Dynamic Model Updating of Al-Al Honeycomb Sandwich Panels for Aerospace Applications

Cássio B. Mainardes[1], Sergio H. S. Carneiro[1]

[1]*Faculdade do Gama, Universidade de Brasília*
Área Especial de Indústria Projeção A, 72.444-240, DF, Brasil
cassiobus@gmail.com

Abstract. In aerospace environment, it is crucial to develop reliable dynamic models to accurately predict the structural behavior of aircraft. The established approach involves constructing numerical models using the Finite Element Method and utilizing experimental data for model updates and improvements. This paper focuses on the construction and updating process of dynamic models applied to Al-Al honeycomb sandwich panels, which serve as the main structure of the Brazilian Geostationary Satellite. Two numerical models are proposed to replicate the honeycomb plate's geometry, including a simple equivalent laminated plate, and a face plate-equivalent solid core model. Experimentally obtained parameters are utilized to update the numerical models using a Bayesian optimization algorithm, which finds equivalent values for physical parameters enhancing the numerical-experimental correlation of natural frequencies. Since this process is probabilistic, Monte Carlo simulations are performed to ensure convergence of the obtained values. The results demonstrate that even the lower complexity equivalent plate model can adequately represent the panel, making it suitable for preliminary analysis and saving computational time compared to the higher complexity model. Overall, this paper presents a comprehensive approach to constructing and updating dynamic models of honeycomb sandwich panels, demonstrating their effectiveness in accurately capturing the dynamical behavior of aerospace structures.

Keywords: Model Updating, Bayesian Optimization Algorithm, Honeycomb Sandwich Panel.

1 Introduction

Aerospace structures are commonly exposed to diverse and severe dynamic loads, which may lead to unwanted dangerous vibrations in aircraft during operation. Therefore, it is evident the need of developing reliable and trustworthy models during the design phase to predict structural behavior correctly and accurately in aircraft operation. The established approach involves the construction of numerical models using the Finite Element Method (FEM), which allows quick experimentation and study of parameters in the model. Also, this model may be adjusted using experimental data, using a model updating algorithm, given that uncertainty is always present in constructed models and is of great influence in modeling, as shown and reviewed by Jorge [1].

These algorithms have as their objective to maximize the correlation between numerical and experimental data, being widely used, for example, to improve numerical models in early design phases and real-time updating of structural models for Structural Health Monitoring (SHM). The model updating problem is an inverse problem in which the outputs are known, and it is of interest the identification of associated input parameters through an unknown function described by the numerical model which gives the desired output.

Several approaches have been proposed to develop a reliable model updating algorithm, as seen in articles using Bayes Inference as constructed by Marwala and Sibisi [2] and Carlon [3], or heuristic and genetic methods, as overviewed by Choze [4] and applied by Gaspar [5]. In this article, the use of an optimization algorithm is proposed to solve the model updating problem, namely the Bayesian Optimization Algorithm (BOA). This algorithm involves the minimization of an objective function, with associated inputs and cost. BOA proposes an algorithm that performs well when the evaluation of the objective function is costly, allocating some time resources to evaluating an acquisition function, that indicates the next point with the best improvement probabilities. This is done by performing a Gaussian Process Regression (GPR) on known points, obtaining a mean function value and associated confidence interval. Then, using the mean and standard deviation of all regressed points the acquisition function expresses the next best point to evaluate. For this work, only honeycomb core properties will be explored in the model-adjusting process.

In the following sections, BOA is better described and formulated. Then it is used with experimental modal data obtained experimentally from impact testing on an Al-Al honeycomb sandwich panel to create an accurate numerical model. The objective function is modeled as an error function between the first five numerical and experimental non-rigid body modes natural frequencies. Finally, results for the natural frequencies and modes are presented.

2 Mathematical Background

2.1 Dynamic Systems

Gomes [6] describes that for a dynamic system, neglecting damping effects, it is possible to calculate its modes and natural frequencies for structural systems according to:

$$(-\omega^2 \boldsymbol{M} + \boldsymbol{K})\{\phi\} = 0. \tag{1}$$

This equation represents an eigenvalue problem in which the matrices K and M are the stiffness and mass matrices respectively, ϕ is a mode vector and ω^2 is the corresponding squared natural frequency. With FEM it is possible to construct K and M matrices allowing the resolution of the eigenvalue problem obtaining modes of vibration and associated natural frequencies for a system. These parameters will allow a comparison of the numerical model to be constructed with the experimental data obtained.

2.2 Bayesian Optimization Algorithm

Optimization algorithms strive to obtain the maximum or minimum of a given objective function. These problems consist of input parameters, an objective function, and associated costs. For the given problem, the objective function is modelled as follows:

$$f(\theta) = \sum_{i=1}^{n} \left(a_i \cdot \frac{\omega_i^{(num)}(\theta) - \omega_i^{(exp)}}{\omega_i^{(exp)}} \right). \tag{2}$$

Where θ is the vector of input parameters, $f(\theta)$ is the cost of the objective function associated with the θ input parameters, and a_i is a weighting factor associated with the ω_i natural frequency. This way, if better correlation in the first mode is desired, the weight a_1 should be of higher value compared to the others.

It should be noted that for every iteration of the objective function given in eq. (2), a full modal numeric analysis must be performed to obtain numerical natural frequencies, which can be quite resource-demanding when the complexity of the model is high. Thus, BOA offers a tradeoff, allocating some computational efforts into calculating the point associated with the best improvement chances, through the evaluation of an acquisition function, thus minimizing the number of iterations of the objective function, as stated by Snoek [7]. The algorithm does that by using some stochastic linear regression, commonly the GPR, on some initial observed data, given by some random evaluated points, which describes the function as a Gaussian Process (GP), defined by a mean function and a covariance function. Wang [8] states that the GP that describes the regression is given by:

$$f_* | f, X, X_* \sim \mathcal{N}\left(\Sigma_*^T \left(\Sigma + \delta_y^2 I\right) f,\ \Sigma_{**} - \Sigma_*^T \left(\Sigma + \delta_y^2 I\right)^{-1} \Sigma_* \right). \tag{3}$$

This notation describes the mean function and the covariance function of the GP on unobserved points f_*, given the known data from observed points f on the domain X, X_*. δ_y is a white noise hyperparameter associated with observations, I is the identity matrix, and Σ is the kernel function, associated with the correlation between close points in the domain. Several kernel functions exist, and these describe the overall shape of the regressed function. For this work, it was used the Matern 5/2 kernel function, described below, as Snoek [7] concludes that this kernel function is well suited for optimization problems.

$$\Sigma(x_i, x_j) = \sigma\left(1 + \sqrt{5}\frac{x_i - x_j}{l} + \frac{5}{3}\left(\frac{x_i - x_j}{l}\right)^2\right) e^{-5\frac{x_i - x_j}{l}}. \tag{4}$$

Where x_i, x_j are points in the X, X_* domain, σ is the verticality hyperparameter and l is the horizontality hyperparameter.

With the regressed function, it is possible to obtain a mean value and a confidence interval given by the standard deviation at each point in the domain. Since the objective is to obtain the global minimum in the given domain, the acquisition function should return points that either have a low mean or a high standard deviation (have not been explored by the algorithm). This is done by the Expected Improvement (EI) function, which maximizes where the function is expected to have the best improvement when evaluated. Kamperis [9] describes the EI as:

$$EI(x, \lambda) = (\mu - f(x_*) - \lambda) \cdot \Phi\left(\frac{\mu - f(x_*) - \lambda}{\sigma}\right) + \sigma \cdot \varphi\left(\frac{\mu - f(x_*) - \lambda}{\sigma}\right). \tag{5}$$

In this equation, μ and σ are the mean and standard deviation of the regressed point x, $f(x_*)$ is the minimum regressed value, ϕ and Φ are the probability density function (PDF) and the cumulative density function (CDF) respectively and λ is an exploration hyperparameter, that defines whether the algorithm should exploit already found minimum values or explore uncertain areas in the domain.

Since the process is stochastic, depending on initial random values, the process is repeated several times to check if results converge within a confidence interval, resulting in a Monte Carlo simulation.

Thus, the BOA can be described in the following steps:

1. Define a domain X, X_* for the analyzed parameters θ;
2. Choose $N_{initial}$ random points to sample in the domain and evaluate the objective function;
3. Perform GPR on observed points and evaluate the EI function;
4. Choose the next evaluation point and repeat step 3 N_{obs} times;
5. Get the minimum regressed value and associated parameters;
6. Perform N_{MC} Monte Carlo simulations to check convergence of the algorithm.

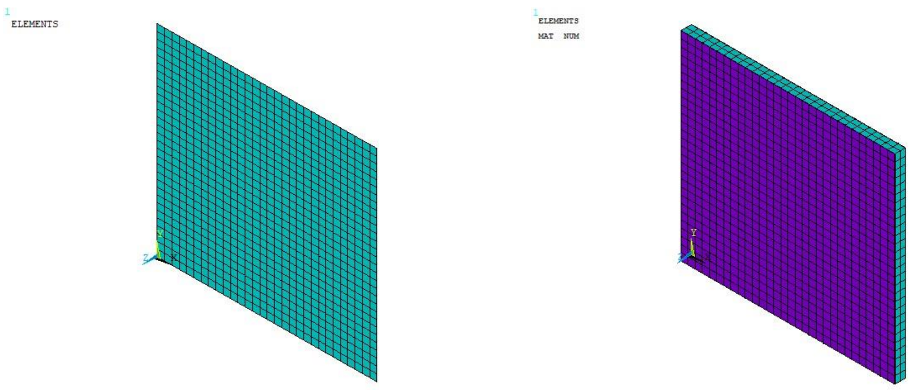
3 Materials and Methods

For this work, experimental data was obtained from an Al-Al honeycomb sandwich panel, provided by the Brazilian Space Agency. The panel is composed of two aluminum 2024 T3 plates 0.3 mm thick, with a HexWeb CRIII – Al 5056 – 1/4” – 0,001P (10P) honeycomb core with 14.4 mm thickness, totaling 15 mm. The panel is 280 mm long in the L direction and 300 mm in the W direction. For the collection of data, impact modal testing was conducted using 49 measurement points distributed along the panel, processing data on SimCenter Testlab Software. Full experimental details were written by Domingues [10]. Data on the properties of the honeycomb core are available by Hexcel [11] and presented in Table 1. Finally, the mechanical properties of the aluminum 2024 T3 are available in MatWeb [12].

As for the numerical models, two are proposed. The first, of lower complexity, is generated using Ansys APDL SHELL181 element, and laminating it into three layers. The bottom and top layers are modeled with isotropic aluminum 2024 T3 with 0.3 mm of thickness and the middle layer is modeled as an orthotropic equivalent material for the honeycomb structure of 14.4 mm of thickness, totaling 15 mm thickness. This model is presented in Fig. 1a, modeled by 900 elements. The panel is in the XY plane, while the Z direction is normal to the plate. The X direction corresponds to the W direction and the Y direction is in the L direction.

Table 1. Mechanical Properties of the honeycomb panel [11].

Equivalent Density	Shear Modulus G_L	Shear Modulus G_W	Compressive Modulus E_t
82 g/m³	221 MPa	103 MPa	400 MPa



(a) (b)

Figure 1. Models of the honeycomb sandwich panel in Ansys APDL (a) Laminated Plate Model (b) Solid-Shell Model

The second model is modeled with two SHELL281 aluminum plates connected by a SOLID185 orthotropic material, being presented in Fig. 1b, totaling 6952 elements. This model requires more computational resources due to different types of elements and contact modeling, however, it may be more suited for certain types of applications, for example, the delamination of the honeycomb structure and the plate. Thus, both models are well suited for different cases and design phases, and BOA is used to estimate the parameters of the orthotropic equivalent material in both cases. In this article, both shear moduli of the honeycomb core in the XZ and YZ planes (W and L direction, respectively) will be optimized in a two-dimensional problem to better suit the natural frequencies of the numerical model to the ones observed.

The parameters used during simulations are shown in Tab. 2.

Table 2. Parameters used during simulations.

Parameter	Laminated Plate Model	Solid-Plate Model
G_{XZ} range	50-400 MPa	50-400 MPa
G_{YZ} range	50-400 MPa	50-400 MPa
$N_{initial}$	10	5
N_{obs}	30	25
N_{MC}	30	30
λ	0.05	0.1
a_1	5	5
a_2, a_3	3	3
a_4, a_5	1	1

4 Results and discussion

Tables 3 and 4 show the adjusted parameters for both models. These values are shown with the mean and standard deviation of the values obtained on each iteration over the Monte Carlo simulations. These values will show how well the algorithm is converging and to which value it is converging, measured by a variation coefficient (CV) given by the division of the standard deviation by the mean value. For comparison, the parameters for the honeycomb core from Table 1 are repeated.

Table 3. Obtained adjusted parameters for the laminated panel model.

Parameter	Manufacturer parameters	Adjusted Mean	Adjusted Standard deviation	CV
G_{YZ}	221 MPa	247 MPa	27.7 MPa	11.2%
G_{XZ}	103 MPa	119 MPa	10.1 MPa	8.46%

Table 4. Obtained adjusted parameters for solid-plate model.

Parameter	Manufactures parameters	Adjusted Mean	Adjusted Standard deviation	CV
G_{YZ}	221 MPa	364 MPa	29.9 MPa	8.22%
G_{XZ}	103 MPa	145 MPa	8.01 MPa	5.54%

From these results, it is observed that data converges to large results, providing shear moduli above the expected from manufacturers data. It is also shown through the values of CV that data converges better for the solid-shell model despite fewer observations being made on each iteration. This might be due to the larger exploration coefficient λ or the different modeling compared to the laminated model and is a topic worth investigating.

Even though parameters differ from what is expected, Tab. 5 and 6 show that experimental natural frequencies and frequencies for the adjusted model are in great accordance with experimental results. These frequencies were obtained using the mean value from the Monte Carlo simulations. For means of comparison only, frequencies were calculated using the manufacturers data and presented as an initial guess for the model.

Table 5. Comparison of natural frequencies for the laminated plate model.

Mode	Experimental (Hz)	Initial Guess (Hz)	Error (%)	Adjusted Model (Hz)	Error (%)
1	666.7	672.8	0.92	679.0	1.85
2	1032	1028	0.36	1034	0.22
3	1332	1276	4.20	1292	2.83
4	1602	1593	0.31	1616	0.91
5	1694	1645	2.88	1676	1.09

Table 6. Comparison of natural frequencies for the solid-plate model.

Mode	Experimental (Hz)	Initial Guess (Hz)	Error (%)	Adjusted Model (Hz)	Error (%)
1	666.7	656.5	1.53	673.5	1.02
2	1032	1010	2.11	1031	0.04
3	1332	1249	6.23	1290	3.14
4	1602	1555	2.93	1624	1.39
5	1694	1604	5.31	1683	0.66

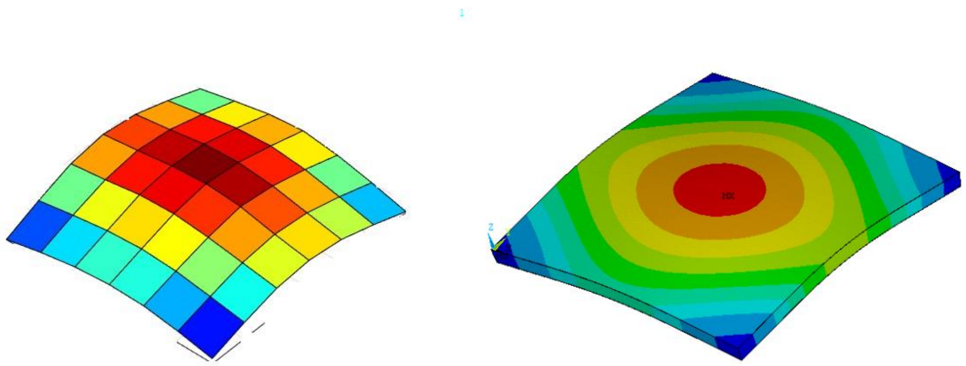
For the laminated plate model, it is observed that some frequencies of the adjusted model stray further from the experimental results, however, the overall error of the first five natural frequencies is smaller than the initial guess.

Meanwhile, in the solid-plate model, the initial guess is way worse when compared with the laminated model, however, the adjusted frequencies are all very much improved. Overall, the adjusted solid-plate model can be seen to better replicate the experimental natural frequencies, performing worse on the third and fourth modes but with significant improvements in the first and fifth modes. Nevertheless, the laminated plate model can also accurately represent the dynamical characteristics of the analyzed model, being advantageous for the lower complexity and computational time expended.

In both models, it is observed that the initial guess underestimates every of the first five modes for the plate. Thus, it is expected that the algorithm would return bigger moduli, as shown in Tables 3 and 4. These results show that the overestimated adjusted parameters are likely due to the process of assembly of the plate when combining the aluminum plates with the honeycomb core, possibly due to resins that unite the core and the aluminum plates.

Also, it is shown a disparity between adjusted parameters when comparing both models. This is likely due to the different types of elements that are present in the more complex model, such as contact elements and interactions between different bodies. Thus, this opens the investigation on the effect of contact modeling in the numerical simulations and the definition of the orthotropic material. Nonetheless, both models achieved great correlation with experimental data, with errors of less than 3.5% for all modes.

Finally, it is observed some degree of difficulty in recreating the third mode with precision in both models. Even though the numerical and experimental modes correspond to each other, as shown in Fig. 2, the numerical frequencies have significantly larger errors when compared with other modes. Improvements on this are currently being made, seen that for this work only the honeycomb shear moduli were adjusted, as these were deemed as the most uncertain parameters. However, several other parameters, such as the elastic and shear moduli of the aluminum plate or the honeycomb compressive modulus, may present related uncertainties, and sensibility studies are being held for the identification of which parameters are more influential on natural frequencies. Then, model adjusting will be performed with these parameters attempting to recreate an even more accurate model.



(a) (b)

Figure 2. Third mode of vibration of the Al-Al honeycomb sandwich panel (a) Experimental [10] (b) Solid-Plate numerical model

5 Conclusions

Overall, model adjusting was successfully implemented with the use of BOA on both models of the plate. Even though adjusted parameters were above expected, natural frequencies show a great correlation to experimental data, with the more complex model presenting an overall better correlation when compared with the simpler model. This suggests that the honeycomb core properties may have been altered during the assembly of the full panel.

Furthermore, some topics are still relevant in the ongoing research. Some disparity is shown when comparing the adjusted parameters for the laminated-plate model and the solid-plate model. This opens the investigation on the effect of the contact elements during the definition of the equivalent orthotropic material for the honeycomb core.

Also, it is discussed some struggles in recreating the natural frequencies of the third mode, opening the possibilities of future works to investigate the effect of other parameters on the natural frequencies of the panel through a sensibility study, performing model updating in higher-dimensional problems attempting to recreate a model with more accurate natural frequencies.

Acknowledgments. The authors wish to acknowledge the contribution of the Brazilian Space Agency for supplying the specimens for the experimental part of the research.

Authorship statement. The authors hereby confirm that they are the sole liable persons responsible for the authorship of this work, and that all material that has been herein included as part of the present paper is either the property (and authorship) of the authors, or has the permission of the owners to be included here.

References

[1] Jorge, Ariosto B., et al. (2022). "Introduction to Probabilistic Methods & Uncertainty Modeling in Direct & Inverse Problems". In Jorge, Ariosto B., et al. (Eds.) Uncertainty Modeling: Fundamental Concepts and Models, Vol. III, UnB, Brasilia, DF, Brazil, pp. 1–18. Book series in Discrete Models, Inverse Methods, & Uncertainty Modeling in Structural Integrity.
[2] T. Marwala and S. Sibisi. "Finite element model updating using bayesian framework and modal properties". Journal of Aircraft, vol. 42, n. 1, pp 275-278, 2005.
[3] Carlon, Andre G., et al. (2022). "Bayesian Optimal Experimental Design". In Jorge, Ariosto B., et al. (Eds.) Uncertainty Modeling: Fundamental Concepts and Models, Vol. III, UnB, Brasilia, DF, Brazil, pp. 479–501. Book series in Discrete Models, Inverse Methods, & Uncertainty Modeling in Structural Integrity.
[4] Choze, Sergio B., et al. (2022). "Overview of Traditional and Recent Heuristic Optimization Methods". In Jorge, Ariosto B., et al. (Eds.) Model-Based and Signal-Based Inverse Methods, Vol. I, UnB, Brasilia, DF, Brazil, pp. 107–142. Book series in Discrete Models, Inverse Methods, & Uncertainty Modeling in Structural Integrity.
[5] C. Marques, J. Beserra and D. Cardoso. "Non-destructive mechanical characterisation of thin-walled gfrp beams through dynamic testing and model updating". Elsevier Ltd., 2021.
[6] Gomes, Guilherme F., et al. (2022). "On the use of Modal Test Data in Inverse Problems: Fundamentals and Applications". In Jorge, Ariosto B., et al. (Eds.) Fundamental Concepts and Models for the Direct Problem, Vol. II, UnB, Brasilia, DF, Brazil, pp. 311–348. Book series in Discrete Models, Inverse Methods, & Uncertainty Modeling in Structural Integrity
[7] J. Snoek, H. Larochelle and R. Adams. "Practical Bayesian Optimization of Machile Learning Algorithms". ArXiv, 2012.
[8] J. Wang. "An intuitive tutorial to gaussian processes regression". Ingenuity Labs Research Institute, 2022.
[9] S. Kamperis. "Acquisition functions in Bayesian Optimization". Available in: < https://ekamperi.github.io/>
[10] A. Domingues. "Identificação de Dano em Estruturas Aeroespaciais Leves Utilizando o Método da Energia de Deformação Modal". Master Thesis, Universidade de Brasília, 2019.
[11] HexCel Composites. "HexWeb™ Honeycomb Attributes and Properties". 1999.
[12] MatWeb. "Aluminum Alloy 2024 T3". Material Property Data. Available online. Available in: <https://www.matweb.com/search/DataSheet.aspx?MatGUID=57483b4d782940faaf12964a1821fb61&ckck=1>