

IDENTIFICATION OF CLIMATE CYCLE INFLUENCE ON MECHANICAL PROPERTIES FOR KNITTED GF/PP TEXTILE COMPOSITES

J. Auzins*¹, E. Skukis¹, K. Kalnins¹, P. Lefort², B. Laure², W. Trümper³

¹ Riga Technical University, Latvia
auzinsjp@latnet.lv, eduards.skukis@rtu.lv, kasisk@latnet.lv

² Volvo Group Trucks Technology, Sweden
{philippe.lefort, laure.bertrand}@volvo.com

³ Technische Universität Dresden, Germany
wolfgang.truemper@tu-dresden.de

Keywords: Identification of mechanical properties, GF/PP textile composites, metamodeling, design of experiments, climatic cycle.

Abstract. *This paper describes a method for determination of mechanical properties (elastic parameters) of weft knitted GF/PP textile composite using the results of modal tests. The method uses the classical approach of minimization of the discrepancy between physically measured and numerically calculated natural frequencies. The method is improved by taking into account the errors caused by spreading the geometrical and physical parameters of sample specimens. The Monte Carlo simulation is used for obtaining correlations between frequency deviations. These correlation coefficients and deviations of physical frequency measurements are used for confidence interval calculations for the identified parameters. The method allows making the optimal choice of frequency sets and weighting coefficients for identification of each identifiable parameter. The error analysis proved that the Poisson's ratio can also be determined from bending oscillation modes of plate type specimens. The method was used to determine the influence of climate cycle temperature effects on composite materials, including cryogenic temperatures, elevated temperatures and thermal cycling between these extremes.*

1 INTRODUCTION

The method of identification of elastic parameters (Young's moduli, shear moduli, Poisson's ratio) using eigenfrequency measurements of specimens is very old [5]. Currently there exists an extensive amount of literature on the identification of elastic properties of layered composite materials using physical measurements and numerical calculations of natural frequencies, mostly using Finite Element Method (FEM) [6, 7, 9, 10, 11]. The traditional numerical-experimental identification procedure is based on the minimization of discrepancy between numerical and experimental results [6, 9, 10]. During the first years of using this method, the main problem was the minimization of the discrepancy functional. Today, using modern numerical experimental designs and nonparametric approximation methods, the discrepancy minimization is not a great problem. However, the estimation of the variance of obtained identified parameters is a pressing problem. The errors of identification depend on errors introduced by material production, cutting testing specimens, physical measurement errors and errors caused by disregarding significant factors in the finite element model. A large amount of literature is devoted to analysis of the accuracy of FEM, but the influence of errors of physical experiments, caused by parameter variance during material production, specimen preparation and errors of registration and measurement of natural frequencies, is significantly less studied.

Here we propose a method of variance calculation using Monte Carlo simulation of geometrical and physical uncertainty, but at the beginning the main idea of vibration-based identification [6, 9, 10] will be explained.

2 VIBRATION-BASED IDENTIFICATION OF ELASTIC PARAMETERS

Identifiable elastic parameters usually are Young's moduli, shear moduli, Poisson's ratio. The classical idea is to find those values of elastic parameters of the mathematical FEM model which will give minimal discrepancy between calculated and physically measured eigenfrequencies.

We will designate the vector-column of n physically measured natural frequencies as \mathbf{f}^{EXP}

$$\mathbf{f}^{\text{EXP}} = [f_1^{\text{EXP}}, f_2^{\text{EXP}}, \dots, f_n^{\text{EXP}}]^T, \quad (1)$$

vector-column of numerically calculated (mostly by FEM) eigenfrequencies as \mathbf{f}^{FEM}

$$\mathbf{f}^{\text{FEM}} = [f_1^{\text{FEM}}, f_2^{\text{FEM}}, \dots, f_n^{\text{FEM}}]^T \quad (2)$$

and vector-column of m physically identifiable parameters of elasticity as vector-column \mathbf{E}

$$\mathbf{E} = [E_1, E_2, \dots, E_m]^T. \quad (3)$$

A superscript T denotes the matrix transpose operation. The number m of identified parameters can be different, including elastic modulus and Poisson's ratio for different composite layers. The discrepancy Φ between measured and calculated natural frequencies is measured as weighted sum of n differences

$$\Phi = \sum_{i=1}^n w_i |f_i^{\text{EXP}} - f_i^{\text{FEM}}|^l, \quad (4)$$

where w_i – nonnegative weighting coefficient for i -th frequency, l – positive exponent. A frequently used weighting method for discrepancy measure is squared relative error

$$\Phi = \sum_{i=1}^n \left(\frac{f_i^{\text{EXP}} - f_i^{\text{FEM}}}{f_i^{\text{EXP}}} \right)^2. \quad (5)$$

The discrepancy minimization approach means that input parameters which give minimal value of functional Φ will be considered as identified values for unknown parameters \mathbf{E} :

$$\mathbf{E}^* = \arg \min_{\mathbf{E}} \Phi(\mathbf{E}) \quad (6)$$

When using FEM software, the minimization requires physical experiments as well as numerical experiments; therefore this approach is called Mixed Numerical-Experimental Technique (MNET). The flowchart of this method is shown in Figure 1.

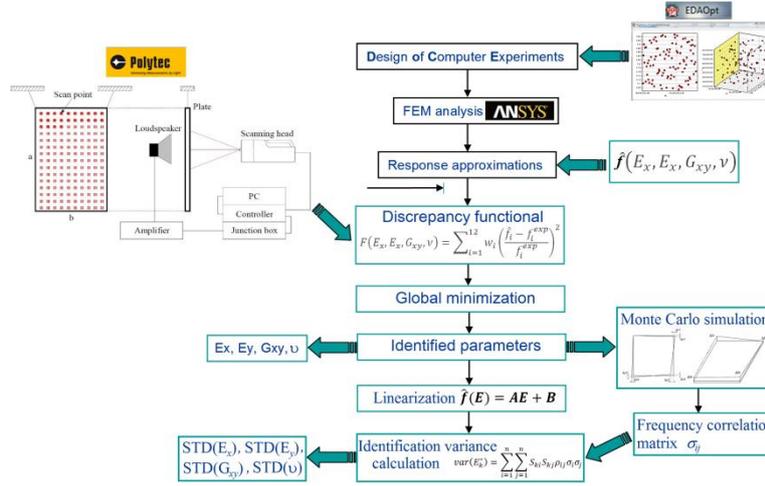


Figure 1: Flowchart of parameter identification with variance estimation.

The traditional MNET steps are:

Step 1. Preparation of specimen samples, providing frequency measurements by resonance measurements or Fourier analysis of free oscillations registered after initial excitation.

Step 2. Design of numerical experiments for FEM software. The variable input factors for eigenfrequency calculations are identifiable elastic parameters. Mostly the Latin Hypercube (LH) type designs are used. Here we use LHs optimized according to Mean Square Error space-filling criterion, introduced in [1]. The values for other input parameters (geometrical, mass, density, layer configuration and others) must correspond to specimens used in physical experiments. The number of runs for numerical experiments depends on the number m of identifiable parameters. For relatively simple plate-type specimens the calculations are fast enough to execute 100-300 trial runs in 15 minutes of computing time.

Step 3. Executing the numerical experiments, registering and grouping the eigenfrequencies according to vibration modes.

Step 4. Building the metamodel (surrogate model) for the dependency of calculated eigenfrequencies f^{FEM} on the input parameters \mathbf{E} .

$$f^{\text{FEM}} = \hat{f}(\mathbf{E}), \quad (7)$$

where the “hat” above a function symbol means approximation. The software EDAOpt [2], created at Institute of Mechanics of Riga Technical University, was used for design of computer experiments, metamodel building and minimization of discrepancy functional.

Quality of approximation is estimated by relative cross-validation error, using leave-one-out cross-validation:

$$\sigma_{cv} = 100\% \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_{-i}(x_i) - y_i)^2}}{\sqrt{\frac{1}{N-1} \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (8)$$

where root mean squared prediction error stands in numerator and mean square deviation of response from its average value stands in denominator, N is the total number of experimental trials and $\hat{y}_{-i}(x_i)$ denotes approximated value for response in i -th point, calculated without taking into account the i -th experimental point.

Practice shows that almost in all cases third order polynomials give the approximation of frequencies with error less than 0.02%. For some more complicated specimens the best accuracy can be obtained using nonparametric approximation methods: kriging, locally weighted polynomials. Some authors use genetic algorithms for the approximation and minimization of the discrepancy [9].

Step 5. Finding the values of identifiable parameters by minimization of approximated discrepancy functional

$$\mathbf{E}^* = \arg \min_{\mathbf{E}} \sum_{i=1}^n w_i |\hat{f}_i(\mathbf{E}) - f_i^{\text{FEM}}|^l \quad (9)$$

The software EDASOpt uses a modified multi-start simulated annealing method [2] and always gives global minimums of the discrepancy functional. It must be noted that the metamodels are relatively simple: for evaluation of the objective function Eq. (9) even several millions of evaluations need only a few minutes of computing time.

Step 6. Traditionally, the next step is the recalculation of the metamodel in the sub-area near to the found values of identified parameter values, and analysis of the significance of different elasticity parameters on natural frequencies [6, 10]. However, this analysis gives insufficient information for the estimation of accuracy of identified values. Therefore in the present work the method for accuracy estimation will be proposed.

3 ESTIMATION OF THE IDENTIFICATION ERRORS

The errors of identification depend on errors introduced by material production, cutting of testing specimens, physical measurement errors and errors of the finite element model. Practice shows that the mode measurements using the PSV-400 vibrometer have very high accuracy. The repeated measurements for a given specimen give almost the same results. At the same time the measurements of 3-6 different specimens from the experimental sample give the estimate of standard deviations from the mean from about 0.5% up to 2%. This means that the variance of parameters introduced by production (elasticity, density, thickness uniformity, etc.) and errors introduced by the preparation of the sample (geometrical errors, errors of density and weight estimation, microdamages created by sample cutting) have determining influence on the variance of identified elastic parameters.

Many works have been devoted to the analysis of the impact of elastic parameters on eigenfrequencies using derivative matrices [4, 6, 10]. In [6], the sensitivity of Poisson's ratio determination on the aspect ratio of a rectangular plate is studied. But it hasn't been taken into account that all frequencies are highly correlated, have different measurement errors and sig-

nificance for parameter estimation. Below the use of Monte Carlo simulation for estimation of identification errors is described.

After finding numerical values of identified parameters \mathbf{E}^* using the discrepancy minimization method, the program **EDAOpt** gives the possibility of linearization of the metamodel (obtained with polynomial or kriging approximations) in the neighborhood of point \mathbf{E}^* in the m -dimensional parameter space, obtaining the linear metamodel:

$$\hat{\mathbf{f}}(\mathbf{E}) = \mathbf{A}\mathbf{E} + \mathbf{B}, \quad (10)$$

where \mathbf{A} – constant matrix $n \times m$, \mathbf{B} – constant vector-column with n components.

The weighted discrepancy functional between calculated frequencies $\hat{\mathbf{f}}$ and measured frequencies \mathbf{f}^{EXP} in the matrix form (exponent $l = 2$):

$$\Phi = (\mathbf{A}\mathbf{E} + \mathbf{B} - \mathbf{f}^{\text{EXP}})^T \mathbf{W} (\mathbf{A}\mathbf{E} + \mathbf{B} - \mathbf{f}^{\text{EXP}}), \quad (11)$$

where \mathbf{W} is the weighting matrix, for example, squared inverse of measured frequencies:

$$\mathbf{W} = \text{diag} \left(\left(\frac{1}{f_1^{\text{EXP}}} \right)^2, \left(\frac{1}{f_2^{\text{EXP}}} \right)^2, \dots, \left(\frac{1}{f_n^{\text{EXP}}} \right)^2 \right). \quad (12)$$

The discrepancy minimization approach gives following:

$$\mathbf{E}^* = \arg \min_{\mathbf{E}} \Phi(\mathbf{E}), \quad (13)$$

and, after equating derivatives $\partial\Phi/\partial E_i$ to zero, we obtain the system of linear algebraic equations

$$\mathbf{A}^T \mathbf{W} \mathbf{A} \mathbf{E}^* + \mathbf{A}^T \mathbf{W} (\mathbf{B} - \mathbf{f}^{\text{EXP}}) = \mathbf{0}. \quad (14)$$

The values of parameters which give minimal discrepancy are therefore vector-column \mathbf{E}^*

$$\mathbf{E}^* = \mathbf{S} \mathbf{f} - \mathbf{H}, \quad (15)$$

where

$$\mathbf{S} = (\mathbf{A}^T \mathbf{W} \mathbf{A})^{-1} \mathbf{A}^T \mathbf{W}, \quad (16)$$

and constant vector-column

$$\mathbf{H} = (\mathbf{A}^T \mathbf{W} \mathbf{A})^{-1} \mathbf{A}^T \mathbf{W} (\mathbf{B} - \mathbf{f}^{\text{EXP}}). \quad (17)$$

From the physical experiments with sample size k (number of specimens in the set of measurements), the mean \bar{f}_i and standard deviation σ_i of i -th frequency can be calculated [3] as

$$\bar{f}_i = \frac{1}{k} \sum_{j=1}^k f_i^{\text{EXP}(j)} \quad (18)$$

$$\sigma_i = \sqrt{\frac{\sum_{j=1}^k (\bar{f}_i - f_i^{\text{EXP}(j)})^2}{k-1}}. \quad (19)$$

As usual, we can assume that the measured means are random variables and have normal probability distribution. Then the standard deviations of frequency measurements Eq. (19) can be used for the calculation of standard deviation using the linear dependence between elasticity parameters and natural frequency Eq. (15). The problem is that measured frequencies may not be considered as independent random variables but are highly correlated with each other.

The Pearson correlation coefficients can be calculated using the set of measured frequency values, but the number of measurements usually is too small to calculate the correlation matrix between the 15-20 frequencies used in identification.

Therefore we propose the following Monte Carlo simulation approach for the calculation of frequency correlation coefficients. The scattering of natural frequency values depends mainly on geometrical errors of the specimen and actual variance of elastic parameters and density of material. For the rectangular plate type specimen we used the Monte Carlo method to simulate the influence of the following geometric parameter variance:

6 error parameters of specimen cutting (plate type specimens are not exactly rectangular), see Figure 2a, and 4 parameters describing the variation of plate thickness, see Figure 2b, parameter φ describing the angle between fiber orientation and edge of rectangle, parameter R - surface curvature of the plate, see Figure 2c.

In addition to geometrical deviations of parameters, 4 values of standard deviation for elastic parameters (E_x , E_y , G_{xy} , ν) were used for Monte Carlo simulation. All these parameters were simulated as random variables with normal density distribution and given standard deviations. The mean values for first 13 error parameters are zero; the mean values of elastic parameters and their deviations are taken from previous experiments, but can be iteratively repeated after identification.

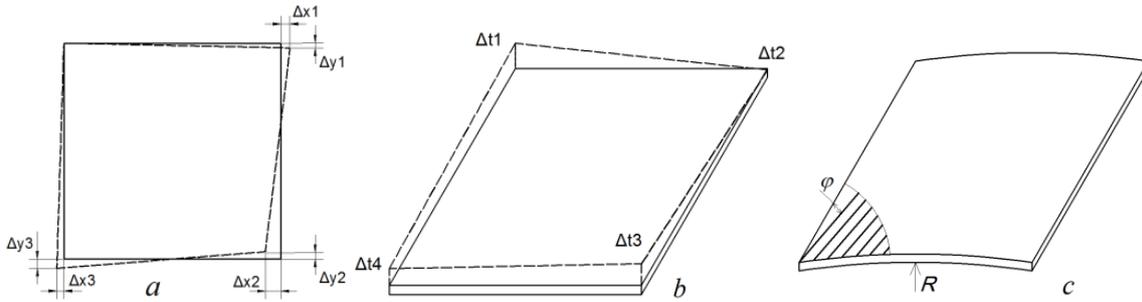


Figure 2: The parameters of geometrical deviation.

The Monte Carlo simulation consists of $N = 2000$ calculations of eigenfrequencies using randomly generated 17 input variables. The results are N values for each of first m frequencies f_{ij} , $i = 1, \dots, N$, $j = 1, \dots, m$. The Pearson product-moment correlation coefficient between i -th and j -th frequency is

$$\rho_{ij} = \frac{\sum_{k=1}^N (f_{ki} - \bar{f}_i)(f_{kj} - \bar{f}_j)}{\sqrt{\sum_{k=1}^N (f_{ki} - \bar{f}_i)^2} \sqrt{\sum_{k=1}^N (f_{kj} - \bar{f}_j)^2}} . \quad (20)$$

Then, according to Eq. (14), the standard deviation of k -th identifiable parameter can be calculated according to the statistical law for correlated random variables [3].

$$STD(E_k^*) = \sqrt{\sum_{i=1}^n \sum_{j=1}^n S_{ki} S_{kj} \rho_{ij} \sigma_i \sigma_j} , \quad k = 1, \dots, m, \quad (21)$$

where S_{kj} ($k = 1, \dots, m$, $j = 1, \dots, n$) are elements of matrix S , see (15), ρ_{ij} is the correlation coefficient between i -th and j -th natural frequency and σ_i is the sample standard deviation of i -th measured frequency ($i, j = 1, \dots, n$). The obtained values of standard deviations can be used for calculating confidence intervals of identified parameters. As usual, the two-sigma principle can be used for obtaining the confidence interval with 95% confidence level.

4 IDENTIFICATION OF ELASTIC PARAMETERS OF KNITTED GF/PP TEXTILE COMPOSITES

The proposed method was used for the identification of elastic properties of weft knitted GF/PP textile composite [12].

4.1 Material specimen

Due to its high flexibility while combining different materials in one structure and furthermore its great possibilities to manufacture near net shape preforms, flat knitting is the chosen textile technology in MAPICC3D project [12]. The high elongation present in knitted fabrics can be reduced and adjusted while integrating straight weft and warp yarns into the structure. The fabrics still show an excellent draping behaviour and are ideally suited for the manufacturing of complex shaped composite parts. Weft knitted fabrics with integrated weft, warp and/or diagonal yarns combine the advantages of woven and conventional weft knitted fabrics.

One aim of the MAPICC3D project [12] is to understand more in detail how the layout of the weft knitted MLG structure and the used loop yarn influences the handling of the textile fabrics and the mechanical properties of the composites.

The reinforcing yarns used within the structures are made by air yet texturizing from glass fibers (reinforcing component) and polypropylene fibers (matrix component). The volume fraction of the reinforcing component within the hybrid yarns is about 52 %. Figure 3 illustrates the general layout of the different weft knitted MLG fabrics and the composite plates made using these fabrics. In order to manufacture the composite plates the stacked fabrics are processed using a thermo press process. The arrangement of the MLG fabric within the composite plates is chosen to ensure the production of plates without inner tension and to avoid buckling.

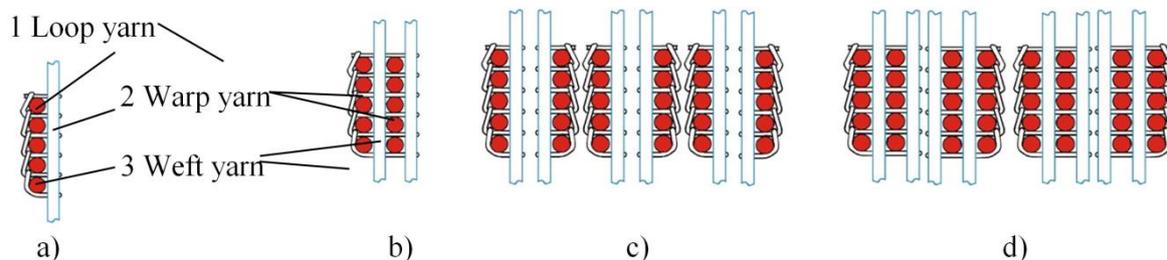


Figure 3: Schematic illustration of MLG fabric with a) 2 and b) 4 reinforcing layers per MLG fabric and arrangement of fabrics within composite plates made from c) fabric with 2 and d) with 4 reinforcing layers

4.2 The climate cycle simulation

A complete temperature cycle test comprises 10 climate cycles according to Renault truck standard STD-423-0055, see Figure 4.

Change in temperature: slope = 0,5 °C/min . Total cycle time is 32 h.

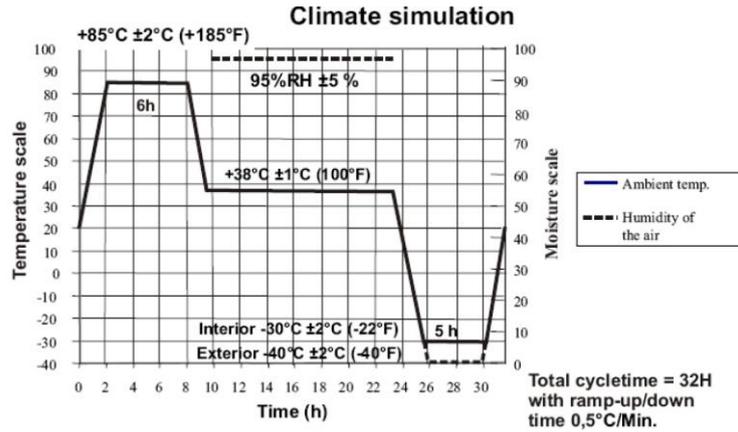


Figure 4: Climate cycle simulation

4.3 Identified elastic parameters of knitted GF/PP textile composite and the influence of climate cycles

In our experiments with knitted GF/PP textile composite plates the PSV-400 vibrometer was employed for non-contact measurement, visualization and analysis of structural vibrations. The mean relative standard deviation of physical frequency measurements was about 0.5-2%. The values of correlation coefficient for first 10 frequencies vary from 0.07 (between first and second mode) up to 0.95 (between 3-th and 8-th mode). The numerical experiments with FEM software were executed according to a 89-point design of experiments [1], which is rotatable and has the orthogonality property for 3rd order Legendre polynomials. Figure 5 shows one projection of this design. All possible two-dimensional projections of this design are equal.

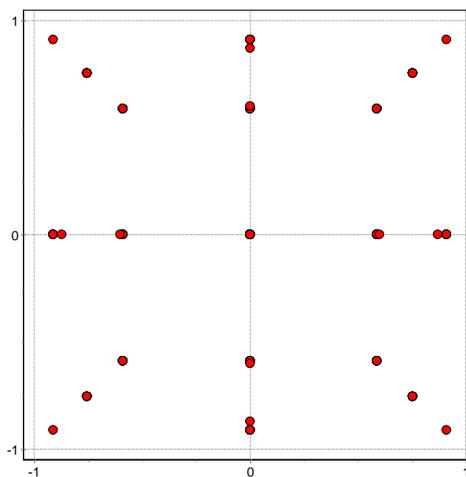


Figure 5: Orthogonal 89-point experimental design for 4 factors

Table 1 shows the estimated parameters, determination errors and best choice of frequency set for identification of each parameter (sample No. 19):

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	Value	2*STD	95%
E_x		x	x	x	x	x				x			22.8GPa	3.5%	± 0.8
E_y		x	x	x	x		x			x			19.8GPa	3.4%	± 0.6
G_{xy}	x	x			x	x	x			x			3.16GPa	3.9%	± 0.1
ν		x	x		x	x	x			x			0.13	15%	± 0.02

Table 1: Optimal choice of frequencies for parameter identification

Table 2 shows the determined values of elastic parameters before and after the climate cycle experiment for four experimental samples (No 9, 11, 17, 19). The values in the table are mean values from parameters, identified from 3 specimens of each sample number.

Property	Before climate cycle simulation				After climate cycle simulation							
	9	11	17	19	9	$\Delta, \%$	11	$\Delta, \%$	17	$\Delta, \%$	19	$\Delta, \%$
E_x , [GPa]	20.7	20.9	19.9	22.8	20.8	-0.48	20.5	1.91	19.8	0.50	22.4	1.75
E_y , [GPa]	18.2	19.9	18.0	19.8	18.1	0.55	19.5	2.01	17.5	2.78	19.5	1.52
G_{xy} , [GPa]	3.3	3.4	2.9	3.2	3.1	6.06	3.3	2.94	2.6	10.3	3.3	-3.12
ν	0.13	0.11	0.07	0.13	0.22	-69.2	0.14	-27.3	0.10	-42.9	0.14	-7.69

Table 2: Influence of climate cycle on the elastic parameters of GF/PP composite.

The authors of [7] doubt the possibility to determine the Poisson's ratio using only out-of-plane bending modes. As can be seen here, the accuracy of determination of Poisson's ratio is about 15%, when the bending eigenfrequencies have a variation of about 1%.

5 CONCLUSIONS

- The presented uncertainty analysis algorithm estimates the uncertainty of the identified elastic parameters from the uncertainties of the experimentally measured quantities and uncertainties of geometrical and physical parameters of experimental specimens. This method allows to estimate confidence intervals of determined parameters with a given confidence level.
- The method gives the possibility of optimal choice of natural frequency set and weighting coefficients obtaining the best identification accuracy for each identifiable parameter separately.
- The accuracy of elastic moduli identification was about 3%, Poisson's ratio – about 14% for 95% confidence level.
- After 10 climate cycles the mean identified values of Young's moduli and shear moduli of knitted GF/PP textile composite decreased by about 2%-5%, but the values of Poisson's ratio increased by about 25%.

ACKNOWLEDGEMENTS

This study has received support from the European Commission through the large-scale integrating collaborative project MAPICC 3D - number 263159-1 - and entitled: One-shot Manufacturing on large scale of 3D up graded panels and stiffeners for lightweight thermoplastic textile composite structures.

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