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COMPOSITE PLATES MODEL UPDATING USING KRIGING METHOD

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Abstract. *Composite laminate are widely used in different industries as aerospace, naval and automobile. Developing accurate models in order to represent manufactured components is necessary to aid the design of structural health monitoring (SHM) systems. In addition, the most part of the SHM strategies consists on compare the intact state with the damaged state to obtain a damage index. In this context, this work presents a model updating strategy to obtain the input parameters used in a Finite Element Method (FEM), which represent the experimental dynamic behavior of a composite plate. For this, a Kriging metamodel is chosen to reduce the computational cost of optimization process into the model update. A set of finite element analyses are used to training the metamodel. After that, the kriging model is used every time when the objective function is evaluated. This strategy provides a considerable reduction in the computational time during the optimization process, where for this paper a PSO are going to be used. These results are analyzed in order to evaluate the potentialities and limitations of the methodology. Therefore, the strategy presented can be helpful in the study of damage detection systems that uses FEM as part of its process.*

Keywords: *Composite Materials, Structural Health Monitoring, Model Update, Kriging Method.*

1. INTRODUCTION

Finite Element Methods (FEM) are very useful to solve engineering problems when complex geometries or phenomena are involved. Reliable finite element analyses can reduce the need for prototype testing and reduce the design validation cost and time. These methods consist of represent the geometry by a high number of elements to solve it. However, sometimes the elements number used to represent the structure is considerable large, or the method used to solve the specific problem requires little time increments, resulting on time demanding process turning the simulation unfeasible. In many real-life situations however, a deterministic analysis is not sufficient to assess the quality of a design. In a design stage, some physical properties of the model may not be determined yet. But even in a design ready for production, design tolerances and production inaccuracies introduce variability and uncertainty (De Munck *et al.*, 2008). In addition, the results obtained by FEM are strongly dependent of the inputs provided by the user. Thus, to match numerical with experimental results, it is necessary the knowledge of the exact value for several parameters. To overcome these issues, some strategies can be used, like the use of approximate models to represent the FEM and obtain results without solve all the equations or use model update techniques as an alternative to find the right parameters to set a simulation.

Model updating methods simultaneously utilize the structural response obtained by the FEM and the measured structural response to calibrate mathematical modeling. Model update aims to reduce the errors between the results from the numerical simulation compared to the results from the experimental data. In the literature, it is possible to find methodologies to use model update via modal parameters even as Frequency Response Function, as presented by Imregun and Visser (1991) and Mottershead and Friswell (1993). Model updating methods can be broadly classified into direct methods, which are essentially non-iterative ones, and the iterative methods. Direct methods are essentially based on changes in the mass and stiffness matrix to obtain the results that better fitting on experimental data, even if these changes are not physically meaningful (Baruch and Bar-Itzhack 1978; Berman and Nagy 1983; Lim 1990). Iterative methods are based on minimizing an objective function that is generally a non-linear function of selected updating parameters. Quite often eigenvalues, eigenvectors or response data are used to construct an objective function (Collins *et al.*, 1974; Chen and Garba, 1980; Kim *et al.*, 1983). Recently, Zang *et al.* (2012) investigated a novel method using the Equivalent Element Modal Strain Energy (EEMSE) and Equivalent Element Modal Kinetic Energy (EEMKE) to localize errors in the finite element model, and applied to select parameters in the model updating process. The results demonstrate the effectiveness of the method and show great potential for industrial application.

Sipple and Sanayei (2014) presented a frequency response function based finite element model updating method and used to perform parameter estimation. The proposed method is used to calibrate the initial finite element model using measured frequency response functions from the undamaged, intact structure. Stiffness properties, mass properties, and boundary conditions of the initial model were estimated and updated. The usefulness of the proposed method for finite element model updating is shown by being able to detect, locate, and quantify change in structural properties. Shadan *et al.* (2016) validated a finite element model updating method using frequency response functions They used a sensitivity-based model updating approach, which utilizes a pseudo-linear sensitivity equation. The method is applied to identify the location and amount of the changes in structural parameters. The results indicate that the location and the size of different level of changes in the structure can be properly identified by the method.

Sensitivity based optimization algorithms have the disadvantage that can be computationally expensive and have difficulties to converge, mainly when applied to complex models. However, intelligent algorithms as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Ant Colony (AC), etc., can avoid calculate the sensitivity. However, theses algorithms need a high number of computation of the Finite Element Analysis problem, being time consuming too. To work around this problem, metamodel techniques, which is known as approximate model or surrogate model, can be used to turn model update a practical tool even for complex models. This technique considers the relationship between the input and output as a black-box system, and other system information, such as internal process of dynamic analysis is not required. It can create a fast running surrogate model to replace the exact FEA, and then the solving time of optimization will be reduced significantly. Thus, the potential of metamodel techniques is indisputable in model updating field. A comparison about the most commonly used metamodels is presented by Simpson *et al.* (2001a). In addition, Simpson *et al.* (2001b) investigated the use of kriging models as alternatives to traditional second-order polynomial response surfaces for constructing global approximations for use in a real aerospace engineering application, namely, the design of an aerospike nozzle. They find that the kriging models yield global approximations that are slightly more accurate than the response surface models.

Kriging model is constructed based on the correlation function theory. Particularly, it is an exact interpolation of given data and goes through all the sampling points. Therefore, the Kriging model usually has a higher approximation accuracy than traditional Root Mean Square (RSM). Jeong *et al.* (2005) applied the kriging-based genetic algorithm to aerodynamic design problems. The kriging model drastically reduces the computational time required for objective function evaluation in the optimization (optimum searching) process. Based on the result of the functional ANOVA, designers can reduce the number of design variables by eliminating those that have small effect on the objective function. Huang *et al.* (2008) proposed a new method that extends the efficient global optimization to address stochastic black-box systems. The method is based on a kriging meta-model that provides a global prediction of the objective values and a measure of prediction uncertainty at every point. The results suggest that the proposed method has excellent consistency and efficiency in finding global optimal solutions, and is particularly useful for expensive systems.

Yuan and Guangchen (2009) presented the metamodeling capabilities of two methods, *i.e.* neural network (NN) and Kriging approximation, in the context of simulation optimization. Preliminary research results reveal that Kriging approximation is in general likely to be preferred. Khodaparast *et al.* (2011) solved the problem interval model updating by using the Kriging method, and the good accuracy of Kriging method was illustrated by beam experiment. Liu *et al.* (2014) calibrated the FEM based on the modal parameters of a complex structure, the Kriging model was taken as a surrogate model. Dey *et al.* (2015) presented the Kriging model approach for stochastic free vibration analysis of composite shallow doubly curved shells. The stochastic natural frequencies are expressed in terms of Kriging surrogate models. The influence of random variation of different input parameters on the output natural frequencies is addressed.

In addition, it is very important to highlight the difficulty to find in the literature valuable scientific contributions to develop accurate models to represent manufactured components to aid the design of structural health monitoring (SHM) systems. In this context, this work presents a model updating strategy to obtain the input parameters used in a Finite Element Method (FEM), which represent the experimental dynamic behavior of a composite plate. For this, a Kriging metamodel is chosen to reduce the computational cost of optimization process into the model update. A set of finite element analyses are used to training the metamodel. After that, the kriging model is used every time when the objective function is evaluated. This strategy provides a considerable reduction in the computational time during the optimization process, where for this paper a PSO are going to be used. These results are analyzed in order to evaluate the potentialities and limitations of the proposed methodology in the context of SHM systems.

2. METHODOLOGY

Regarding the high computational cost involved in dynamic analyses, this work proposes a strategy to use a Kriging model in instead of FEM dynamic analyses during the process of model updating, as is shown in Figure 1.

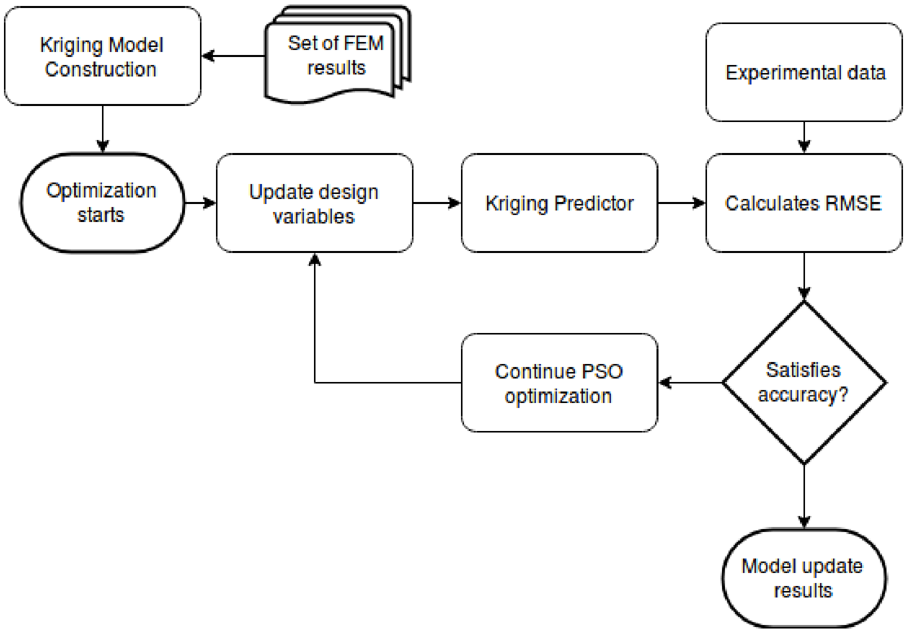

Figure 1. Methodology used for the model update strategy

Firstly, the Kriging model construction must to be done. For this, the procedure need a set of initial data from the model, which should be represented by the Kriging approximation. During this step, an optimization problem is solved aiming to define the coefficients for the Kriging estimator. To construct the Kriging model, a set of date composed by values of design variables, and its respective results obtained by the FEM is used. Afterwards, the metamodel is ready to represent the FEM during the model updating process. As aforementioned, the model update aims to find the best parameters to set numerical analysis that results in a good representation with the experimental data. Thus, within the model update process an optimization problem must to be run to find these parameters.

This work aims to use the model update process to find the best input parameters to use in the FEM and obtain a good approximation to the experimental data. Then, the parameters used as design variables into the optimization of the model update process are: Young's modulus at fiber direction (E_{11}), Young's modulus at normal to fiber direction (E_{22}), Shear modulus in ply plane (G_{12}) and the plate thickness. These variables were chosen based on the previous study provided by Souza *et al.* (2017), in this work, a screening design is conducted to identify the most significant variables that affect the dynamic behavior. After that, a Particle Swarm Optimization (PSO) is used to carry on the model update process, and find the best combination of the input parameters that results in a minimal difference from the numerical modal frequency and the experimental modal frequency. As objective function these differences are evaluated at each frequency using a Root Mean Square Error, and the optimization problem consists on minimize the sum of this difference. The objective function can be stated as,

$$RMSE = \sum_{i=1}^{6} \sqrt{\left(\frac{(f_n^i - f_e^i)}{f_e^i}\right)^2} \quad (1)$$

where f_n^i is i^{th} frequency mode from the numerical data, f_e^i is i^{th} frequency mode from the experimental data.

3. MODEL UPDATE USING FEA

As reference, a model update procedure has been carried out using FEA and PSO. From this model update, it is possible to obtain the variables updated, and the time consuming to compare with the procedure using the kriging method. In a first step, the model update has applied for the same experimental data, changing the PSO parameters. This procedure allows identifying the better configuration via PSO algorithm. Table 1 shows the error, number of call function and number of iterations for different configurations of; particle number (N), inertia parameter (w), cognitive parameter (φ_1), social parameter (φ_2). The cognitive parameter represents the effect of self-knowledge and the social parameter is associated with the collective effect of the population (Vaz *et al.*, 2013).

Table 1. PSO parameter testing results

N	w	φ_1	φ_2	Error	Call function	Iterations	Convergence
16	0.5	0.5	0.5	0.140	512	32	NO
16	0.8	0.5	0.5	0.090	496	31	NO
25	0.8	0.2	0.8	0.066	825	33	NO
40	0.6	0.5	0.5	0.066	920	23	OK
40	0.6	0.5	0.5	0.066	920	23	OK
50	0.6	0.5	0.5	0.113	1450	29	OK
60	0.6	0.5	0.5	0.113	1260	21	OK

The objective of this analysis is to obtain the better PSO configuration, concerning the convergence of the problem, and the lowest number of call functions. Therefore, the configuration with N = 40, w = 0.6, $\varphi_1 = 0.5$ and $\varphi_2 = 0.5$ has presented the better results. After that, using these PSO parameters and carrying out the model update procedure for another experimental sets, it is possible to evaluate the updated values.

Table 2 presents the updated parameters resulted from the model update process. With these parameters it is possible to evaluate the dynamic numerically behavior, and compare with the experimental data, to verify the quality of the model update process.

Table 2. Updated variables results from FEA model update

	E_{11}[GPa]	E_{22}[GPa]	G_{12}[GPa]	Thickness [mm]
Plate	134.8536	9.8907	4.822	3.2724

Table 3 presents the numerical and experimental results obtained for the natural frequencies. Comparing the experimental data with the numerical result obtained from the updated parameters, it is possible to note the good approximation for the modes 1, 2, 4 and 5, resulting in a difference lower than 1%. Modes 3 and 6 are essentially torsional modes, which are harder to consider in the design variables chosen, resulting in a difference around 2%.

Table 3. Comparison between FEA updated results and experimental results

	Experimental	Numerical	Difference
f_1 [Hz]	104.1520	104.1878	0.0344%
f_2 [Hz]	139.8840	140.0312	0.1052%
f_3 [Hz]	261.0910	253.5284	-2.8965%
f_4[Hz]	320.6900	320.7774	0.0273%
f_5 [Hz]	367.0790	367.0878	0.0024%
f_6 [Hz]	411.4550	404.8923	-1.5950%

These results demonstrate the quality of the model update, showing how good the numerical model fits the experimental data. However, the disadvantage of this method is the time consuming. For the case, the whole model update process takes around 2 hours (desktop computer, memory: 4Gb, processor: intel i5), to run the 900 finite element problems needed to converge the optimization process. Depending on the complexity of the problem, it could become unfeasible due to the time required to simulate each finite element analysis in the optimization algorithm.

4. KRIGING MODEL CONSTRUCTION

The best linear unbiased predictor, also known as Kriging, is a surrogate model, frequently used to represent a physic phenomenon or process, which is difficult to represent by numerical models or to measure experimentally. This paper uses the ordinary Kriging, which assumes the form,

$$y(x) = \boldsymbol{f}^T(x)\boldsymbol{\beta} + \boldsymbol{z}(x), \tag{2}$$

where $\boldsymbol{z}(x)$ is the realization of the stochastic process, $\boldsymbol{f}^T(x)$ is a polynomial vector of training sample x, and β is the coefficient of the linear regression. The $\boldsymbol{f}^T(x)$ term approximates the drift of the Kriging model, and $\boldsymbol{z}(x)$ approximates the local deviation of the Kriging model. In the Kriging model, a set of sample data **x**, with the observed responses **y,** should be used to make a model allowing to predict the response in a new point **x**. First, it is necessary to correlate each sample data with each other, using the basis function,

$$Cor[\boldsymbol{X^i}, \boldsymbol{X^l}] = e^{-\sum_{j=1}^{k}\theta_j(x_j^i - x_j^l)^2}, \tag{3}$$

where x_j^i and x_j^l are two training samples, k is the number of design variables and θ_j is the unknown coefficient of correlation. Then, the correlation matrix with all observed data can be constructed,

$$\boldsymbol{\Psi} = \begin{pmatrix} cor[(x^1),(x^1)] & \cdots & cor[(x^1),(x^n)] \\ \vdots & \ddots & \vdots \\ cor[(x^n),(x^1)] & \cdots & cor[(x^n),(x^n)] \end{pmatrix} . \tag{4}$$

And a covariance matrix,

$$Cov[\boldsymbol{X}, \boldsymbol{X}] = \sigma^2\boldsymbol{\Psi}. \tag{5}$$

where, σ^2 is the square of the standard deviation. Then, the set of variables **x** is correlated in some way, described by the matrix **Ψ**. These correlations depend on the absolute distance between the sample points and parameters theta. To find the better value for theta to fits the interpolation problem, it is necessary to maximize the likelihood of **y**. Therefore, the problem becomes an optimization problem with the form,

$$Min - \left(-\frac{n}{2}\ln(\sigma^2) - \frac{\mathbf{1}}{\mathbf{2}}\ln|\boldsymbol{\Psi}|\right), \tag{6}$$

$$\sigma^2 = \frac{(\boldsymbol{y}-\mathbf{1}\mu)^T\boldsymbol{\Psi}^{-1}(\boldsymbol{y}-\mathbf{1}\mu)}{n}, \tag{7}$$

$$\mu = \frac{\mathbf{1}^T\boldsymbol{\Psi}^{-1}y}{\mathbf{1}^T\boldsymbol{\Psi}^{-1}\mathbf{1}}, \tag{8}$$

where μ is the mean and **1** is a vector of ones. To solve this optimization problem, global methods usually produces the best results, since it is not possible to differentiate the objective function. In this paper, a simple genetic algorithm is used to find the best theta vector. The detailed development of these calculation can be found on Forrester *et al.* (2008).

When the Kriging model is constructed with the obtained θ_j, it can be used to predict the output response at untried location with unbiased estimation. The predicted response is given by,

$$Y(x) = \mu + \psi\boldsymbol{\Psi}^{-1}(\boldsymbol{y} - \mathbf{1}\mu), \tag{9}$$

where, ψ is the correlation vector of the untried location and the sample points.

Therefore, once determined the values of theta for a given sample set, Kriging model can be used to predict any other point. In this study 20 sample points have been chosen randomly, and one Kriging model was developed for each natural frequency. Table 4 shows the results for each model.

Table 4. Kriging model coefficients

Mode	θ_1	θ_2	θ_3	θ_4
1	50.9819	0.0106	7.5364	8.8166
2	0.2563	1.6861	0.2883	6.3691
3	0.1800	0.1831	0.8422	1.6571
4	50.5699	0.0015	0.0366	6.2119
5	52.5642	0.4028	0.1510	6.6605
6	53.9085	0.6790	0.1968	8.2307

To verify the quality of the Kriging predictor, some checking points are evaluated and compared with results obtained by the FEM algorithm. Figure 2 presents the numerical data (FEM) and the values of the Kriging predictor.

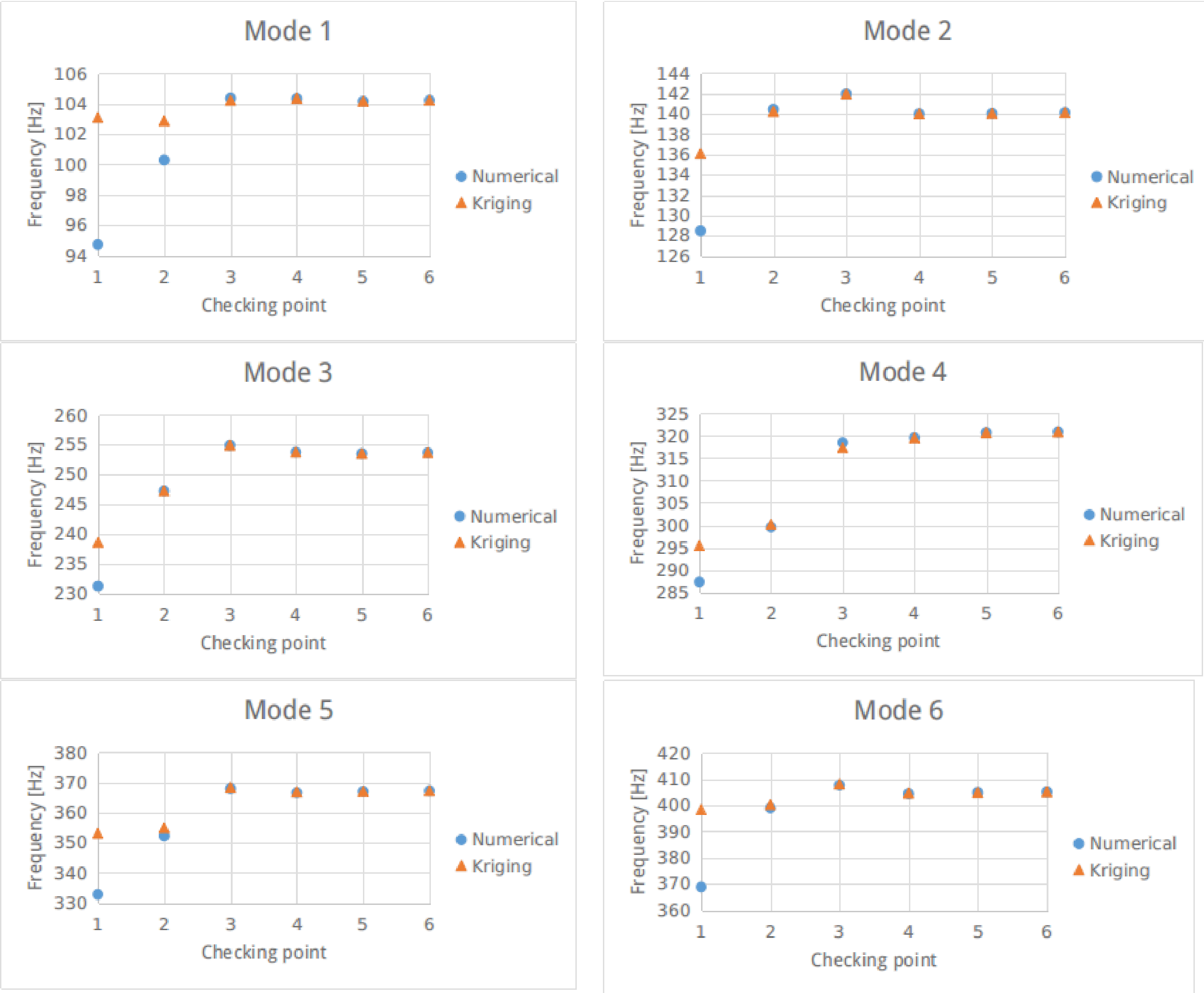

Figure 2. Frequency values of the checking points.

The Kriging model, constructed with the available data, demonstrates low error when predicting values between the points used to training the model. However, for the check point one, the design variables are out of the range used as data training, then the difference to the numerical model becomes higher. Therefore, these results show that the Kriging model is well conditioned to be used as predictor in the model update process.

5. MODEL UPDATE USING KRIGING MODEL

The model update process was modified to include the Kriging predictor, i.e., call the Kriging model in instead of the FEM. Then, the PSO algorithm searches for the best combination of design variables to fit the experimental results. A reduction in the computational time is expected, since the Kriging model is faster than FEM to make the calculations.

In addition, using the Kriging model, the total time to carry out the model update procedure takes around 10 minutes (desktop computer, memory: 4Gb, processor: intel i5). The design variables resulted from this process is presented in Table 5, and the comparison between the frequencies predicted with the Kriging model and the experimental data is presented in Table 6. Also, Figure 3 shows the convergence of the optimization algorithm.

Table 5. Kriging model coefficients

	E_{11}[GPa]	E_{22}[GPa]	G_{12}[GPa]	Thickness [mm]
Plate	128,7924	9,1055	5,0954	3,3916

Table 6. Natural frequencies obtained with the Kriging model compared with the target experimental frequencies.

	Experimental	**Kriging**	**Relative Difference**
f_1 [Hz]	104.1520	104.3708	0.2101%
f_2 [Hz]	139.8840	139.8839	-0.0001%
f_3 [Hz]	261.0910	261.0917	0.0003%
f_4 [Hz]	320.6900	320.6866	-0.0011%
f_5 [Hz]	367.0790	367.4869	0.1111%
f_6 [Hz]	411.4550	405.4654	-1.4557%

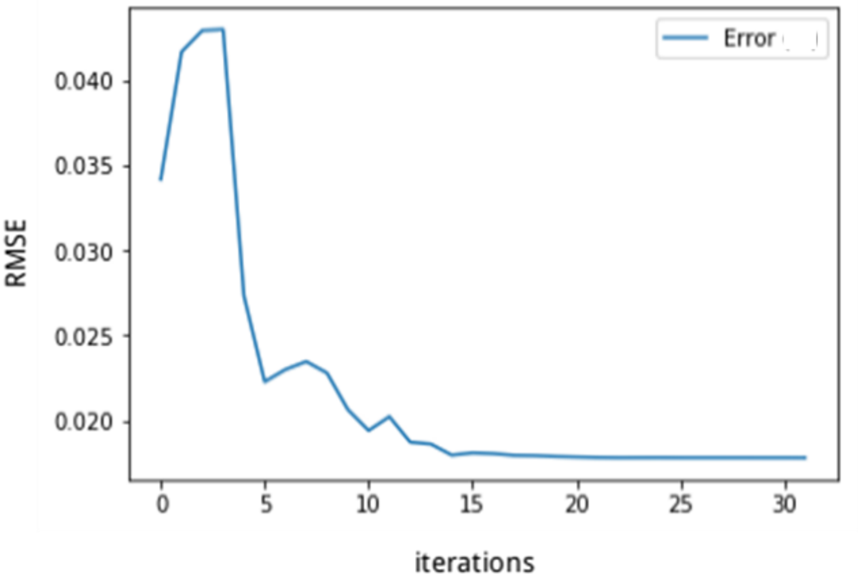

Figure 3. Convergence of the PSO algorithm although iterations

The result obtained by the model update using the Kriging model fits the experimental data relatively well. Considering only the Kriging predictor, the model update process has achieved response values with an error lower than 0,1% in some modes. Finally, the design variables obtained in the model update using Kriging are used as input in the finite element algorithm. Table 7 shows the natural frequencies obtained using FEA, with the inputs defined by the model updating using Kriging, the relative difference presented in this table is in relation of the FEA results and the experimental data.

Table 7. Comparison between FEA results with experimental data and Kriging values.

	f_1 [Hz]	f_2 [Hz]	f_3 [Hz]	f_4 [Hz]	f_5 [Hz]	f_6 [Hz]
Experimental	104.15	139.88	261.09	320.69	367.08	411.46
FEA/Kriging	108.06	140.00	260.00	324.88	371.30	408.17
Difference FEA vs Experimental	3.7522%	0.0829%	-0.4179%	1.3066%	1.1499%	-0.7984%

The model update using the Kriging model shows excellent results in relation to computational time and accuracy. This procedure can help to obtain a good approximation of values for design variables to be used in the computational model in instead of to carry out a complete model update using FEA. The final design variables configuration obtained with the procedure proposed in this paper, results in a better approximation for almost all modes, except for the first mode. This behavior could be due to the lack of quality of the training samples used for the Kriging model, which is not representing accurately the finite element model.

6. CONCLUSIONS

Model update processes are very important in the engineering environment to calibrate numerical models. Using some experimental data and an optimization procedure, it is possible to adjust the design variables to obtain a numerical model equivalent to the physical phenomena. Metamodel techniques can simplify the FEA to a surrogate model as a fast running model which can facilitate the application of the intelligent algorithms in model updating. Reducing computational time and obtaining reliable results. This paper presented an analysis of a model update procedure replacing the FEA for a Kriging model. Comparisons about the relative difference obtained from the model update using FEA and the model update using Kriging have been done. The Kriging metamodel shows to be very promising to be used in instead of the FEA to carry out a quick update of the main design variables, and then, utilize it in the FEM. This procedure demonstrates to be very reliable, since the higher error obtained is around 3.7% and the lower one is about 0.08%. It is important to remark that no kind of pre-processing has been used to choose the best points to training the Kriging model, then future studies could be done to improve the results. This procedure can be used to define the parameters to be monitored in a SHM system, and also how these parameters have influence on the process, helping engineers to develop better SHM systems.

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