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Evaluation of dynamic response variability in aluminum honeycomb sandwich panels using PCE and Kriging-based metamodel

Alüminyum petek sandviç panellerde dinamik tepki değişkenliğinin PCE ve Kriging tabanlı meta-model kullanılarak değerlendirilmesi

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Highlights

- ❖ The response of the core cell walls is particularly decisive at high frequencies and cannot be captured when the core is taken as an equivalent volume.
- ❖ The uncertainties in the core structure mostly originated from the inhomogeneity of adhesive fillets.
- ❖ The variability at low frequencies is due to the facing sheets, while the variability at high frequencies is dominated by the core.

Graphical Abstract

In this work, the dynamic response variability in 35 aluminum honeycomb sandwich panel samples is examined using a PCE and Kriging-based metamodel.

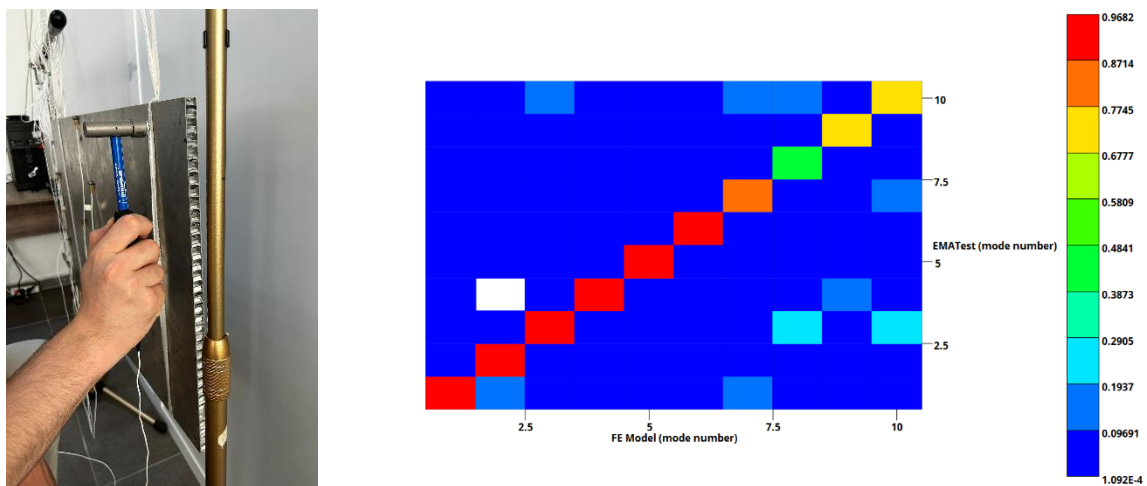


Figure. Experimental modal analysis of aluminum honeycomb sandwich panels

Aim

To model the dynamic response variability in commercial aluminum honeycomb sandwich panels.

Design & Methodology

The experimental data are acquired through experimental modal analysis techniques. The computational model is constructed using shell modeling. The modal frequency values obtained for the samples are compared with the computational results and deviations are referred to as errors.

Originality

A data-driven meta-model called PCE-Kriging is created to express the relationship between error and the stochastic variables.

Findings

The results show that the variability at low frequencies is due to the facing sheets, while the variability at high frequencies is dominated by the core.

Conclusion

The uncertainties in the core structure mostly originated from the inhomogeneity of adhesive fillets which alter the effective cell wall thickness

Declaration of Ethical Standards

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Evaluation of Dynamic Response Variability in Aluminum Honeycomb Sandwich Panels Using PCE and Kriging-Based Metamodel

Araştırma Makalesi / Research Article

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ABSTRACT

The aim of this study is to model the dynamic response variability in commercial aluminum honeycomb sandwich panels. An experimental modal analysis is performed on 35 identical commercial AHSPs. Based on 10,000 samples, a computational model is constructed according to the estimated weight of the panel. The modal frequencies of the 35 samples for the first 10 flexible modes are compared with the computational results and deviations are referred to as errors. The thickness of the facing sheets and thickness of the cell wall of the core are considered as sources of uncertainty. A data-driven meta-model called PCE-Kriging is created.

Keywords: Kriging, modal analysis, polynomial chaos expansion (PCE), uncertainty quantification, variability.

Alüminyum Petek Sandviç Panellerde Dinamik Tepki Değişkenliğinin PCE ve Kriging Tabanlı Meta-Model Kullanılarak Değerlendirilmesi

ÖZ

Bu çalışmanın amacı, ticari alüminyum petek sandviç panellerdeki (APSP) dinamik tepki değişkenliğini modellemektir. Özdeş 35 ticari APSP üzerinde deneysel modal analiz çalışması gerçekleştirilmiştir. Panelin tahmini ağırlığına göre 10.000 örnek temel alınarak bir hesaplama modeli oluşturulmuştur. İlk 10 esnek mod için 35 numunenin deneysel modal frekansları, deterministik hesaplama modelinin sonuçlarıyla karşılaştırılmış ve sapmalar hata olarak nitelenmiştir. Kaplama levhalarının kalınlıkları ve çekirdek hücre duvarının kalınlığı belirsizlik kaynakları olarak kabul edilmiştir. Hata ve stokastik değişkenler arasındaki ilişkiyi ifade etmek için PCE-Kriging adı verilen veri güdümlü bir meta-model oluşturulmuştur. Sonuçlar, düşük frekanslardaki değişkenliğin kaplama tabakalarından kaynaklandığını, yüksek frekanslardaki değişkenliğin ise çekirdek tarafından domine edildiğini göstermektedir.

Anahtar Kelimeler: Kriging, modal analiz, çokterimli kaos açılımı, belirsizlik sayısallaştırma, değişkenlik.

1. INTRODUCTION

Aluminum honeycomb sandwich panels (AHSPs) have been commonly designed and implemented due to their benefits. Some of these benefits include high strength to weight ratio, crashworthiness, energy absorption, and effective acoustic insulation [1–5]. AHSPs are used in the rail systems, ship construction, automotive, and aviation industries [6–14]. Apart from specialized applications such as artificial satellite construction [15–17], commercial AHSPs are generally used in industrial applications.

Due to manufacturing uncertainties in commercial AHSPs, there may be significant variances between panels considered identical. It is important to consider these variances when designing or testing any engineering structure where AHSPs are employed. The term variability can be categorized as inter variability and

intra variability. Inter variability is defined as variances in the response of identical systems under the same environmental conditions while intra variability as variances in the response of a system under different environmental conditions [18, 19]. Intra variability arises due to environmental parameters such as different operating conditions and different ambient temperatures. Inter variability arises occasionally due to production errors, assembly procedure and tolerances in modeling. The terms variability and uncertainty are sometimes used interchangeably, leading to confusion [20, 21]. Variability in this work is related to aleatory uncertainty rather than epistemic uncertainty. Depending on the aleatory uncertainties, the dynamic response of the AHSPs is said to be stochastic. Uncertainties in material properties, geometric and physical parameters also cause variability. In the commercial AHSPs the sources of uncertainty are the geometry heterogeneity and the

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effective mechanical properties of materials which are mostly altered due to the presence of adhesives used for assembling the AHSPs [22].

Engineering structures are often exposed to dynamic loading [23, 24]. In the relevant literature it is shown that the dynamic response of honeycomb structures is sensitive to geometric variables [25–27]. Besides the geometric variables, the mechanical properties of materials also affect the dynamic response results which are shown in model update studies [22, 28]. The response of AHSPs to dynamic loading is an important concern that must be validated at the design stage. The aim of the current study is to model the dynamic response variability in commercial AHSPs.

Geometrical irregularities occur in the honeycomb cells due to the manufacturing procedure. These irregularities cause uncertainties in the mechanical performance of the panels. Zhao et al. developed a fast Fourier transform based method to predict the in-plane elastic properties of irregular hexagonal cores [29]. Dey et al. proposed multivariate adaptive regression splines-based uncertainty quantification method for composite sandwich structures [30]. According to the researchers, this approach effectively replaces the Monte Carlo based stochastic models for sandwich composite structures with a computationally efficient model, making the overall uncertainty quantification process much more cost-effective. Zhang et al. [31] conducted a computational study on a honeycomb sandwich structure to attain its real strength boundary at failure considering the randomness of its parameters as characterized by Latin hypercube sampling using Matlab. Lajili et al. [32] investigated the wave propagation features in a sandwich panel with honeycomb core over a large frequency domain in presence of uncertainties. They use the generalized polynomial chaos method with Latin hypercube sampling. In a study aiming to increase the strength of a honeycomb structure [33], grey relational grade is assigned to three objective functions consisting of von Mises stresses computed according to three different standards. The results of a uniform design of experiment and grey relational grades were used in surrogate models created using Kriging interpolation.

Polynomial chaos expansion (PCE) and Kriging-based metamodels are often used in reliability-based design optimization (RBDO) studies and many successful results are reported in literature [34–36]. This metamodeling algorithm utilizes the advanced techniques of PCE [37, 38] and Kriging (Gaussian process modeling) [39–41]. To model the dynamic response variability in commercial AHSPs, a PCE and Kriging-based metamodel is adopted in this work. The structure of this paper is as follows. To obtain modeling data, 35 samples measuring 750mm×500mm×15 mm are subjected to experimental modal analysis as explained in Section 2. In Section 3, fundamental notions of the three surrogate models, generalized polynomial chaos expansion (gPCE), Kriging metamodeling, and PCE-Kriging, are briefly explained and then the section copes

with how these models are implemented for various engineering and applied science problems in literature. The construction of the data-driven meta-model called PCE-Kriging for the AHSP is introduced in Section 4. Finally, a few brief conclusions are drawn in the last section.

2. EXPERIMENTAL MODAL ANALYSIS

Important dynamic properties are the natural frequencies, mode shapes, and damping ratios. Experimental modal analysis (EMA) is a testing and analysis procedure used to determine these dynamic properties through measured frequency response functions (FRFs). The experimental procedure includes data collection and analysis of the samples. The analyzed data makes it possible to examine the impact of system properties on the response. To obtain reliable test data, the excitation (input) and response (output) locations must be successfully determined through a pre-test model [42, 43].

To build a pre-test model, a computational model is first constructed in Siemens Simcenter 3D. The first step in preparing the model is to draw the core structure. The most important detail to note in the drawing is that some of the joints in the core structure have double cell walls, not single. Any hexagonal cell has a manufacturing-induced double cell wall on two sides. Since glue will be used at the joints, tolerance values should be adjusted accordingly. Since the material is isotropic, it is realistic to create a mesh structure with two-dimensional elements. Since the mesh structure will be created using the shell/shell/shell (SSS) approach with two-dimensional elements, the midsurface of the entire geometry is extracted, where a section is shown in Figure 1 [22]. For a detailed discussion on VVV, SVS and SSS modeling the interested readers are referred to Ref. [44]. The dimensions of the AHSP model and the mechanical properties of the materials are tabulated in Table 1 and Table 2, respectively. The commercial AHSP is obtained from Altigen Co. [45]. Total number of elements and nodes are 189,452 and 348,726, respectively.

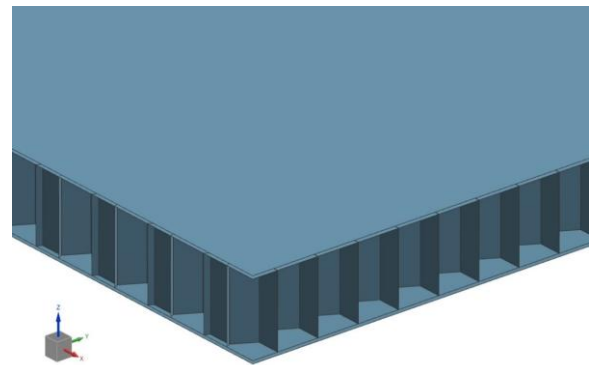


Figure 1. The midsurfaces of CAD used in the modeling

To extract the eigenfrequencies and eigenvectors of the panel, the eigenvalue problem is solved using Lanczos algorithm built-in Siemens Simcenter3D. Then, a pre-test model is created. The pre-test model is used to determine the excitation and response locations at which

accelerance FRFs (a/F) will be acquired in the experiment. The critical node locations to be measured are determined with the min-MAC algorithm.

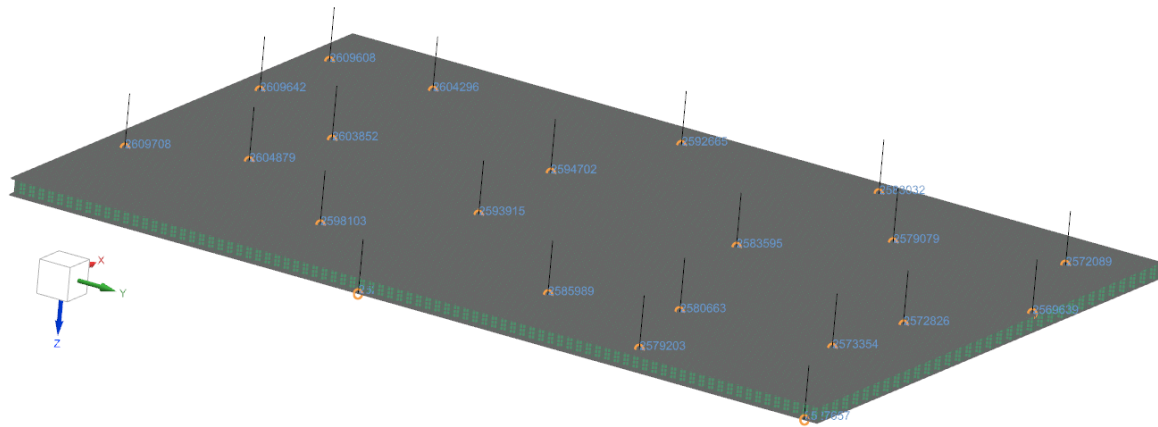
Table 1. The dimensions of the AHSP

Components	Parameter	Dimension (mm)
Facing sheets	Length (l)	750
	Width (w)	500
	Height (h)	1
Core	Cell side length (l_c)	5
	Cell radius (R)	8.66
	Cell wall thickness (t)	0.05
	Height (h)	13

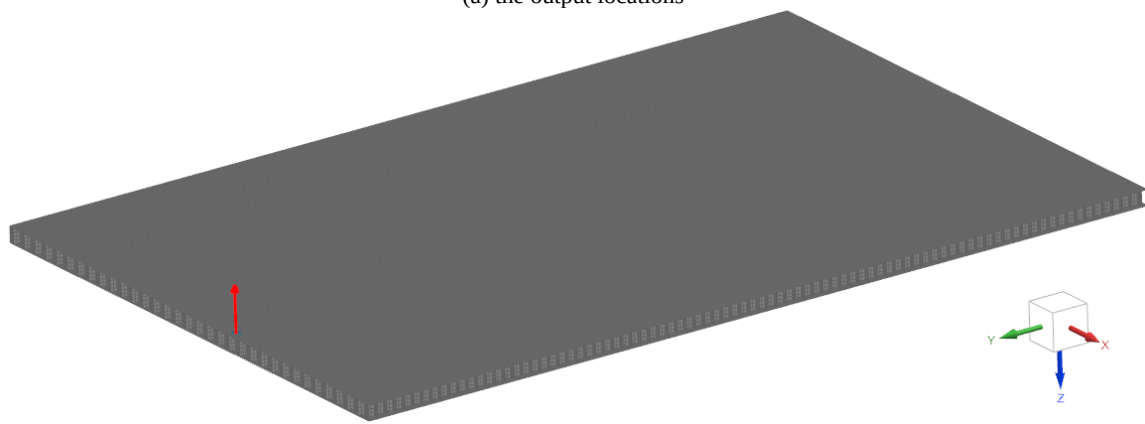
freedom (dof) and adds one dof for the uniaxial sensor and three dof for the triaxial sensor. The dof are added by selecting one at a time from the candidate set. The algorithm keeps track of a subset of off-diagonal MAC terms during the selection process. This subset starts with the largest available diagonal term of the MAC matrix. Other terms are added to the watchlist as they become the largest diagonal term of the MAC matrix. Optimum excitation locations are determined by the normal mode indication function (NMIF). Through the pre-test model with Guyan reduction, 21 output locations and 1 input location are identified. The locations are shown in Figure 2.

Table 2. Mechanical properties of materials

Material	Geometry	Elastic modulus (MPa)	Poisson's ratio	Density (kg/m ³)
Aluminum 5754	Facing sheet	70,300	0.33	2,670
Aluminum 3005	Core	69,000	0.34	2,700
Polyurethane hard	Adhesive	900	0.40	1,200



(a) the output locations



(b) the input location

Figure 2. Sensor locations determined through pre-test analysis.

The algorithm uses the SOL103 solution file to determine the node locations such that the diagonal terms in the autocorrelation modal assurance criterion (Auto-MAC) matrix are 1 and the diagonal terms are 0.2 or less. The algorithm starts with the required set of degrees-of-

A Sinus analyzer, a Dytran roving hammer and Dytran uniaxial accelerometers are used to measure the FRFs from the 21 determined sensor locations. The experimental data are obtained under free boundary

conditions. To achieve the free boundary conditions, elastic ropes are used where shown in Figure 3.

values is shown in Figure 4. The dimensions and weights of the samples were measured before the modal test. It



a) AHSP samples



b) Modal test

Figure 3. Modal test of 35 AHSP samples

The frequency range is 1.2 kHz, and the number of spectral lines is 3,200. The experimental raw data is processed through nCode software using a linear least squares regression fit. The variation in the dynamic response of AHSPs in terms of flexible modal frequency

was observed that the weights of the samples, which were assumed to be identical, were not equal. The weights of the samples are tabulated in Table 3. From a commercial point of view, the samples are considered to be identical. Since the samples were precision cut from larger

Table 3. The weights of AHSP samples (error term = weight of the panel – average)

Panel #	Weight (gram)/error	Panel #	Weight (gram)/error
1	2,461.5/-45.5	19	2,498.2/-8.8
2	2,487.3/-19.7	20	2,548.0/41
3	2,516.7/9.7	21	2,622.0/115
4	2,433.0/-74	22	2,505.0/-2
5	2,472.9/-34.1	23	2,646.3/139.3
6	2,419.7/-87.3	24	2,560.7/53.7
7	2,525.4/18.4	25	2,511.7/4.7
8	2,397.1/-109.9	26	2,468.6/-38.4
9	2,491.6/-15.4	27	2,492.0/-15
10	2,568.3/61.3	28	2,593.2/86.2
11	2,537.1/30.1	29	2,586.2/79.2
12	2,387.0/-120	30	2,502.4/-4.6
13	2,551.0/44	31	2,524.5/17.5
14	2,460.4/-46.6	32	2,465.8/-41.2
15	2,410.6/-96.4	33	2,505.8/-1.2
16	2,519.8/12.8	34	2,479.0/-28
17	2,498.7/-8.3	35	2,643.5/136.5
18	2455.0/-52		
average	2,507.0	std. deviation	63.94

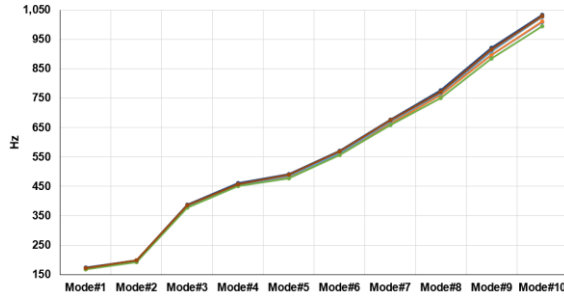


Figure 4. The variation in the dynamic response of AHSPs in terms of modal frequency values (Experimental results)

commercial panels measuring 3,000 mm × 1,500 mm, it was observed that the samples met the specified dimensions of 750 mm × 500 mm × 15 mm. Precise measurements with calipers showed that the facing sheet heights were not exactly 1.00 mm at each position along the panel, but had a height between 0.96 mm–1.03 mm. It is noted as a source of uncertainty to be evaluated in the modeling phase (see Section 4). In order to study the core structure and adhesive state, a cut piece supplied with the specimens was studied. The cell wall thickness (t) was measured as 50 microns with a digital caliper. It was observed that the corners of the honeycomb cells were not ideal as assumed in the drawing but had a rounded appearance. This is one of the uncertainties associated with manufacturing. Also, as expected, the distribution of the cell structure is not homogeneous. The main element of uncertainty to consider is the condition of the adhesive layers. The adhesive flows during manufacturing, creating a fillet-shaped residue between the cell walls and facing sheets. After curing, the adhesive fillet layer hardens and alters the buckling strength of the thin cell walls, as analyzed in detail in a previous study [22]. This is another source of uncertainty worth considering in the modeling phase (see Section 4). The weight of the computational model is the same as the average weight of the panels. When the mentioned density values are assigned, the weight of the panel in the computational model is 2,507.0 grams. The mode number and frequency values obtained from the modal test results are given in Section 4, where a data-driven meta-model called PCE-Kriging for the AHSP is introduced. But before that, the following section briefly explains the basic concepts of the three surrogate models - generalized polynomial chaos expansion (gPCE), Kriging metamodeling and PCE-Kriging - and then discusses how these models are implemented to engineering solutions and applied science problems in literature.

3. METAMODELING

This section is composed of two main subsections: while the first part (Section 3.1) deals with briefly explaining the fundamental notions of the three surrogate models, the second part (Section 3.2) copes with how these

models are implemented for various engineering and applied science problems in literature.

3.1. Surrogate Models

3.1.1. Generalized polynomial chaos expansion (gPCE)

The computational burden of simulations in engineering and applied sciences is huge. Thus, more effective methods are suggested in the literature. These methods are based on quantifying intrinsic uncertainty between input variables and output variables by representing input variables as well-known probability distributions such as Gaussian, Weibull, and Gamma. This approach is called metamodeling or surrogate modeling entitled generalized polynomial chaos expansion (gPCE) that generates an approximation function for the computationally known model or fits dataset of real input values and stochastic output variables produced by simulation methods, e.g., Monte Carlo. Thus, spectral representation on a suitably constructed basis of orthogonal polynomials is generated to represent a model between a set of input variables and an output variable as follows:

$$E(Y^2) = \int M^2(\mathbf{x}) f_{\mathbf{x}}(\mathbf{x}) d\mathbf{x} < \infty \quad (1)$$

where $\mathbf{x} \in D_{\mathbf{x}}$ denotes the function domain and $\mathbf{x} = (x_1, x_2, \dots, x_n)^T$ represents n -dimensional input vector, $E(\cdot)$ represents the expected value operator, $f_{\mathbf{x}}(\mathbf{x})$ denotes n -dimensional joint probability density function with independent random variables. So, gPCE is defined as follows:

$$Y = M(\mathbf{X}) = \sum_{\alpha \in N^M} (y_{\alpha} \psi_{\alpha}(\mathbf{X})) \quad (2)$$

where the term $\psi_{\alpha}(\mathbf{X})$ in Equation (2) denotes multivariate polynomials basis orthonormal to $f_{\mathbf{x}}(\mathbf{x})$, $\alpha \in N^M$ shows a multi-index identifying multivariate polynomials' coefficients, $\psi_{\alpha}(\mathbf{X})$, and the coefficients are denoted by y_{α} . Since the truncation of Equation (2) is required at some power, Equation (2) is rewritten approximately as follows:

$$M(\mathbf{X}) \approx M^{PCE}(\mathbf{X}) = \sum_{\alpha \in A} (y_{\alpha} \psi_{\alpha}(\mathbf{X})) \quad (3)$$

where $A \subset N^M$ denotes the set of picked multi-indices of multivariate polynomials. Univariate orthonormal polynomials, $\phi_k^{(i)}(x_i)$, are used to construct $\psi_{\alpha}(\mathbf{X})$ polynomials basis as follows:

$$\begin{aligned} \langle \phi_j^{(i)}(x_i) \phi_k^{(i)}(x_i) \rangle &= \\ \int \phi_j^{(i)}(x_i) \phi_k^{(i)}(x_i) f_{x_i}(x_i) dx_i &= \delta_{jk} \end{aligned} \quad (4)$$

where superscript i , subscripts j , and k , δ_{jk} , and $f_{x_i}(x_i)$, represent orthogonal polynomials concerning i th input, corresponding polynomial degrees for j and k , the Kronecker symbol, i th input variable probability mass or density function.

3.1.2. Kriging metamodeling

Kriging *aka* Gaussian process modeling assumes the realizations of the output variable stemming from the Gaussian random process defined in Equation (5) [46]

$$M(\mathbf{X}) = M^K(\mathbf{X}) = \boldsymbol{\beta}^T f(\mathbf{x}) + \sigma^2 Z(\mathbf{x}) \quad (5)$$

where the trend also called the mean of the Gaussian process is denoted by $\beta^T f(\mathbf{x})$, σ^2 is called variance and, $Z(\mathbf{x})$ represents a stationary Gaussian process whose means and variance are 0 and 1, respectively.

Since Kriging is employed to construct an approximation function and interpolation for a given computationally known function or a design matrix of input and out variables, a simple global error measurement showing the meta-model's precision is not available due to Kriging's interpolating attributions. Leave-one-out (LOO) is a method to globally measure errors defined by Equation (6) [46].

$$Err_{LOO}^K = \frac{1}{N} \sum_{i=1}^N (y^{(i)} - \mu_{y(\neg i)}(X^{(i)}))^2 \quad (6)$$

where the first term in the parathesis is the response value and the next term is the estimated value using the Kriging model.

3.1.3. PCE-kriging

PCE-Kriging is a surrogate model that combines both gPCE and Kriging defined by Equation (7).

$$M(\mathbf{X}) \approx M^{PCK}(\mathbf{X}) = \sum_{\alpha \in A} (y_{\alpha} \psi_{\alpha}(\mathbf{X})) + \sigma^2 Z(\mathbf{x}) \quad (7)$$

where $y_{\alpha} \psi_{\alpha}(\mathbf{X})$, A , and $Z(\mathbf{x})$ represent a weighted sum of orthonormal polynomials called the average of the Gaussian process, the index set of the polynomials, and a stationary Gaussian process whose means and variance are 0 and 1, respectively.

Two different frameworks are used in PCE-Kriging, which are called sequential and optimal, and they are abbreviated as SPCE-Kriging and OPCE-Kriging. Santner et al. [46] suggest that OPCE-Kriging is superior to SPEC-Kriging when the experimental design is under consideration since it has the lowest generalized statistical error.

3.2. Implementation of PCE-Kriging Surrogate Model

The differences observed in the modal frequency values obtained from the experimental model and from the computational model are termed as errors. The errors are assumed to stem from the stochastic properties of the AHSP samples. As analyzed throughout the study, it is assumed that the samples are identical, but they are not. It is more realistic to model uncertainty to come up with a reliable solution. Thus, one can assume that the deviations observed between the experimental and computational results originated from uncertainties associated with the geometric properties of honeycomb panels, which are determined as the thicknesses of the upper facing sheet, core structure, and the lower facing sheet.

The surrogate model called gPCE has been implemented for simulation-based models as alternative easy-to-implement models and generated predictions [47–50]. Hady et al. [47] dealt with designing the parameters of a wind turbine's two-stage gearbox. Umesh and Ganguli [48] researched the materials' uncertainty impact to control the vibration of smart composite plates by utilizing piezoelectric sensors. Azrar et al. [49] examined

the impact of uncertain parameters affecting viscoelastic Carbon Nanotubes (CNT) dynamical behavior when a viscous fluid is conveyed in it. Peng et al. [50] investigated composite laminated plates by using micro and macro parameters based on random and interval variables to represent uncertainty. Chen et al. [51] suggested a method to design underwater vehicles using composite materials whose mechanical properties are represented by PCA. On the other hand, the PCE-Kriging method has proven itself in several engineering modeling processes. Aversano et al. [52] proposed a method that predicts 2D combustion data when unexplored operating conditions are under consideration. García-Macías and Ubertini [53] proposed a method that estimates automatic damage identification for large-scale structures. Sinou and Denimal [54] suggested a method that tracks traverse cracks and pinpoints them in rotating components using the PCE-Kriging method based on uncertain parameters of position and depth.

4. DATA ANALYSIS

In the analysis, 3 geometric variables of AHSPs are considered as sources of uncertainty; these are the thicknesses of the upper and lower facing sheets and the cell wall thickness of core. Their distributions are assigned as follows: upper and lower facing sheets are uniformly Gaussian with mean 1 and standard deviation 0.05, and the core structure is Gaussian with mean 0.9 and standard deviation 0.05. These distributions are determined through experimental measurements and computational analysis. Precise measurements with calipers showed that the facing sheet heights were not exactly 1.00 mm at each position along the panel, but had a height between 0.96-1.03 mm. Computational analysis performed on one of the AHSP samples which is selected according to the statistical analysis revealed that even the cell wall thickness of the core elements are 50 μm , the effective cell wall thickness (t_c) is computed as 92 μm , as shown and explained in the previous work [22]. The t_c value is different from the actual one. This is mainly due to the adhesive fillets that form at the bonding interface of facing sheets and the honeycomb core during the manufacturing process. The data-driven meta-model called PCE-Kriging is constructed. The first 10 flexible modal frequency values of 35 AHSP samples (experimental values) and the results of the computational model are tabulated in Table 4. Error values between each AHSP sample and the computational model for each modal frequency are tabulated in Table 5.

Furthermore, 10,000 samples are run to find the estimated average weight of AHSP. The outcomes are tabulated in Table 6. All calculations are performed with SPSS version 27.0. Since the bias value is too small, the estimated weight of 2,507.0 grams is used in the computational model.

In the case of AHSPs, various intrinsic properties can lead to uncertainties. These uncertainties can be

Table 4. The first 10 flexible modal frequency values of 35 AHSP samples and the computational model

Sample #	Modal frequencies									
	1	2	3	4	5	6	7	8	9	10
1	171.20	195.20	382.90	455.50	482.10	561.20	667.60	767.10	891.60	1,018.80
2	169.90	195.30	379.20	455.30	483.10	563.40	663.40	761.40	896.90	1,008.90
3	169.70	193.80	378.50	451.90	481.10	556.70	662.70	760.20	897.40	1,010.60
4	172.40	197.60	384.40	459.40	489.00	566.70	672.00	770.00	913.30	1,025.10
5	170.40	196.00	382.60	454.50	486.10	563.50	671.00	765.80	909.00	1,025.80
6	170.40	196.00	382.60	454.50	486.10	563.50	671.00	765.80	909.00	1,025.80
7	168.60	192.80	376.60	449.70	476.30	555.90	657.60	750.30	884.10	995.20
8	173.80	198.80	387.50	460.60	491.20	571.30	676.00	775.40	921.00	1,033.10
9	172.00	197.80	385.20	457.30	489.30	567.90	674.00	769.90	914.30	1,028.40
10	169.60	194.70	379.60	449.80	482.60	560.10	665.90	761.60	907.90	1,018.60
11	172.20	197.60	383.80	455.10	491.40	568.00	675.70	768.20	926.00	1,033.90
12	174.10	198.00	385.90	461.40	489.70	571.00	674.60	772.30	914.10	1,026.40
13	169.00	192.60	377.90	451.40	476.10	557.90	659.60	755.50	884.10	1,001.00
14	170.40	194.20	380.30	456.60	480.90	560.60	663.50	760.90	890.20	1,005.90
15	172.80	172.80	385.30	459.30	487.00	568.90	672.90	769.70	906.10	1,023.20
16	170.20	193.70	378.10	450.90	482.20	560.20	663.90	757.80	899.50	1,012.10
17	170.90	196.20	382.90	453.50	484.30	566.00	669.10	765.40	911.70	1,020.70
18	171.40	195.90	381.30	454.00	484.40	565.50	666.10	762.20	899.80	1,014.00
19	169.20	194.70	379.50	453.60	482.20	559.70	663.20	760.90	897.90	1,010.20
20	167.40	191.80	374.90	447.60	476.10	552.20	656.70	752.10	885.70	999.40
21	167.70	190.50	373.00	445.70	473.40	550.60	653.00	746.80	885.20	998.30
22	168.80	192.70	377.90	450.60	476.30	557.20	658.90	752.20	888.50	1,003.00
23	166.90	189.40	372.80	445.00	469.40	549.30	649.00	745.50	872.30	990.60
24	168.40	193.20	376.40	451.40	477.60	558.20	655.10	756.20	892.20	998.90
25	160.20	194.70	378.10	454.10	482.00	561.80	662.00	758.70	897.50	1,005.50
26	169.60	195.50	380.70	452.30	487.70	562.80	665.90	760.80	906.00	1,014.60
27	169.70	195.10	379.20	451.80	485.20	562.00	666.40	760.10	906.40	1,015.40
28	168.70	191.00	374.60	445.80	477.00	556.40	659.00	749.10	884.60	1,002.10
29	168.40	191.80	376.00	446.90	477.50	556.50	661.10	752.00	893.80	1,008.00
30	170.10	195.50	380.00	451.90	485.20	562.50	667.00	763.60	913.40	1,022.00
31	170.10	194.30	381.50	#AD?	480.10	560.00	665.20	760.60	898.20	1,014.20
32	172.00	197.40	384.80	457.60	487.90	572.80	672.30	767.60	920.10	1,023.70
33	170.40	195.50	378.60	455.10	483.70	566.10	663.20	759.20	908.00	1,007.90
34	171.00	196.10	382.00	453.80	484.90	565.50	668.90	763.60	908.40	1,016.60
35	168.10	190.80	375.50	447.00	474.10	554.10	657.40	751.20	883.40	1,002.10
Computational	178	205	396	473	501	583	687	782	921	1,035.00

practically observed by taking the difference of each modal frequency value between experimental and computational results. They arise due to complex manufacturing processes, design complexities, assembly stages and quality control issues. Consequently, when it comes to better optimization and increased performance, it is very important to mathematically analyze and incorporate uncertainties into the model. The coefficient of variation (CoV) is defined by Equation (8)

$$\text{CoV} = \frac{s_i}{\bar{x}_i}, i = 1, 2, \dots, 35 \quad (8)$$

where s_i denotes the standard deviation of 10 modal frequencies of each panel; $\bar{x}_i$ denotes the average of 10 modal frequencies of each panel. Means and standard

deviations based on 10 modal frequency values are used to calculate the CoV for each AHSP sample. The results are tabulated in Table 7. The greatest variation is observed in Sample#29 (0.49) and the least variation is observed in Sample#6 (0.36). The AHSP and its estimated weight used for the computational stage are chosen using CoV statistics and a sampling scheme called bootstrap.

Based on the information obtained in the study, it is assumed that the errors are due to the uncertainties in the thickness of the upper and lower facing sheets and the thickness of the core cell wall. All three features are utilized to account for errors by running the PCE-Kriging model. However, before running the PCE-Kriging

Table 5. Errors between 35 experimental modal frequencies and the computational modal frequencies

Honeycomb #	Error=experimental value–computational value (in Hz)									
	1	2	3	4	5	6	7	8	9	10
1	-7.1	-9.4	-12.9	-17.0	-18.6	-22.2	-18.98	-14.98	-29.65	-16.20
2	-8.4	-9.3	-16.6	-17.2	-17.6	-20.0	-23.18	-20.68	-24.35	-26.10
3	-8.6	-10.8	-17.3	-20.6	-19.6	-26.7	-23.88	-21.88	-23.85	-24.40
4	-5.9	-7.0	-11.4	-13.1	-11.7	-16.7	-14.58	-12.08	-7.95	-9.90
5	-7.9	-8.6	-13.2	-18.0	-14.6	-19.9	-15.58	-16.28	-12.25	-9.20
6	-7.9	-8.6	-13.2	-18.0	-14.6	-19.9	-15.58	-16.28	-12.25	-9.20
7	-9.7	-11.8	-19.2	-22.8	-24.4	-27.5	-28.98	-31.78	-37.15	-39.80
8	-4.5	-5.8	-8.3	-11.9	-9.5	-12.1	-10.58	-6.68	-0.25	-1.90
9	-6.3	-6.8	-10.6	-15.2	-11.4	-15.5	-12.58	-12.18	-6.95	-6.60
10	-9	-10	-16	-23	-18	-23	-20.68	-20.48	-13.35	-16.40
11	-6	-7	-12	-17	-9	-15	-10.88	-13.88	4.75	-1.10
12	-4	-7	-10	-11	-11	-12	-11.98	-9.78	-7.15	-8.60
13	-9	-12	-18	-21	-25	-26	-26.98	-26.58	-37.15	-34.00
14	-8	-10	-15	-16	-20	-23	-23.08	-21.18	-31.05	-29.10
15	-6	-7	-10	-13	-14	-15	-13.68	-12.38	-15.15	-11.80
16	-8	-11	-18	-22	-18	-23	-22.68	-24.28	-21.75	-22.90
17	-7	-8	-13	-19	-16	-17	-17.48	-16.68	-9.55	-14.30
18	-7	-9	-14	-19	-16	-18	-20.48	-19.88	-21.45	-21.00
19	-9	-10	-16	-19	-18	-24	-23.38	-21.18	-23.35	-24.80
20	-11	-13	-21	-25	-25	-31	-29.88	-29.98	-35.55	-35.60
21	-11	-14	-23	-27	-27	-33	-33.58	-35.28	-36.05	-36.70
22	-10	-12	-18	-22	-24	-26	-27.68	-29.88	-32.75	-32.00
23	-11	-15	-23	-28	-31	-34	-37.58	-36.58	-48.95	-44.40
24	-10	-11	-19	-21	-23	-25	-31.48	-25.88	-29.05	-36.10
25	-18	-10	-18	-18	-19	-22	-24.58	-23.38	-23.75	-29.50
26	-9	-9	-15	-20	-13	-21	-20.68	-21.28	-15.25	-20.40
27	-9	-9	-17	-21	-15	-21	-20.18	-21.98	-14.85	-19.60
28	-10	-14	-21	-27	-24	-27	-27.58	-32.98	-36.65	-32.90
29	-10	-13	-20	-26	-23	-27	-25.48	-30.08	-27.45	-27.00
30	-8	-9	-16	-21	-15	-21	-19.58	-18.48	-7.85	-13.00
31	-8	-10	-14	-20	-21	-23	-21.38	-21.48	-23.05	-20.80
32	-6	-7	-11	-15	-13	-11	-14.28	-14.48	-1.15	-11.30
33	-8	-9	-17	-17	-17	-17	-23.38	-22.88	-13.25	-27.10
34	-7	-8	-14	-19	-16	-18	-17.68	-18.48	-12.85	-18.40
35	-10	-14	-20	-26	-27	-29	10.20	-30.88	-37.85	-32.90

model, ANOVA (Analysis of Variance) is run to check whether the errors of the 10 modal frequencies are statistically different. Otherwise, 10 different PCE-Kriging models need to be created. ANOVA is run at a significance level of 0.05 and a Duncan post hoc test is employed to determine which error of the 10 modal frequencies is statistically significant using SPSS version 27.0. The ANOVA results tabulated in Table 8 indicate that there are 3 groups. The results show that the least errors occur at modal frequencies #1 and #2, while the highest errors occur at modal frequencies #4 to #10. On the other hand, the error of modal frequency #3 appears to remain as a separate group.

Table 6. The statistical results

Weight (based on 10,000 samplings)	Bias
2,507.06	0.0996

The ANOVA result shows that 3 different OPCE-Kriging surrogate models need to be created to account for errors. UQ-Lab software [55] is used for all modeling processes. Leave-one-out (LOO) measure is used to determine how successful the model would be. Table 9 summarizes the coefficients of the three input variables and the LOO

Table 7. The coefficient of variations (CoV) of the 35 AHSP samples

AHSP#	CoV	AHSP#	CoV	AHSP#	CoV	AHSP#	CoV	AHSP#	CoV
1	0.48	8	0.48	15	0.43	22	0.49	29	0.49
2	0.48	9	0.45	16	0.41	23	0.42	30	0.45
3	0.49	10	0.41	17	0.45	24	0.48	31	0.42
4	0.55	11	0.43	18	0.40	25	0.43	32	0.45
5	0.41	12	0.47	19	0.45	26	0.42	33	0.44
6	0.36	13	0.47	20	0.45	27	0.39	34	0.46
7	0.42	14	0.41	21	0.37	28	0.40	35	0.42

Table 8. ANOVA results

Mode#	Group 1	Group 2	Group 3
10	-21.86		
6	-21.79		
8	-21.52		
9	-20.74		
7	-20.57		
4	-19.62		
5	-18.28		
3		-15.76	
2			-9.89
1			-8.44

Table 9. The results of PCE-Kriging models

	Lower facing sheet	Core cell wall thickness	Upper facing sheet		
Mode#	Coefficients			Optimization method	LOO
1-2	0.5185	0.2241	0.3831	Hybrid genetic algorithm	6.3725e-01
3	0.8031	3.4130	0.0529	Hybrid genetic algorithm	6.5984e-01
4 to 10	0.6516	9.8257	0.0156	Hybrid genetic algorithm	6.5484e-01

measure for each model and shows the results of the 3 models.

The three coefficients, lower facing sheet, core cell wall thickness and upper facing sheet, represent the contributions of the three stochastic variables to the errors between the experimental and computational 10 flexible mode frequency values. For modes #1 and #2, the first and third coefficients are larger than the second coefficient, indicating that errors occurring in these modes are more related to the facing sheets. Leave-one-out (LOO) is calculated for each model representing how many errors occurred when the prediction is conducted, and the value is 0.06. For modes #4 to #10, the second coefficient, core cell wall thickness, has a more dominant influence on the errors between experimental and computational values. Almost the same LOO value is attained by the predictions. Although the coefficient of the core structure is larger than the coefficients of the facing sheets, its dominance has just started to increase and is statistically different from modes #4 to #10, so it can be called a transition model for the errors. All models are optimized by UQLab using a Hybrid genetic

algorithm. Similarly, the LOO is around 0.06 in this model.

Thus, the results tabulated in Table 9 show that the lowest modes (mode#1 and mode#2) are dominated by upper and lower facing sheets, mode#4 and higher modes are dominated by the core structure. Mode#3 plays the transition role with a relatively higher core effect.

5. CONCLUSION

In this work, the dynamic response variability in 35 aluminum honeycomb sandwich panel (AHSP) samples are examined using a PCE and Kriging-based metamodel. The experimental data is acquired through experimental modal analysis (EMA) techniques. Accelerance frequency response functions (FRFs) are obtained at 21 predetermined locations in a response to the impulse response function generated by a modal hammer for every sample. The computational model is constructed using shell/shell/shell (SSS) modeling. As shown in a recent work [44], SSS modeling is statistically more successful in the prediction of the dynamic characteristics of AHSPs compared to the other two

modeling alternatives which are volume/volume/volume (VVV) and volume/shell/volume (SVS). The modal frequency values obtained for the first 10 flexible modes of the 35 samples are compared with the computational results and deviations are referred to as errors. Based on the information obtained in the study, it is assumed that the errors are due to uncertainties in the thicknesses of the upper and lower facing sheets and the thickness of the core cell wall. The outcomes of the study show that:

- The variability in the dynamic response of AHSPs increases with increasing frequency.
- The least variability occurs at low modal frequencies, mode#1, and mode#2, which are dominated by facing sheets rather than the core.
- The highest variability is observed at higher frequencies, mode#4 to mode#10, with an increasing trend. In this range the core is dominant.
- Mode#3 appears as a transition zone between the low frequency range, where the facing sheets dominate the dynamic response, and the high frequency range, where the core dominates the dynamic response.
- The dynamic response of the core walls is dominant in the high frequency region. As studies have shown, this response cannot be realized when the honeycomb core is taken as an equivalent volume [56–58].
- The uncertainties in the core structure mostly originated from the inhomogeneity of adhesive fillets which alter the effective cell wall thickness [22].
- In the relevant studies, it has been shown that the out-of-plane compressive strengths alter when the cell wall thickness value is changed at the junctions due the presence of adhesive fillets [59–61].

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DECLARATION OF ETHICAL STANDARDS

The authors of this manuscript declare that the materials and methods used in their studies do not require ethics committee approval and/or legal-specific permission.

AUTHORS' CONTRIBUTIONS

Akin OKTAV: Writing original draft, Computational and experimental analysis, Validation, Methodology, Funding acquisition.

Murat Alper BAŞARAN: Data curation, Investigation, Software, Conceptualization.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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