International Forum on Aeroelasticity and Structural Dynamics
IFASD 2024
17-21 June 2024, The Hague, The Netherlands

ROBUST DESIGN THROUGH IDENTIFICATION OF MAIN COMPONENTS FROM MULTIVARIATE RANDOM LOADS

Cyrille Vidy[1], Carlo Aquilini[1]

[1] Airbus Defence & Space GmbH, Rechliner Strasse, 85077 Manching, Germany

Keywords: buffet, random loads, turbulence, design, POD

Abstract: Important progresses in terms of methods and computer technique made possible to numerically analyze the dynamic response of the aircraft and loads with high level of accuracy. Also, modern testing techniques can capture highly dynamic pressure fluctuations and accelerations for full wetter surfaces. All of this leads to important amounts of data that, in case of turbulence or buffeting analyses, produce complex and fluctuating loading conditions that need to be considered in structural design adequately.

Aircraft structural design traditionally relies on a down-selection of critical loading conditions, using adequate monitoring stations in order to derive nodal load cases. This process is especially complex for stochastic phenomena such as buffeting, where unsteady patterns need to be robustly captured with a large number of monitoring stations. Consequently, many unneeded similar load cases are derived for airframe sizing due to the high correlation of some results.

This problem is addressed in the current paper. Accepting that one cannot predict the unsteady patterns and that these need to be captured, a finer monitoring grid is applied. But instead of deriving directly nodal load cases associated to each monitoring station, a principal component analysis (also called proper orthogonal decomposition) is applied to the results either at full aircraft or at component level, extracting the main loading components to be applied for airframe sizing. Therefore, the accuracy provided through the huge input data is kept and the number of sizing cases is drastically reduced for structural design, still covering the most critical load cases.

This method is applied to a full aircraft configuration, using high accuracy buffeting loading and response data. The main loading directions are identified and structural sizing cases are derived. A comparison in terms of quality, robustness and efficiency is presented in order to underline the advantage of applying this method for structural design loads compared to the traditional process.

To conclude, measurement and analysis of very complex multivariate random loads has become possible, and the presented method allows to adequately take benefit of this unprecedented level of quality for structural design.

1 INTRODUCTION

Random loads analysis is used for deriving aircraft design and certification loads in the fields of buffet (see [1] and [2]) or continuous turbulence (see [3] and [4]). It is appropriate for assessing this kind of stochastic phenomena and treats loads as random variables in a stationary Gaussian process, deriving their covariance matrix out of the Cross-Spectral Density of the input variables via the transfer function of the system. These input variables may be the unsteady pressure fields for buffeting or the turbulence spectrum for continuous turbulence loads. This process is well described in the literature (see [3], [4] and [5]) and is therefore not presented further in this paper.

The starting point of this paper is the obtained covariance matrix of loads. This can be used for drawing the typical ellipsoids as monitoring station loads envelopes in case of random loads analysis. It can be also used further for deriving balanced nodal load cases needed for loading the structural model in the sizing process (see [4] and [5]).

In general, the monitoring stations for loads are defined first, according to engineering knowledge and experience. This works well for loads with predictable distributions as maneuver or low frequency dynamic loads. In the case of turbulence and, even worse, in the case of buffeting loads, it is less reliable. In order to cope with this uncertainty, loads analysts can increase the number of monitoring stations for loads. Unfortunately, any additional monitoring station or loads direction considered in the loads selection criteria let the number of selected load cases increase considerably (see [1]).

This paper shows how the principal component analysis (PCA, see [6], also called Proper Orthogonal Decomposition, POD) can help solving this issue. It extracts the main loading components out of detailed loads selection criteria, keeping the same accuracy but reducing the numbers of dimensions of the mathematical problem. Therefore, the number of dimensions is not increasing anymore linearly with the number of monitored loads. This allows a detailed monitoring of aircraft loads while delivering only the number of independent variables really needed for characterizing the phenomenon.

This paper is structured into a theoretical part, presenting the mathematical process developed based on the PCA. Then its application is demonstrated for two different cases.

2 THEORY

The following process takes advantages from the fact that, nowadays, the PCA is implemented in mathematical tools as MatLab (see [7]) or Python.

2.1 A short summary of the principal component analysis (PCA)

The PCA is based on the diagonalization of a covariance matrix COV. Since the covariance matrix is symmetric and real, such a diagonalization always exists.

$$\mathrm{COV} = \Phi \Sigma^2 \Phi^{\mathrm{T}} \tag{1}$$

The matrix Φ is a unitary matrix that contains the modes of the PCA in each column. The matrix Σ^2 is diagonal and contains the variance of each independent PCA variable. It is sorted from the highest variance to the lowest one.

Some description of the use of the PCA for signal processing can be found in many papers and books (see [6]), as well as in the documentation of mathematical tools (see [7]). For this paper, it is only relevant to understand that the PCA leads to a decomposition of correlated signals into a basis of independent signals. In terms of geometrical understanding, one can understand the transformation performed with the transformation matrix Φ to be the rotation between the basis of the main axes of the ellipsoid associated to COV and the basis in which the original signals was defined.

2.2 Reduction of the system order using a truncation of the PCA basis

Similarly to a dynamic modal analysis of a structure, it is possible to reduce the modal content of the PCA, truncating the last modes with the lowest variance. In this case, it is sensible to evaluate the power ratio of the truncated basis with respect to the full power. The power is directly linked to the variance of the signal, therefore the overall power reads:

$$\mathrm{P} = sum(diag(\Sigma^2)) \tag{2}$$

Please note that the "diag" function transforms a vector to a diagonal matrix with the diagonal equal to the vector. It is also the function producing the back-transformation.
For a PCA modal base limited to its first N modes and power P_N, the power ratio reads:

$$\rho_{\mathrm{N}} = \mathrm{P_N}/\mathrm{P} \tag{3}$$

Achieving a power ratio near to 1 means that mostly no loss occurs while reducing the number of modes. The stronger the reduction, the lower the power ratio goes. Whereas some loss of accuracy is inevitable while truncating the PCA modal basis, the loss of conservatism can be addressed. For this, the following approach is used: knowing the original covariance matrix COV and the one rebuilt out of the truncated basis COV_N, one can extract the vector of the Root-Mean-Square of the original signals without and with truncation:

$$\Sigma = \sqrt{\mathrm{diag(COV)}} \tag{4}$$

Defining the matrix Λ as the diagonal matrix where the diagonal is the ratio of Σ to Σ_N, one obtains the modified truncated modal matrix Ψ_N:

$$\Psi_{\mathrm{N}} = \Lambda\Phi_{\mathrm{N}} \tag{5}$$

In the further steps of process, COV_N is then reevaluated as follows:

$$\mathrm{COV_N} = \Psi_{\mathrm{N}}\Sigma^2\Psi_{\mathrm{N}}^{\mathrm{T}} \tag{6}$$

This new covariance matrix based on the modified truncated modal matrix has the property to have the same diagonal as the original covariance matrix COV. Therefore, the variance of each signal is kept, and the impact of reducing the number of modes in the truncation process affects only the correlation factors.

In the case that the methodology presented in [1] or in [5] is not used, it is possible to extract a first set of design conditions also based on the PCA results. It extracts the loads at the ellipsoid correlated with each kept PCA mode. The associated load cases LC are the main axes of this ellipsoid. LC and -LC have to be considered as load cases for design. In the following, the modified modal matrix is already considered in order to match each loads variance as for COV_N.

$$\mathrm{LC} = \Psi_N diag(\Sigma_N) \tag{7}$$

This method is not as complete as conservative discretizations of the full ellipsoid but can provide a handful of very good first design load cases in early design phases. The number of load cases is 2 times the number of kept PCA modes, what is very low.

As an alternative to using the covariance matrix as presented in this chapter, it is also possible to apply the process to the correlation matrix CORR, as:

$$\mathrm{COV} = \mathrm{diag}(\Sigma) * \mathrm{CORR} * \mathrm{diag}(\Sigma) \tag{8}$$

In this case, the load cases can be obtained by multiplying left with diag(Σ) the LC obtained with CORR.

The main advantage of using the correlation matrix instead of the covariance matrix is to ignore the units or scaling effects of the loads. This effect can lead to some loads being numerically of low amplitude, and others of very high amplitude, what in the case of the covariance matrix will lead to a loss of accuracy for the low amplitude signals. If the model has meaningful units and discretization of loads, it can be on the contrary sensible to work with the covariance directly, but in many cases, working with the correlation matrix is more robust.

3 APPLICATIONS

The process described in the former section will be illustrated using two different cases already presented in former papers. Both cases provide test data that has already been used for demonstrating the use of the random loads analysis process for assessing buffeting. In both cases, the test data were well matched by analytical results based on RANS-DES analysis and aeroelastic response of the structure to this excitation.

For both cases, the PCA modal reduction is analyzed based on the given covariance or correlation matrix of the loads. The impact in terms of loads envelopes and the expected number of load cases is presented.

3.1 Main landing gear doors of a commercial transport aircraft

In the frame of the European project AFLoNext, the main landing gear door of an Airbus A320 has been analyzed (see [1], [9], [10] and [12]). The phenomenon observed in this case is a turbulent flow induced by flow detachment at the nose landing gear of the aircraft when the landing gears are extracted. The main landing gear door crosses this turbulent flow downstream and unsteady loads are found acting at its hinges and actuator.

During this project, the dynamic model of the door has been improved and validated during a Ground Resonance Test. The excitation flow itself has been modelized using various CFD techniques up to DES and RANS-LES, providing unsteady pressure distributions at the door surface. These buffet loads have been used to excite the door in a one-way CFD-CSM approach.

Figure 1: A320-212 with opened main landing gear doors ([8])

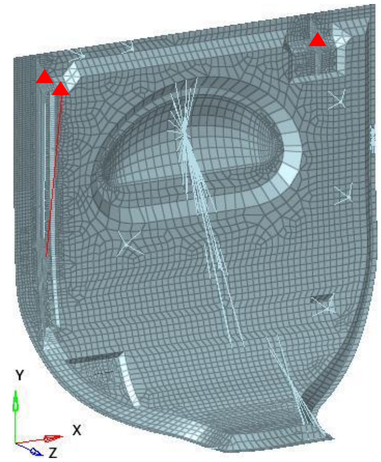

Figure 2: Main landing gear door (actuator in red), forward hinge (left) and rear hinge (right)

In this case, the loads of interest are the forward hinge forces (Fx, Fy and Fz), the rear hinge forces (Fy and Fz) and the actuator force. This leads to a 6x6 covariance matrix obtained out of the aforementioned analyses.

First, the PCA analysis is performed on the correlation matrix, in order to give to each signal the same importance for accuracy. The first result analyzed is the power ratio obtained.

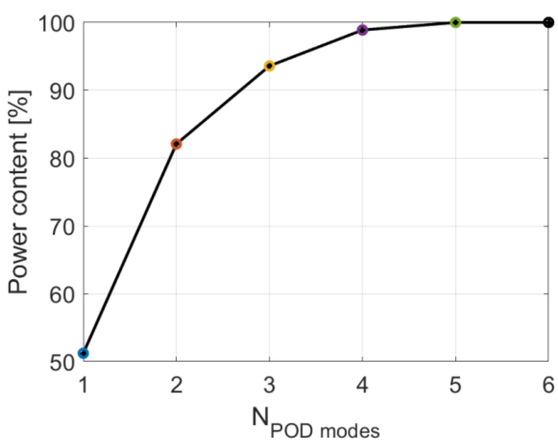

Figure 3: power ratio vs. number of modes

In Figure 3 the effect of the modal reduction is observed. Keeping all modes of the PCA (6 modes, black circle) leads evidently to a 100% ratio. It can be observed that this ratio is also mostly achieved in the case of 5 modes (green circle). For 4 modes (violet circle) and less, the ratio gets down. Using only the first mode of the PCA would lead to around 50%. This means that the first PCA mode is responsible for more than half of the signal power. The higher the mode, the lower the participation. The last mode of the PCA has mostly no impact. In the next step, this is visualized using the 2D elliptic loads envelopes built out of all combinations of the 6 monitored loads.

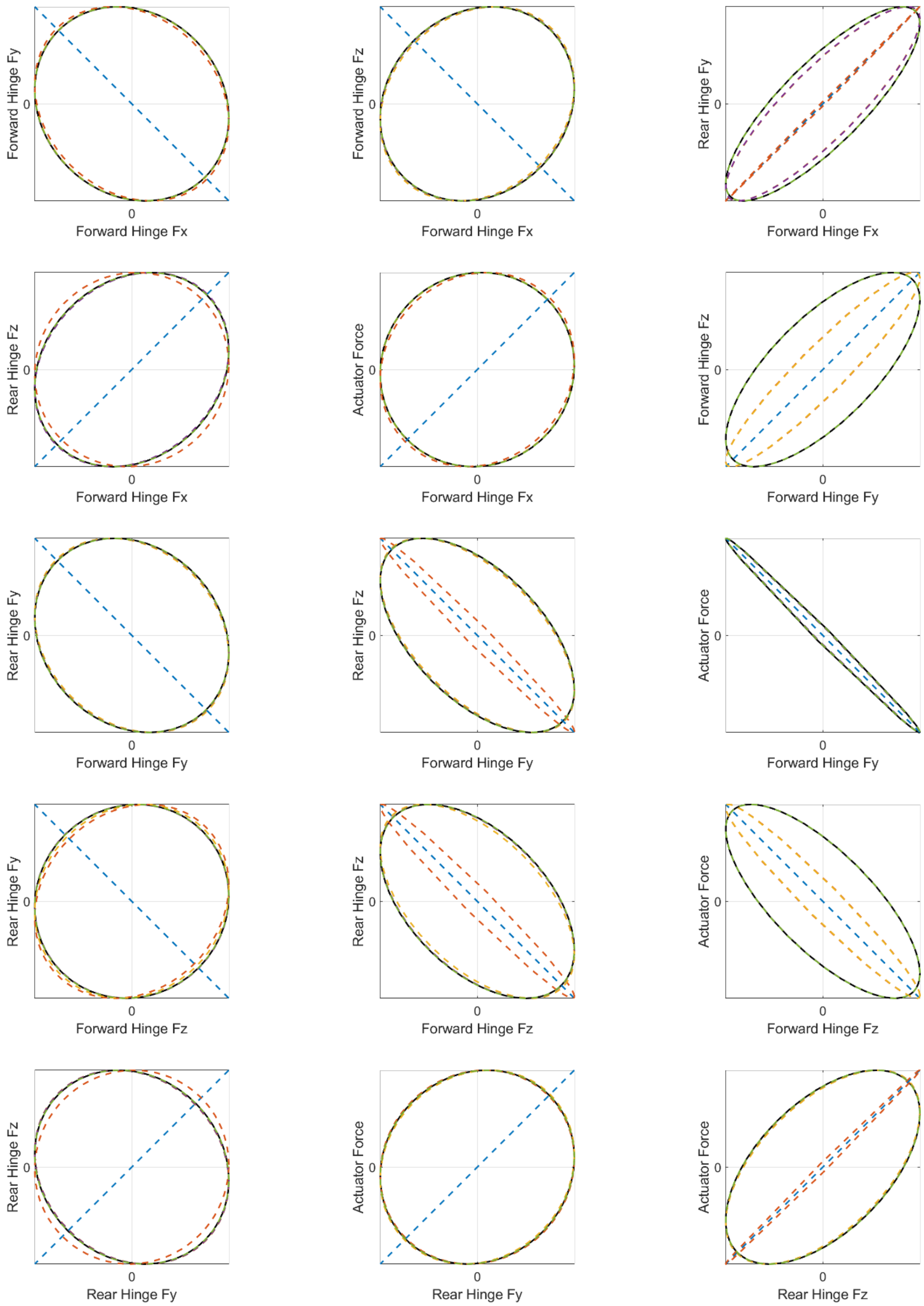

Figure 4: loads envelopes of the main landing gear door

Figure 4 presents all 2D loads envelopes of the main landing gear door. These are ellipsoids directly obtained using the covariance matrix. The covariance used for plotting these ellipsoids are the ones obtained after the PCA modal reduction and the conservative compensation of the loss of power. The color code is the same as for the circles of Figure 3, blue being for only 1 mode, then red for 2, yellow for 3, violet for 4, green for 5 and black for 6 modes kept. It is the authors decision to consider all possible ellipsoids without reduction based on engineering knowledge. This is meant to show that this method can be used also when a simple engineering judgement is not possible, and that it can support a robust process of reduction keeping the data quality.

It can be observed than keeping only one mode leads only to flat ellipses since all loads are always correlated to 100%. Still, the maximum values are all kept. This confirms that the compensation of the loss of power presented in this paper is working and leading to usable results, at least as a first guess. With only 2 load cases, one can load the structure in a way that all maxima of loads are achieved. Also, the main directions of the ellipsoids are very often met, the exceptions (e.g., rear hinge Fy vs. rear hinge Fz) being found at loads with very low correlation anyway. This can be used for preliminary sizing studies where some conservatism can be accepted as long as the sizing effort is kept low.

Increasing the number of modes quickly improves the correlation quality. Whereas only using 2 or 3 modes still leads to visible discrepancies with respect to the black ellipses (no reduction), the case with 4 modes (violet ellipses) leads to mostly no difference but for one ellipse with slight differences (forward hinge Fx vs. rear hinge Fy).

The case with 5 modes (green ellipses) cannot be distinguished from the unreduced case (black ellipses), confirming the conclusion obtained with the power ratio that the mode 6 can be ignored.

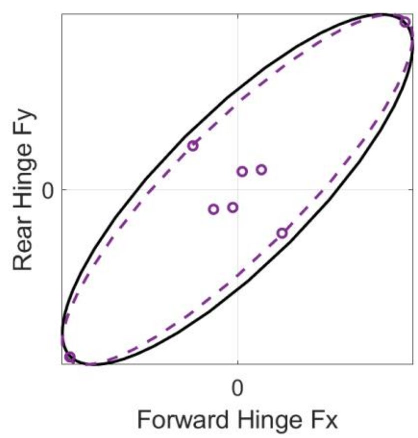

Figure 5: preliminary design load cases for a 4 modes PCA

Using the preliminary design cases approach of chapter 2.2, the full set of preliminary design load cases would be 12 cases. Using 5 modes and then 10 cases, the same quality is obtained. Using 4 modes and 8 load cases, mostly the same applies, as can be seen in Figure 5. Using only 2 load cases (1 mode) would still lead to meaningful results: for the case presented in Figure 5, this would be the max forward hinge Fx linked to the max rear hinge Fy, and the min forward hinge Fx and min rear hinge Fy, since the correlation is 1 in this case (see Figure 4).

This example with a limited complexity shows the potential of reduction using the PCA approach. Other discretization approaches of the ellipsoids as in [1] that are more adequate for detailed design loads would even see higher reduction in number of load cases on the one side, but also on their inherently induced level of conservatism, since the number of dimensions of the overall ellipsoid is increasing this level over proportionally.

Independently of the method chosen for deriving the design load cases used for sizing the structure, having such a reduction that guarantees conservatism is a powerful gain in terms of efficiency.

3.2 Aeroelastic wind tunnel model of a generic fighter aircraft

In the following, the present method is applied to the buffeting response of the aeroelastic wind tunnel model of a generic fighter aircraft developed by Katzenmeier et al. in order to validate buffeting simulations using wind tunnel measurements at low to high angles of attack (see [13], [14] and [15]). The generic fighter aircraft model is a half model configuration, with a stiff aluminum fuselage and an elastic wing and horizontal tail plane (HTP) 3D-printed with polylactide (PLA) with 100% filled density (Figure 6). The HTP can be rotated. This allows some “trimming” of the aircraft and is also used in order to avoid creating additional detached flows at the HTP itself.

Figure 6: aeroelastic wind tunnel model at the Technical University of Munich

In addition to the wind tunnel model, an aeroelastic model is built, based on a FEM model (Figure 7). This FEM model has been matched for its lower modes to the results of the Ground Vibration Test of the wind tunnel model.

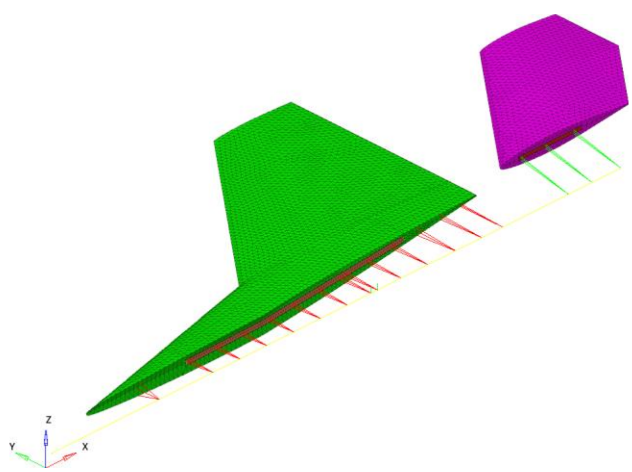

Figure 7: FEM of the aeroelastic wind tunnel model

The aeroelastic wind tunnel model generates strong unsteady pressures at high angles of attack due to a detached flow at the wing, characterized by a system of two interacting vortices that burst over the wing. Both wing and HTP are excited by these unsteady buffeting loads.

The flow field simulation used for obtaining the buffet excitation is based on a rigid aerodynamic model and uses an Improved Delayed Detached Eddy Simulation turbulence approach with Spalart-Allmaras statistical modelling in the RANS zones (see [14]). As presented in [13] and [15], the unsteady flow field results are then reduced- using a similar PCA technique as presented in this paper in order to improve the computational efficiency of the one-way response analysis described in [1]. The result of this random response analysis is the covariance matrix of the loads at the desired monitoring stations. This is the starting point of the current analysis.

The monitoring stations used in this paper have been chosen deliberately in a larger number than in classical aircraft design loads analyses. It is meant to guarantee the capture of the main buffeting loads effects along the wing and the HTP. It is also meant to show that, using the PCA approach, the number of monitoring stations can be increased without necessary increasing the number of dimensions of the response problem.

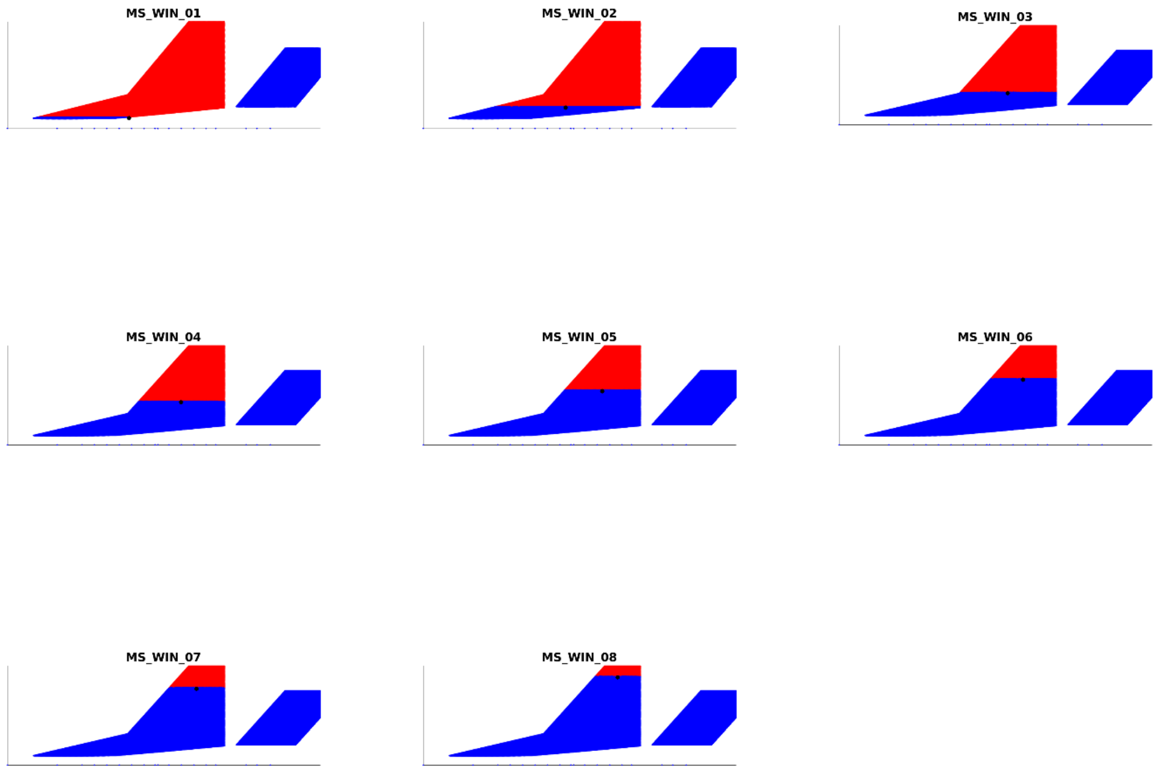

Figure 8: loads monitoring stations of the aeroelastic wind tunnel model

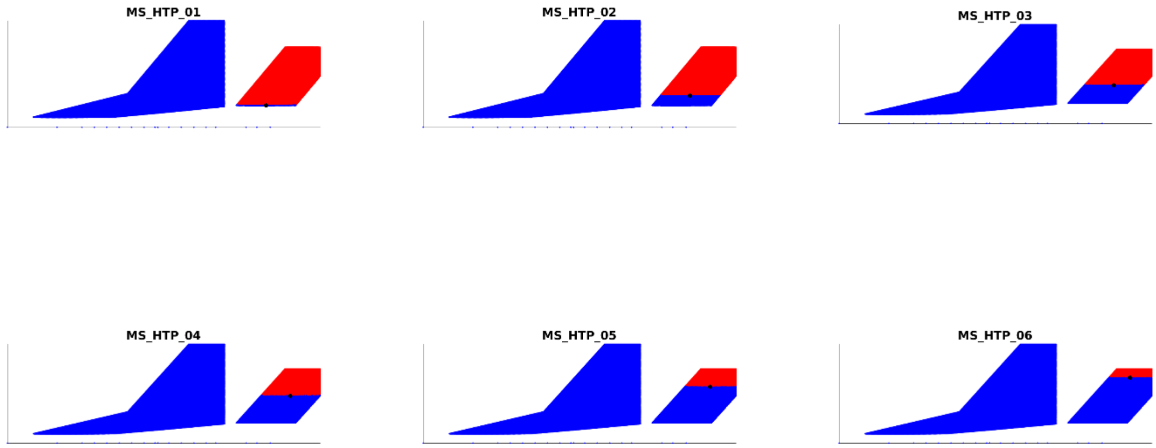

Figure 9: loads monitoring stations of the aeroelastic wind tunnel model

Along the wing, 8 monitoring stations have been regularly distributed from the wing root to the wing tip, and along the HTP, 6 monitoring stations have been regularly distributed also. The loads to be monitored are the loads integrated from tip to the monitoring station reference point (black dot, at 50% of the chord, integration domain in red). Only the vertical shear force Fz, the bending moment Mx and the torsional moment My (in the coordinate system of Figure 7) are used in this exercise. These monitoring stations are presented graphically in Figure 8 and Figure 9.

Considering 14 monitoring stations and 3 loads per station leads to a covariance matrix with 42 rows and 42 columns. As in 3.1, the PCA is applied to the correlation matrix in order to give the same importance to all loads, independently of their respective numerical amplitude (RMS value). The power ratio is again used for a sensible down-selection of the relevant PCA modes.

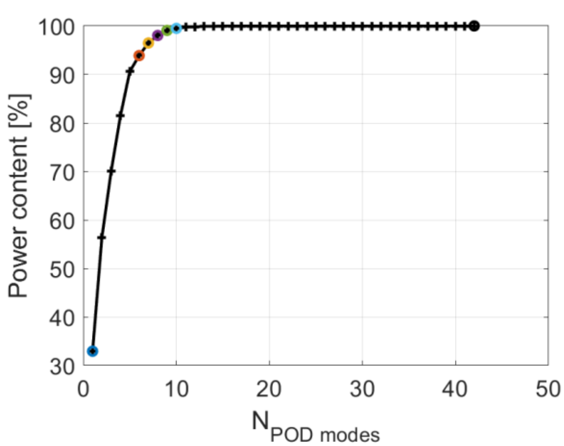

Figure 10: power ratio vs. number of modes

In Figure 10, the PCA modal reduction can be assessed. The following number of modes is analyzed in terms of loads envelopes, with the following color code: 1 mode (blue), 6 modes (red), 7 modes (yellow), 8 modes (violet), 9 modes (green), 10 modes (cyan) and all modes / no reduction (black). It has been observed that the monitor stations MS_WIN_01 and MS_HTP_01 did include some attachment loads, what did not affect the PCA quality, but it was not representative of the expected root loads. Therefore, the loads are presented for each monitoring station from 2 to tip at the wing and at the HTP. At each station, the three 2D envelopes combining Fz, Mx and My are shown for the full system and for the reduced numbers of modes.

A first result out of the observation of the correlation matrix is that the loads at the wing are mostly not correlated with the ones at the HTP, since the maximum correlation coefficient found in absolute value is not exceeding 16.05%. This means that it is possible to work with the wing and with the HTP loads separately if helpful. In this case, the PCA is still done at full model level, since it is not affecting the conclusions of this paper.

In Figure 11 and Figure 12, the wing results are presented. One can observe that along the span of the wing, the loads envelopes are changing. Around the half of the span, an important change in correlations is observed, what can be interpreted with the presence of a vortex bursting in this area in the direction of the outer wing. The PCA modal reduction leads to the expected behavior, with very good match between the 10 modes case and the unreduced case. In many envelopes, 8 or 9 modes are also a very good solution. And even the 1 mode case shows its already explained conservative behavior.

Figure 13 shows a similar dependency in the number of modes, excellent results being found from 9 PCA modes on, 8 being acceptable, and again, 1 being conservative. On top, the root of the HTP is loaded differently from the inboard part, that is again different from the outboard part. This is also due to the flow pattern.

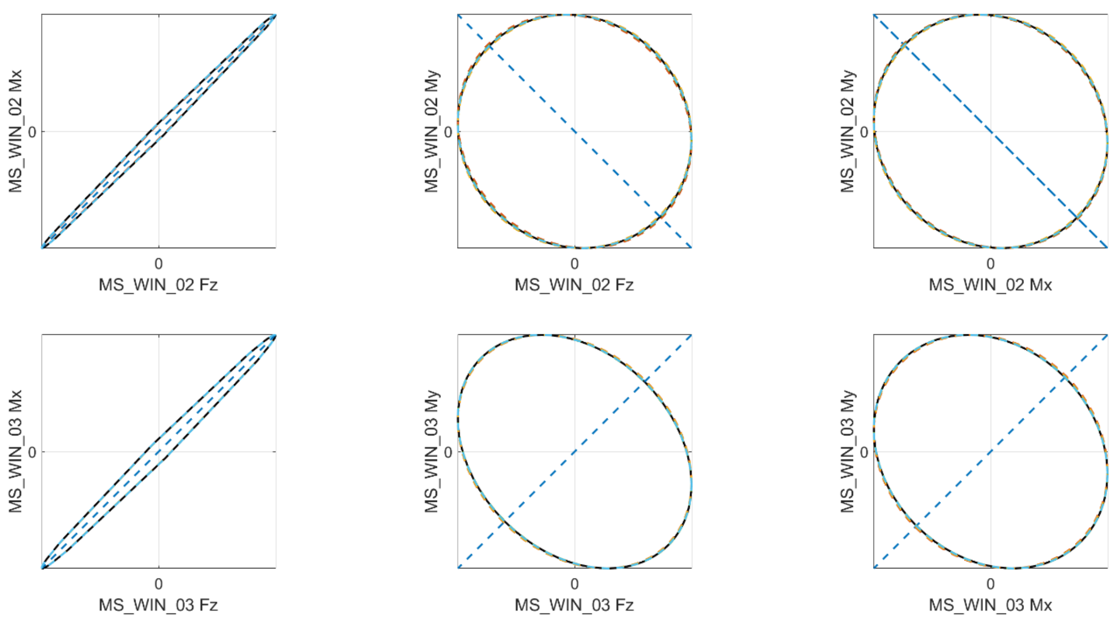

Figure 11: loads envelopes of the aeroelastic wing tunnel model (MS_WIN_02 to 03)

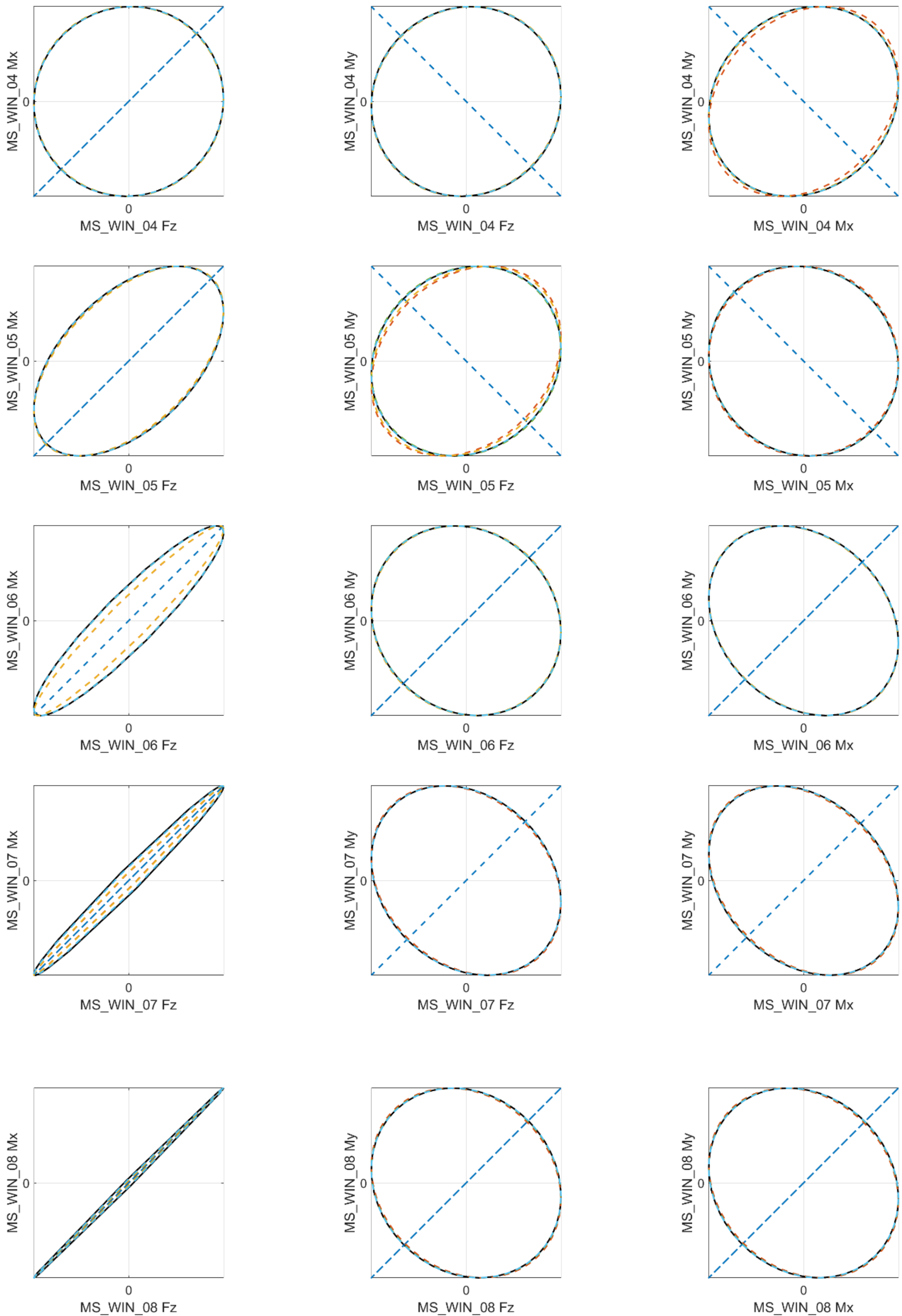

Figure 12: loads envelopes of the aeroelastic wing tunnel model (MS_WIN_04 to 08)

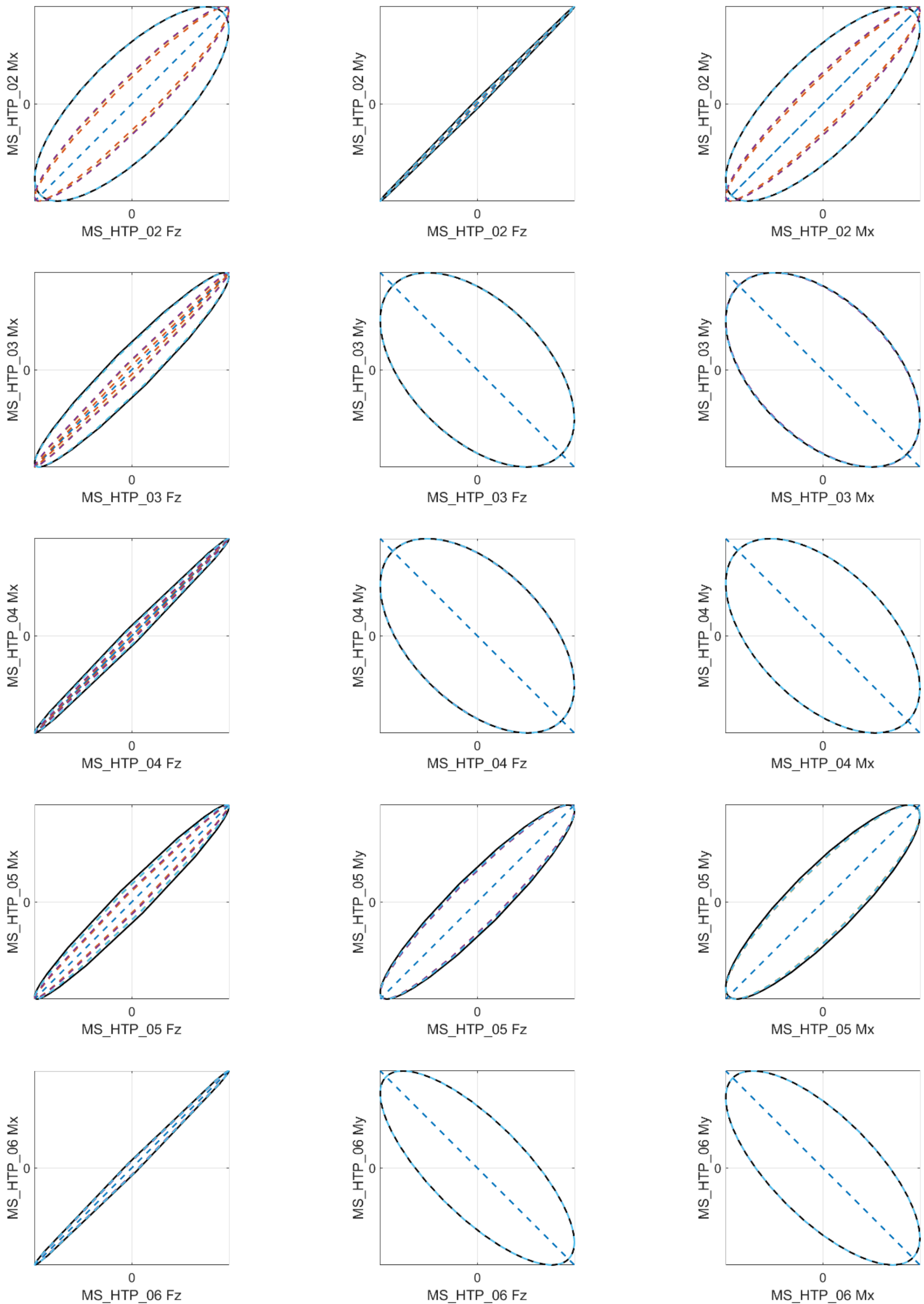

Figure 13: loads envelopes of the aeroelastic wing tunnel model (MS_HTP_02 to 06)

In order to better understand the flow pattern impact in terms of loads, and also the capability of the PCA of keeping this information, an additional study is done. The correlation factor between the vertical force Fz at each monitoring station of the wing and the vertical force at the other monitoring station of the wing is extracted. This study is performed for the unreduced case (full line in Figure 14), and also for the 8 modes case (dashed dotted lines) and the 10 modes case (dashed lines). This study is also repeated for the bending (Mx) and torsional moments (My). And the full exercise is also done at the HTP.

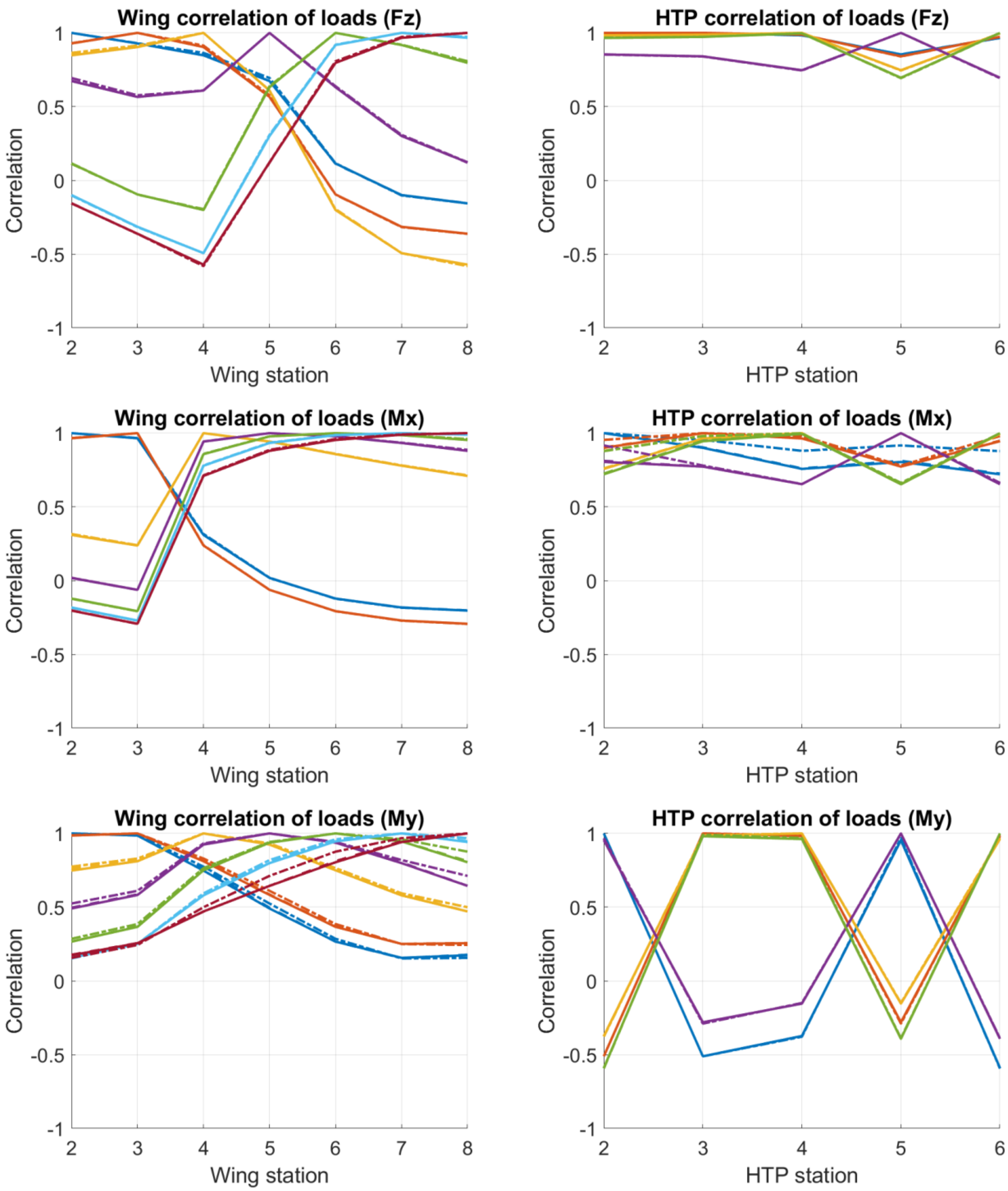

Figure 14: loads correlation for the aeroelastic wind tunnel model

In order to understand Figure 14, the following is explained. Each monitoring station (as reference for the correlation with the other ones of the same component) is linked to a certain color (station 2 is blue, station 3 is red, 4 is yellow, 5 is violet, 6 is green, 7 is cyan and 8 is purple). At the station itself, the line gets to 1 (full correlation), with or without PCA modal reduction. What can be observed in general is that using a reduction with a number of PCA modes associated to a high power ratio shows limited influence on the correlation factors. This means that, even in a reduced case, the physical understanding of the loads and of their distribution is still possible.

In Figure 14, one can observe strongly correlated results at the inner wing (MS_WIN_02 and 03). Then, a different pattern takes over at the inboard part of the outboard wing (MS_WIN_04 and 05), especially in Fz, before the last pattern is identified at the outboard part of the outboard wing (MS_WIN_06 to 08). This shows that the potential of this analysis for understanding the buffet excitation and the buffeting response of the model, also when using the PCA modal reduction.

In Figure 14, the same conclusions for the analysis occur for the HTP results. Here, the most variation is found in My, this is due also to the position of the buffeting excitation on the HTP associated to the inertial loads of the response. It shows that it may be even more beneficial to have more monitoring stations in order to obtain smoother results, and to rely then on the PCA for reducing the order of the system back to a similar level as in the current example. In any case, the loads pattern has been captured, without and with some PCA modal reduction.

4 CONCLUSIONS

The current paper presents a methodology for working with results of dynamic random analyses. These results can be buffeting loads as in the examples used here, but it can also be turbulence loads or any other stochastic results represented with a covariance matrix.

Working with correlations and covariances is not new in dynamic loads engineering, however, it is difficult to estimate a priori the need for a higher number of monitoring points required for ensuring an accurate physical capture of the loads patterns. This can lead to studies, and to many monitoring stations, increasing rapidly the dimension of the problem. And for many methods, having a high dimension makes it less efficient to solve and also increases the number of design load cases required for loading the structural model.

In this paper, the PCA, also called Proper Orthogonal Decomposition, has been introduced in order to solve this issue and to allow a finer monitoring grid of the loads without increasing the dimension of the problem automatically. The dimension of the problem converges to the minimum number of states needed for estimating the loads at a given accuracy.

An additional advantage of the presented method is its conservatism at lower number of PCA modes. The correlation factors are then higher, leading to higher loads combinations, and keeping each single loads extrema. This can be very powerful in the case of an early sizing analysis with only a handful of load cases, with no time for too detailed studies.

A last point is that the present method allows the analysis of the loads patterns along the model components. It is not only good for simplifying a single envelope but gives a better understanding of the overall phenomenon.

Both models analyzed in this context have shown very good results while keeping the handling effort low on the side of the engineer. This confirms that this process can be used in an industrial way with evident benefits.

ACKNOWLEDGEMENTS

Special thanks to Daniele Parisse for all his mathematical support along the common working years. He provided to the authors the required introduction in the usage of the PCA and in its mathematical basis.

We are also grateful to Lukas Katzenmeier for providing us with a photograph of the wind tunnel model and the modal amplitudes covariance matrix from his analysis.

REFERENCES

[1] Aquilini, C., Parisse, D. (2017). *A Method for Predicting Multivariate Random Loads and a Discrete Approximation of the Multidimensional Design Load Envelope.* IFASD 2017, Como, Italy.

[2] Farokhi, S., Mauk, C. S., Locke, J. E. (1996). *Stochastic Modeling of Antisymmetric Buffet Loads on Horizontal Stabilizers in Massively Separated Flows*. DOT/FAA/AR-95/7. US Department of Transportation Federal Aviation Administration.

[3] Hoblit, F.M. (1988). *Gust Loads on Aircraft, Concepts and Applications.* AIAA Education Series

[4] European Union Aviation Safety Agency (2023). *Certification Specifications for Large Aeroplanes, CS-25, Amendment 28*, CS 25.341 (b) & AMC 25.341

[5] Aquilini, C., Grasso, G., Vidy, C. (2024). *From Multivariate Random Loads to Deterministic Load Distributions: An Exact Method for Aeroelastic Design*. IFASD 2024, The Hague, The Netherlands.

[6] Jolliffe, I.,T. (2002). *Principal Component Analysis*. New York: Springer-Verlag New York, Inc. 2nd ed.

[7] The MathWorks Incorporated (several authors). *MatLab online Documentation*. https://www.mathworks.com/help/stats/pca.html

[8] *CAA Airbus A320 Potters-2.jpg - Wikimedia Commons.* (2011). https://commons.m.wikimedia.org/wiki/File:CAA_Airbus_A320_Potters-2.jpg.

[9] Abarca, R., Aquilini, C., Lubrina, P., Peng, S. H., Schwochow, J. (2019). *Aeroelastic Coupling and Control Means for Reduction of Main Landing Gear Doors Responses under Operational Conditions*. IFASD 2019, Savannah, Georgia, USA.

[10] Peng, S. H., Jirasek, A., Dalenbring, M., Eliasson, M. (2016). *Aerodynamic excitation on MLG door exposed to vortices emanating from NLG of an aircraft model*. AIAA Paper 2016-4043. AIAA Aviation 2016. Washington DC.

[11] Tomac, M., Rizzi, A., Charbonnier, D., Vos, J. B., Jirasek, A., Peng, S. H., Winkler, A., Allen, A., Wissocq, G., Puigt, G., Dandois, J., Abarca, R. (2016). *Unsteady Aero-Loads from Vortices Shed on A320 Landing Gear Door: CFD compared to flight tests*. AIAA Paper 2016-0803.

[12] Aquilini, C., Abarca, R. (2022). *Modelling of Dynamic Vibration Absorbers to Reduce Landing Gear Doors Vibration of Commercial Transport Aircraft*. IFASD 2022, Madrid, Spain.

[13] Katzenmeier, L., Vidy, C., Kolb, A., Breitsamter, C. (2021). Aeroelastic Wind Tunnel Model for Tail Buffeting Analysis using Rapid Prototyping Technologies. *CEAS Aeronautical Journal*, pp. 633-651.

[14] Katzenmeier, L., Hilfer, M., Stegmüller, J., Breitsamter, C. (2023). Application of fast-response pressure sensitive paint to low-speed vortical flow at high angles of attack. *Experiments in Fluids*, Article 166.

[15] Stegmüller, J., Katzenmeier, L., Breitsamter, C. (2022). Horizontal tail buffeting characteristics at wing vortex flow impact. *CEAS Aeronautical Journal*, pp. 779-796.

COPYRIGHT STATEMENT