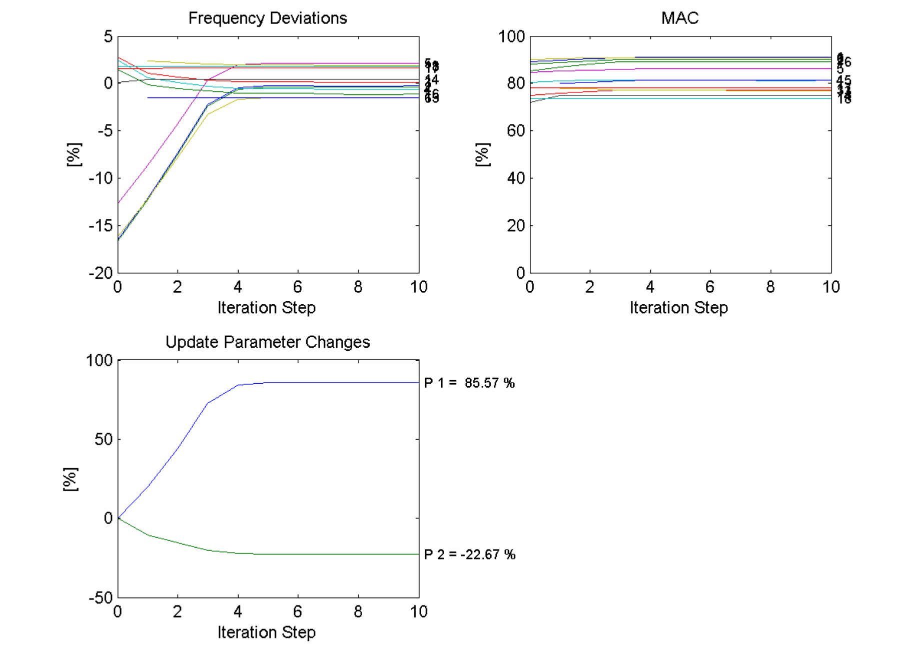

Figure 12: Update progression, eigenvector transformation applied

Table 5 and Figure 13 show the correlation after updating with eigenvector transformation. Again, an obvious decrease of the eigenfrequency deviations below 3 % is reached by using computational model updating methods. The MAC values (utilizing the eigenvector transformation) are again only slightly improved. In general, the results are comparable to those without the eigenvector transformation. Only the average frequency deviation is somewhat smaller.

Nr.	EMA Nr.	FEA Nr.	EMA Freq. [Hz]	FEA Freq. [Hz]	Freq. Dev. [%]	MAC [%]
1	1	7	48,39	48,27	-0,26	91,04
2	2	8	48,77	48,58	-0,39	90,17
3	3	9	73,67	73,76	0,12	77,15
4	4	10	76,12	75,66	-0,60	81,23
5	5	11	122,13	124,72	2,12	86,13
6	6	12	127,41	125,48	-1,51	90,90
7	13	19	195,34	199,06	1,91	77,02
8	14	20	200,11	200,91	0,40	74,98
9	15	21	204,25	201,24	-1,47	81,28
10	16	22	212,80	210,44	-1,11	89,29
11	17	23	238,85	242,69	1,61	78,05
12	18	24	239,31	243,62	1,80	73,66

Table 5: Correlation after updating with eigenvector transformation

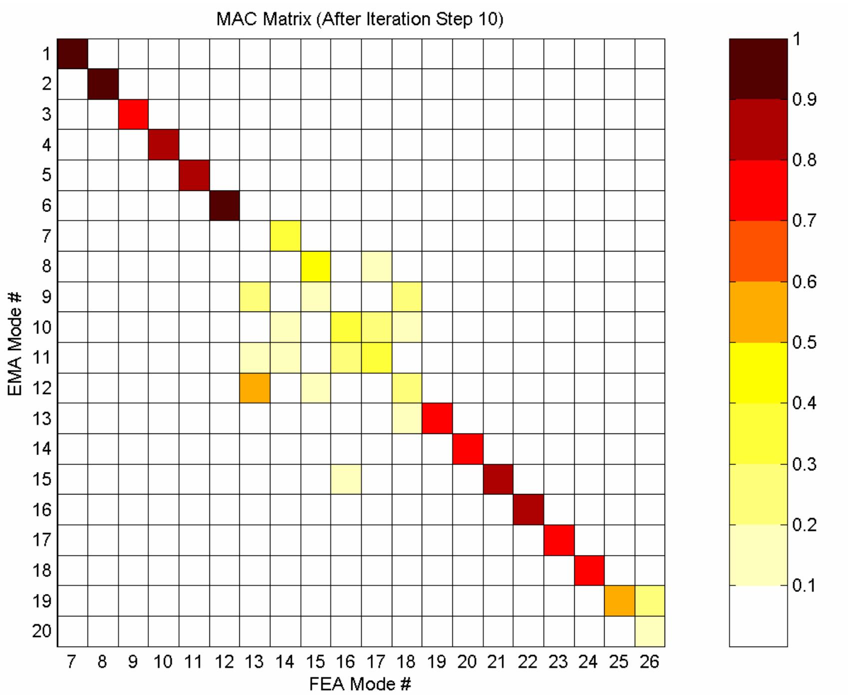

Figure 13: MAC matrix, after updating with eigenvector transformation

4 Summary

In this paper the model validation of axis symmetric systems using computational model updating techniques is discussed. These systems exhibit (nearly) repeated roots, which often leads to a different orientation of the experimental and the analytical eigenvectors with respect to the axis of symmetry.

Since misalignments between experimental and analytical eigenvectors yield difficulties in the utilization of eigenvectors for both test/analysis correlation using MAC values and computational model updating using eigenvector residuals, different approaches for validating axis symmetric systems are described. In particular, a general method for transforming analytical eigenvectors is presented, which allows for an easy and especially automated compensation of misalignments.

For a real life example from the aerospace industry the different approaches are investigated. For this particular application all methods produce equivalently good results. This is most likely caused by the choice of the utilized update parameters, which have an axis symmetric characteristic as well (area moments of inertia of surrounding flange beams).

However, the presented eigenvector transformation generates better and more plausible correlation results. This is a great advantage for more complex systems, where local parameters are to be considered in the computational model updating process.

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