Journal of Materials and Engineering Structures

Research Paper

Experimental sensitivity analysis of sensor placement based on virtual springs and damage quantification in CFRP composite

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A R T I C L E I N F O

Article history :

Received : 22 March 2022

Revised : 5 june 2022

Accepted : 12 june 2022

Keywords:

Experimental modal analysis

Model updating

Inverse problem

TLBO and FEA.

A B S T R A C T

This paper suggests a method for vibration sensor placement in Carbon Fibre Reinforced Polymer (CFRP) composite structures in small structure applications where the measuring instrument weight can affect the vibrational characteristics. Considering the actual weight of the beam and the actual weight of the vibrational sensor and connecting cables. We performed a set of structural vibration experiments in various sensor positions and used the experimental results as a reference through the inverse problems technique. And Finite Element Analysis (FEA) for numerical modelling, in which the sensors are modelled as an additional mass on the beam and the virtual springs are modelled with variable rigidity. We employ the Teaching-Learning-Based Optimization Algorithm (TLBO) to identify the optimal sensor placement location. The results indicate that this application can explain the effect of sensor placement. In a second application, we consider the problem of the cracked beam and the prediction of damage severity and crack depth with the help of a formulation for crack location. Results of this Application show that the proposed approach can serve in solving both problems.

1 Introduction

Composite materials have become critical in modern engineering applications, such as aerospace, marine and civil engineering. Where in many cases, structural Health Monitoring (SHM) is required as part of the maintenance procedure. And because the vibrational behaviour of composites is complex. The vibration sensor placement can play a decisive role in the quality of data collected during vibration-based civil structure health monitoring. However, more sensors generally translate to better understanding, but there are usually only a limited number of positions where the sensors can be placed

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e-ISSN: 2170-127X,

RESEARCH REVIEW of Sciences and Technologies

due to structural design constraints. The quality of vibration measurements depends mainly on the placement of sensors. Thus, the quality of damage prediction can be impacted. Hence, optimal sensor placement (OSP) is an essential constituent in the SHM of composite structures.

Gomes and Cunha [1] considered the Genetic Algorithm for optimal sensor placement, evaluating techniques and objective functions in a laminated CFRP plate, and observed that the final result of sensors location does not necessarily correspond to vibration peaks. In damage detection studies, Vanli et al. [2] presented a sensor placement method for composite plates, considering two numerical examples and one experimental study. Ručevskis et al. [3] evaluated sensor placement in a composite plate using machine learning techniques and visualization in order to reduce the number of strain sensors and mode shape used for damage detection and structural health monitoring. An et al. [4] considered the uncertainties in material properties, layer thicknesses, and ply orientation angles in their sensors optimization approach, for the goal of efficient damage detection in laminated composite structures.

Ostachowicz [5] presented a review of optimal sensor placement approaches. Optimization techniques have been widely employed in large-scale structures due to their computational efficiency for solving OSP problems. For the structures with low complexity shapes, the optimal placement of the sensors can be calculated directly by the constrained deterministic optimization methods such as the recursive quadratic programming method since their mode shapes and frequencies can be accurately described using the analytical expression. Moreover, some unconstrained methods, such as Newton and constrained deterministic optimization methods, can be used for SHM. These gradient descent optimization techniques are used to solve local and constrained search problems.

Metaheuristic optimization algorithms have been used efficiently in the field of structural health monitoring, Sunar and Rao [6] studied the problem for the cantilever beam-like structures well by using the quasistatic equations. And Khatir et al. [7] solved the problem of delamination in composite beam structure was detected using a virtual crack closure technique (VCCT) and modal flexibility based on dynamic analysis. Tiachacht et al. [8, 9] presented different optimization techniques in identification and used improved damage indicators for complex structures. The continuous optimisation techniques' advantages are more mature than other methods, but these techniques need to use the gradient of the objective function. Thus, they are easy to fall into local optimum. Metaheuristic optimization algorithms have gained a strong interest in the last decade due to their high ability to overcome local optima [10, 11]. Structural health monitoring researchers use these algorithms to solve complex and large-scale problems.

We presented multiple damage detection and localization techniques in structures using static and dynamic data in the literature [12-21]. Both in homogeneous and composite materials SHM studies, metaheuristics served in inverse problem studies of cracks identification, such as the Cuckoo Search (CS) algorithm, in the case of carbon fibre reinforced polymer (CFRP) [22]. Ayawardhana et al. in [23] presented an experimental analysis based on wireless sensor networks for damage identification. The relatively New optimization algorithm of moth-flame was shown to be effective for structural damage detection based on MAC flexibility and frequency [24]. Ghannadi and Kourehli [25] investigated the accuracy of different FEM reduction techniques in complex structures.

Sepulveda et al. [26] presented a control-augmented structural synthesis methodology in which the actuator and sensor placement are treated in terms of (0, 1) variables. Combining approximation concepts with the branch and bound techniques allows tracking the mixed (0, 1) continuous variable design optimization problem. Benaissa et al. proposed an approach for crack identification, where the sensor placement in complex structures is optimized using Particle Swarm Optimization [27, 28]. Yi et al. proposed a hybrid optimization algorithm called the niching monkey algorithm (NMA) for the optimal selection of sensor location on large-scale structures [29].

Dinh-Cong et al. proposed a model order reduction technique for OSP and found the Jaya algorithm to be an efficient optimization tool for solving both discrete and continuous optimization problems [30, 31]. Zhang et al. proposed an improved particle swarm optimization (IPSO) algorithm to determine the optimal sensor number and locations [32]. Zhou et al. compared the performances of the Genetic Algorithm (GA) and the Firefly Algorithm (FA) for sensor placement in structural health monitoring of a large bridge structure [33]. Sun et al. studied the OPS in large building structures using the Artificial bee colony (ABC) algorithm [34]. And Generalized Genetic Algorithms (GGA) [35] have been applied to the OSP problems.

Khatir et al [36, 37] presented improved damage indicator for Structural Health Monitoring (SHM) in complex structures. The objective to eliminate the healthy elements. Next, the improved indicators were used for the quantification as an inverse problem using a recent optimization techniques. A crack identification in steel beam structures was presented by Khatir et al

[38] based on inverse analysis. Crack identification based on static and dynamic analysis in steel plate using improved GWO was presented in Ref [11]. Crack identification in plate structures using inverse problem, model reduction, and ANN were presented in Refs [39-41].

This paper is structured as follows. The first section is devoted to a literature review about Optimal Sensor Placement and damaged composite structures. The description of Teaching–Learning-based optimization (TLBO) is presented in section 2. In section 3, we present an experimental set-up and position of sensors in the CFRP beam. Damage quantification is provided in section 4.

2 Implementation of TLBO for sensors placement

The main task of the presented damage identification approach is solving the optimization problem with an objective function based on the dynamic parameters of the structure. The solution to the inverse optimization problem is performed by applying different optimization techniques.

2.1 Teaching–learning-based optimization (TLBO)

The Teaching–learning-based optimization (TLBO) algorithm is well established in the literature as an efficient meta-heuristic algorithm. It was proposed by Rao et al. [42]. And its idea is to divide the search strategy into two phases, first the '*Teacher phase*' then the '*Learner phase*'. This search strategy is explained bellow.

2.1.1 Teacher phase

In the first phase, the teaching, we consider learners the individual search agents, aslo expressed as potential solutions. At any iteration i, we suppose that there are 'm' subjects, 'n' learners (population size) where $M_{j,i}$ is the mean result of the learners in a particular subject 'j' $\left(j=1,2,\ldots,m\right)$. The population is represented by the following matrix:

$$\text{Population}=\begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,n} \end{bmatrix} \quad \begin{pmatrix} n:\text{Nb of element} \\ i:\text{Nb of Generation} \end{pmatrix} \tag{1}$$

The best solution $X_{j,kbest,i}$ is the best solution compared to all the individual solutions obtained from all populations. It is considered the best learner k_{best}. The difference between the existing mean and the solution corresponding to the teacher for each subject is expressed:

$$Difference\_Mean_{j,k,i}=r_{j,i}\left(X_{j,kbest,i}-T_F M_{j,i}\right) \tag{2}$$

where, $X_{j,kbest,i}$ is the result of the best learner in subject j. r_i is a random number in the range $\left[0,1\right]$, and T_F is the teaching factor. The Value of T_F is set randomly either 1 or 2 using the following equation:

$$T_F=round\left[1+rand\left(0,1\right)\left\{2-1\right\}\right] \tag{3}$$

The algorithm randomly decides the T_F within equal probability. And the existing solution is updated in the teacher phase based on the $Difference\_Mean_{j,k,i}$, according to the following expression.

$$X'_{j,k,i}=X_{j,k,i}+Difference\_Mean_{j,k,i} \tag{4}$$

where, $X^{'}_{j,k,i}$ is the updated value of $X_{j,k,i}$. $X^{'}_{j,k,i}$ is accepted if it gives better function value.

2.1.2 Learner phase

In the second part, the learners increase their knowledge by interacting among themselves, and then the learner interacts randomly with other learners to enhance their knowledge. According to the population size of 'n', randomly select two learners P and Q as:

$$X^{'}_{total-P,i} \neq X^{'}_{total-Q,i} \tag{5}$$

where, $X^{'}_{total-P,i}$ and $X^{'}_{total-Q,i}$ are the updated function values of $X_{total-P,i}$ and $X_{total-Q,i}$ of P and Q, respectively.

$$\begin{cases} X^{"}_{j,P,i} = X^{'}_{j,P,i} + r_i\left(X^{'}_{j,P,i} - X^{'}_{j,Q,i}\right) & if\ X^{'}_{total-P,i} < X^{'}_{total-Q,i} \\ X^{"}_{j,P,i} = X^{'}_{j,P,i} + r_i\left(X^{'}_{j,Q,i} - X^{'}_{j,P,i}\right) & f\ X^{'}_{total-Q,i} < X^{'}_{total-P,i} \end{cases} \tag{6}$$

The implementation rules of the TLBO for damage identification are summarized as follows:

1. **Rule 1**: Ser the initial search parameters:
   - The size of the search population size (the number of individuals in each iteration)
   - The maximum number of iterations
   - Number of parameters
   - Search space (The constraints of the design variables)
1. **Rule 2**: In each Iteration, select the best learner.
2. **Rule 3**: Evaluate Equation 2. The difference between the mean of the current solutions and best solution.
3. **Rule 4**: Update the learners and the teacher based on the current evaluation.
4. **Rule 5**: Update the learners according to Eq. (6) (in our case, updated the damaged elements for each iteration).
5. **Rule 6**: Repeat steps 2 to 5 until the maximum number of iterations is reached.

3 Application

An M+P International Analyzer of 9234 acquisition card, Hammer PCB 086C03, PCB Accelerometers 356A15 were used see Figure 1. The frequency of the first three modes for each position of the sensor are measured after the average of 8 positions of the strike. The mass of the accelerometer used is 14 grams, including the cable connector. The mechanical and geometrical properties are presented in Table 1. The frequencies of each scenario are presented in Table 2.

Table 2. Mechanical and geometrical properties of CFRP beam

Properties	Mean value
Length (mm)	360
Width (mm)	38.6
Thickness (mm)	1.47
Young Modulus	93850
Density (Ns^2/mm^4)	1.95e-10
Poisson's ratio	0.3
Mass Beam (g)	33
Mass Accelerometers	10

Fig 1 – Experimental set-up for vibration CFRP beam

Table 2 – Frequencies measured with different sensor positions.

		Mode $[Hz]$		
		1	2	3
Position 1	= 40 mm	112.50	267.50	481.88
Position 2	= 80 mm	102.19	249.38	518.13
Position 3	= 120 mm	90.625	265.94	570.83
Position 4	= 160 mm	85.62	295.00	512.81
Position 5	= 200 mm	85.62	288.13	525.00
Position 6	= 240 mm	92.50	255.00	564.06
Position 7	= 280 mm	105.63	254.06	506.25
Position 8	= 320 mm	112.50	280.00	503.75

To solve the model updating issue, we identify the best sensor position using the inverse problem approach. We added virtual springs into FEA beam and simulated the presence of the sensor by additional mass at the position of accelerometers. The details can be presented in Figure 2.

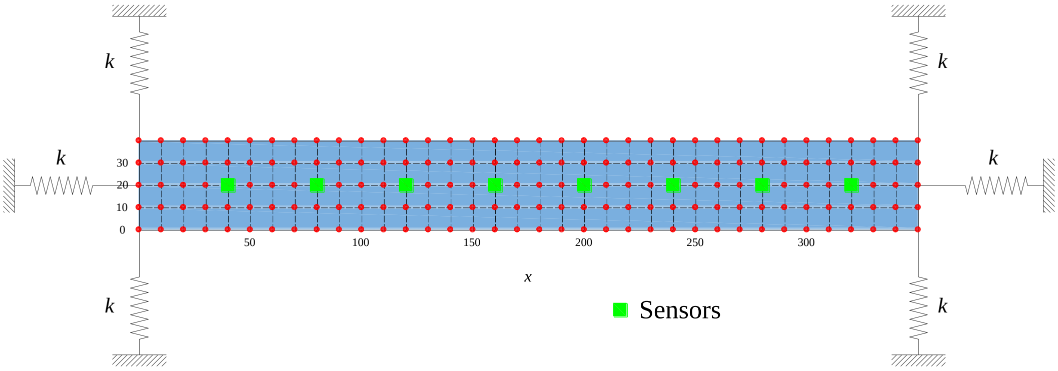

Fig. 2 – FE model and sensors position with virtual spring

We consider the rigidity of each spring as a design variable and consider the TLBO algorithm to identify them. Using the frequencies in the objective function that compares the experimental and calculated frequencies by FEA. The results of each position of the sensor are presented in Figures 3-10. Showing the vibrational frequency, the photo of the set-up, the optimization algorithm convergence curve, and lastly, the bar graph that compares the Mode results of the experimental and simulation.

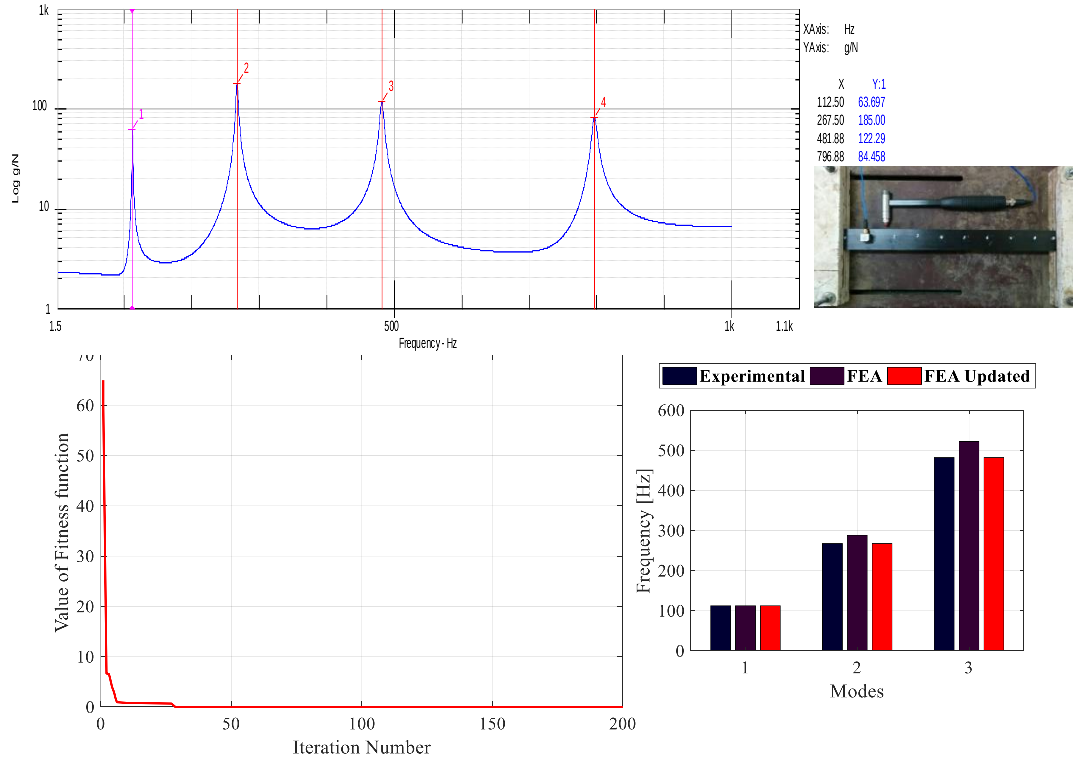

Fig. 3 – Model updating for Position 1 = 40 mm

Figure 3 shows the FRF of the first position of accelerometer, convergence study of model updating, and frequency after calibration.

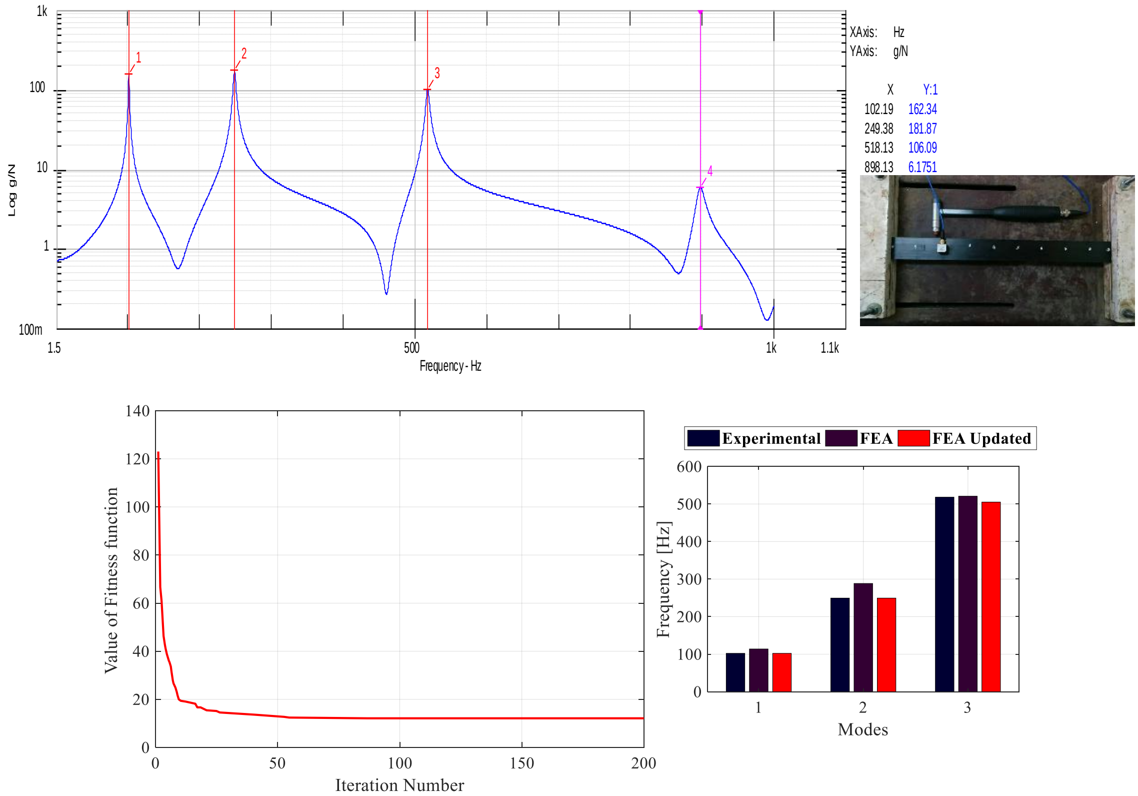

Fig. 4 – Model updating for Position 2 = 80 mm

Figure 4 shows the FRF of the second position of accelerometer, convergence study of model updating, and frequency after calibration.

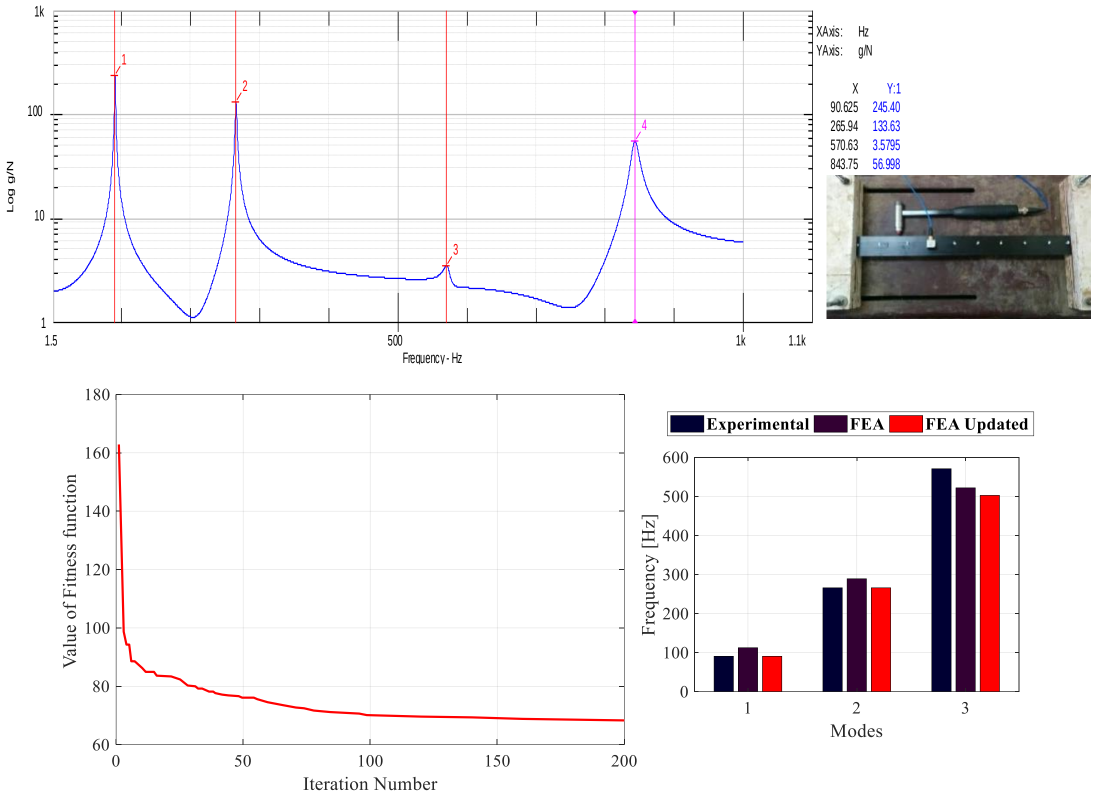

Fig. 5 – Model updating for Position 3 = 120 mm

Figure 5 shows the FRF of the third position of accelerometer, convergence study of model updating, and frequency after calibration.

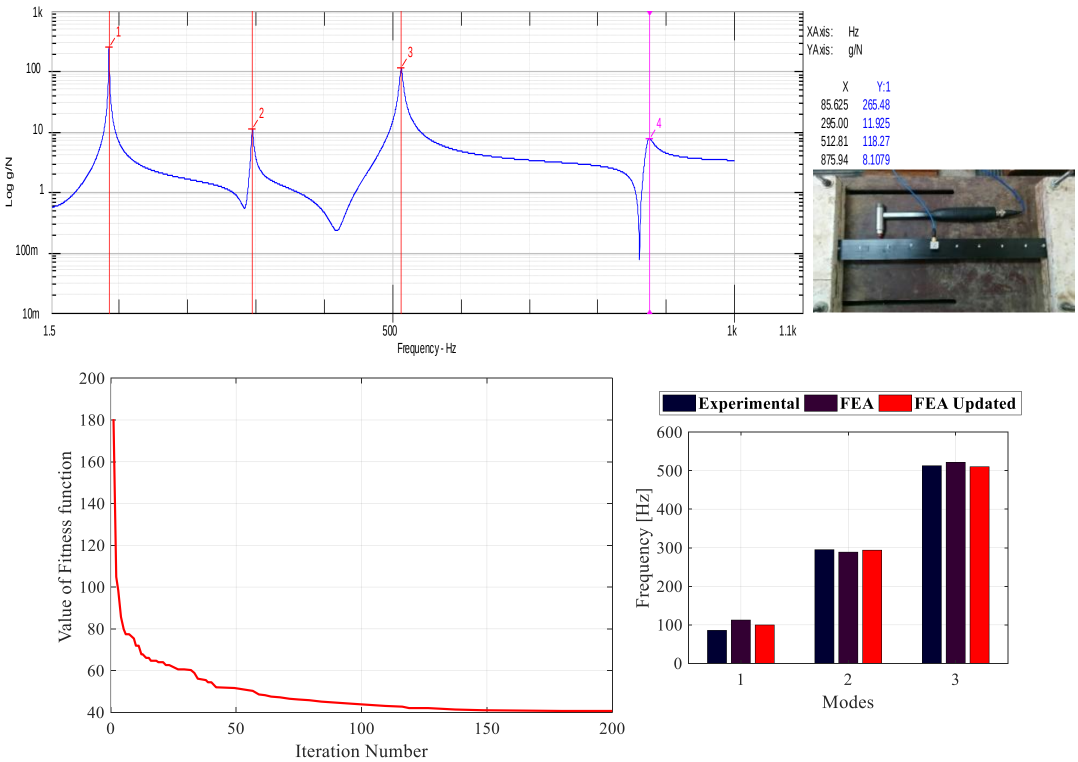

Fig. 6 – Model updating for Position 4 = 160 mm

Figure 6 shows the FRF of the fourth position of accelerometer, convergence study of model updating, and frequency after calibration.

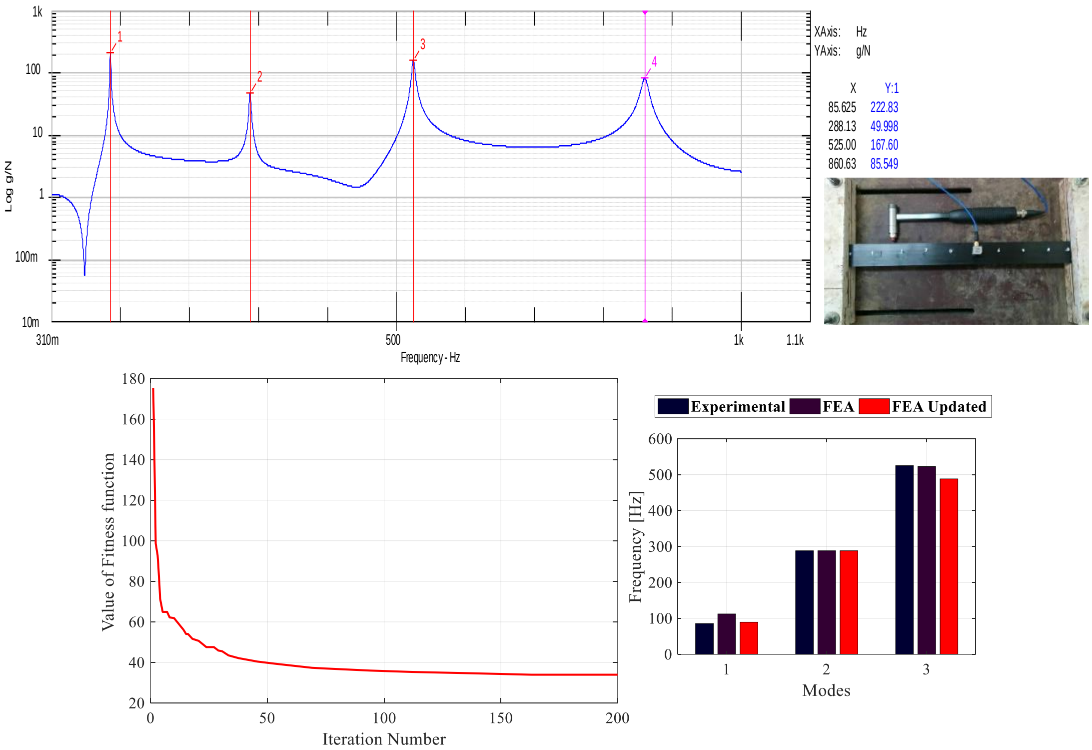

Fig. 7 – Model updating for Position 5= 200 mm

Figure 7 shows the FRF of the fifth position of accelerometer, convergence study of model updating, and frequency after calibration.

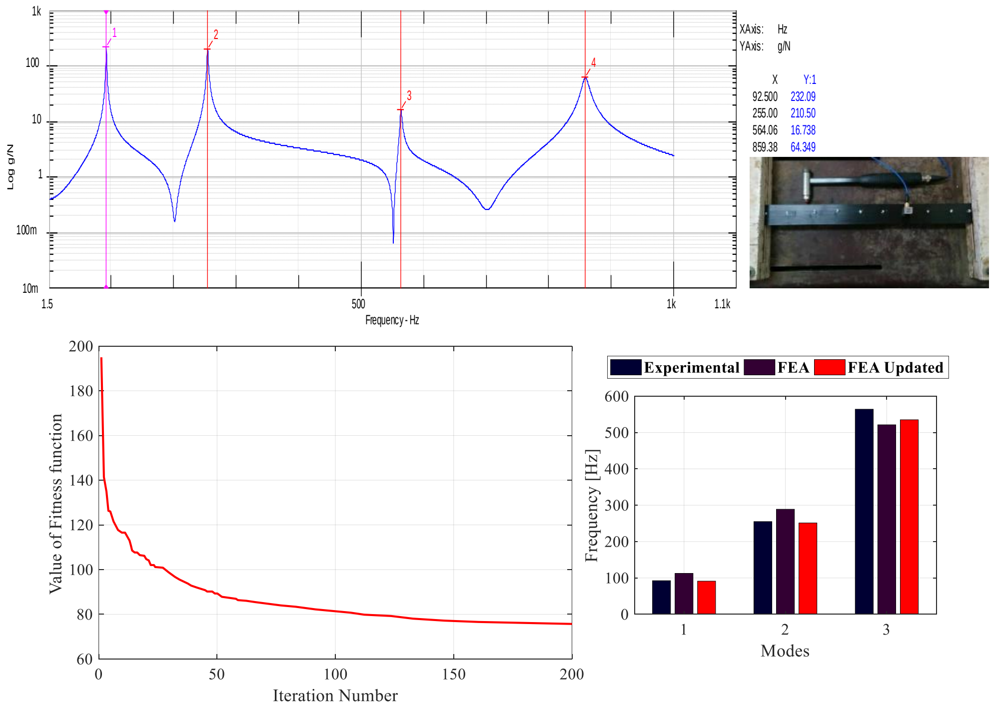

Fig. 8 – Model updating for Position 6 = 240 mm

Figure 8 shows the FRF of the sixth position of accelerometer, convergence study of model updating, and frequency after calibration.

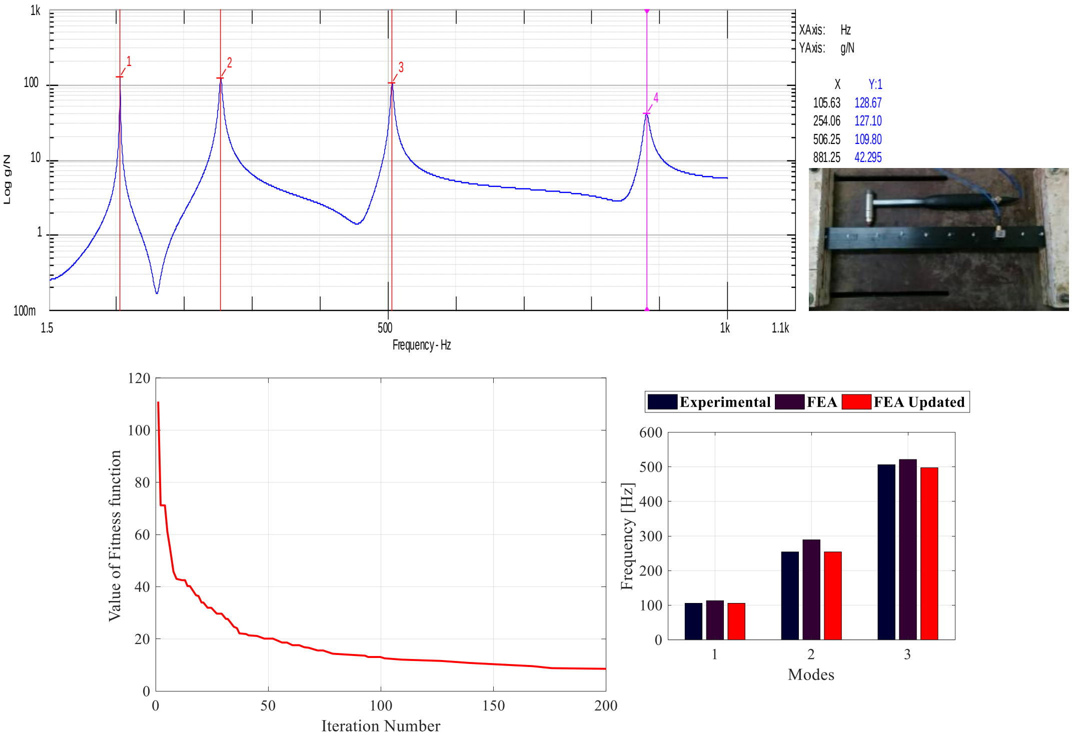

Fig. 9 – Model updating for Position 7 = 280 mm

Figure 9 shows the FRF of the seventh position of accelerometer, convergence study of model updating, and frequency after calibration.

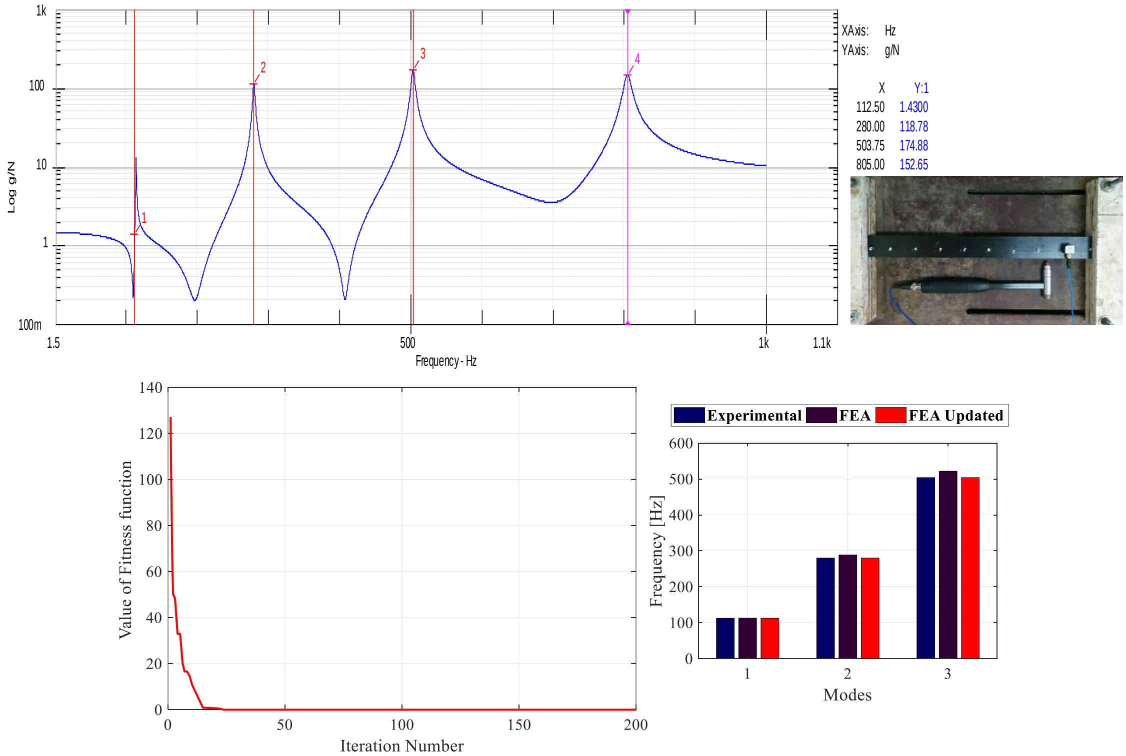

Fig. 10 – Model updating for Position 8 = 320 mm

Figure 10 shows the FRF of the eighth position of accelerometer, convergence study of model updating, and frequency after calibration.

Through the moving of the sensor left to right with a step of 40 mm we can see that the best position calculated by TLBO is 40 and 320 mm according to the first three frequencies measured by experimental and FEM. For the other positions, we can see the identical frequencies between experimental and numerical only for the two modes. For the convergence of best positions 40 and 320 mm we can see that the best convergence was found by the 320 positions only after 22 iterations.

We observe that the updated FEA has better accuracy in most cases compared to the conventional FEA, although the measured frequencies are different in each position. The updated FEA predicted the actual frequency in all modes 1,2 and 3. Within the high accuracy standard. The 3ed mode constituted the most challenge for both FEA and updated FEA. As the prediction error tends to be higher than the first two modes. There is only one case where the prediction frequency by FEA was more accurate than the updated FEA, it is where the sensor was positioned at point 3 (Figure 5). Particularly at mode 3. We also notice that the Log G/N value in the third mode is considerably lower than in the other modes.

From the optimization perspective, we observe that some points correspond to a more challenging objective function friend than the others. For example, the optimum is reached very early when the sensor is positioned at points 1, 2 and 10 (Figures 3, 4 and 12, respectively). However, it requires much more iterations to reach it when the sensor is positioned at points 3,6 and 7 (Figures 5, 8 and 9, respectively). This is due to the different sensitivities between the variables and the objective function results.

We Also notice that the frequencies tend to go higher for the 3ed mode, when changing the sensor position from 1 position 1 to position 3 (Figures 3 to 5), then stabilize around 500 Hz after that, except for the case where the sensor is positioned at point 6 (Figure 8). But for the mode 1 and 2. We observe that there is consistency in frequency in all cases. This may indicate that the third mode vibration is less stable relative to the senor position, which may explain the reason why the FEA and updated FEA prediction error is higher in the 3ed mode. Relative to the first two modes.

4 Optimization-based damage detection problem

In the optimization-based damage detection problem, the damage detection process is the iterative search for the optimum parameters that correspond to the minimum of an objective function, generally based on the frequencies measured by experimental and calculated by the search algorithm. In our study, this is expressed by the following function:

$$\Pi = \frac{\left| f_{\exp} - f_{FEA}^{d} \right|}{f_{\exp}} \tag{7}$$

The crack location is presented in the position 260 mm with a depth of 1.16 mm, which is presented by the elements 27,63,99 and 135 see Figure 11. And the damage qualification results are shown in Figure 12. These results show that the quantification of damage elements 27,63,99 and 135 is 65%. The TLBO can quantify the damage after 32 iterations.

After introducing the crack, the frequencies in all modes are lower than the sain beam (Figures 11). However, the inverse approach based on updated FEA prediction was able to predict the damage parameters correctly. The optimization algorithm in this case could reach the optimum parameres within 50 iterations. The further application considers the problem of crack depth, using the computed loss of rigidity, based on the following formulation:

$$EI(x) = \frac{EI_0}{1 + C.\exp\left(-2\alpha \frac{\left|x - x_j\right|}{d}\right)} \tag{8}$$

where $C = \left(I_0 - I_{cj}\right) / I_{cj}$, $I_0 = wd^3/12$ and $I_{cj} = w\left(d - d_{cj}\right)^3 / 12$ are the second moment of areas of the undamaged beam and at the jth crack. w and d are the width and depth of the undamaged beam, and d_{cj} is the crack depth. x is the position along the beam and x_j the position of the crack. α is a constant that Christides and Barr estimated from experiments to be 0.667.

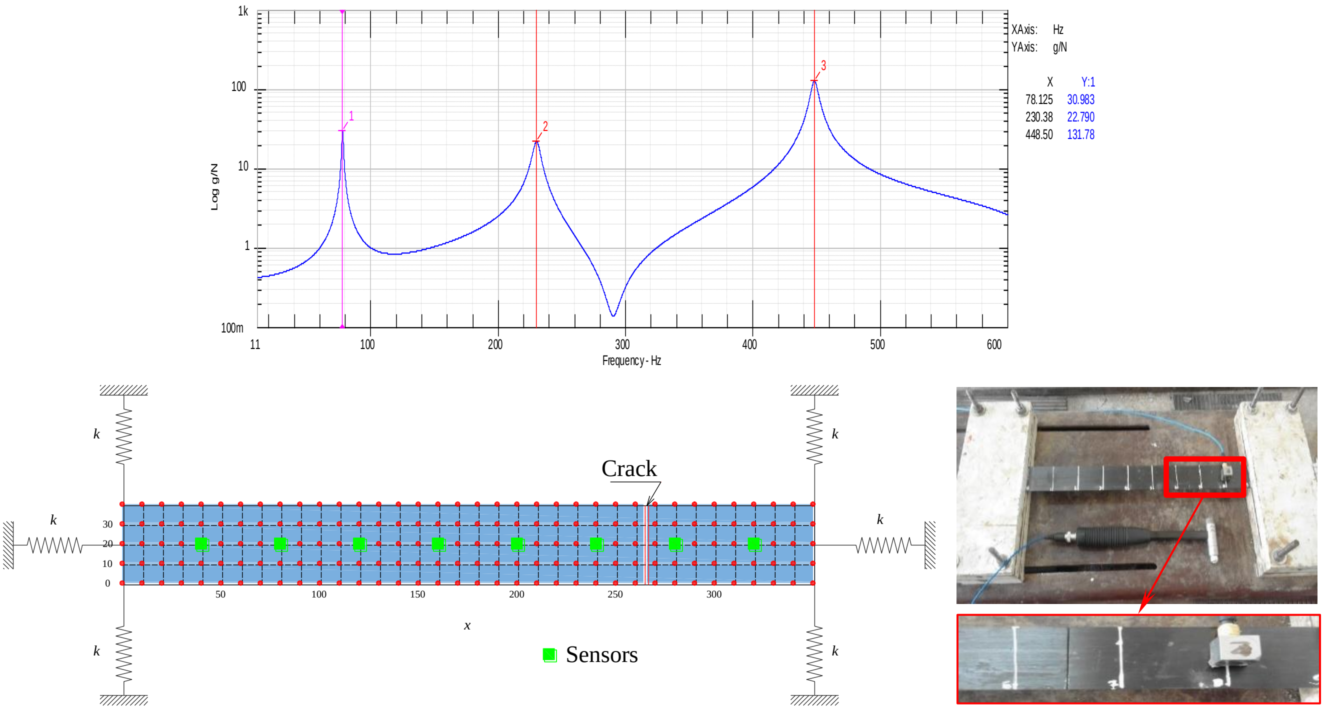

Fig. 11 – Experimental and FE damaged beam

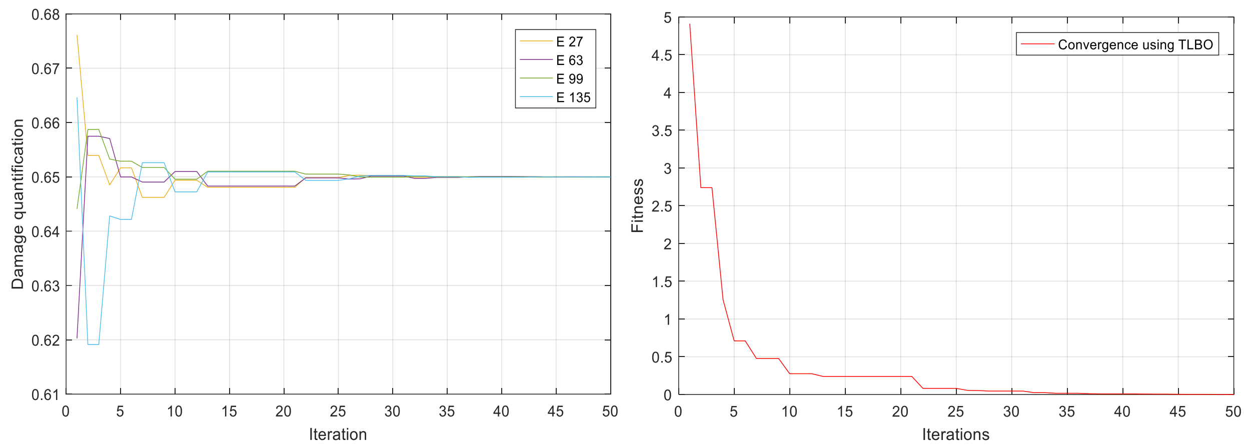

Fig 12 – Damage quantification using TLBO

Christides and Barr [43] considered the effect of a crack in a continuous beam and calculated the stiffness, EI, for a rectangular beam to involve an exponential function given by Sinha et al [44]. The inclusion of the stiffness reduction of Christides and Barr [43] in an FE model of a structure is complicated because the flexibility is not local to one or two elements, and thus the integration required to produce the stiffness matrix for the beam would have to be performed numerically every time the crack position changed.

$d_{cj} \approx 1.2\ mm$ and $d_{cj}^{Exp} = 1.17\ mm$

Based on the provided results, the proposed application has the ability to improve the quantification based on crack depth using equations 7 and 8.

5 Conclusion

The article proposes an approach for sensor placement based on a metaheuristic algorithm, namely the Teaching-Learning Based Optimizer. In the first stage, we studied the calibration by considering the simulation of the composite beam.

Next, damage identification in CFRP composite structures is considered using the inverse problem approach. The optimal sensor placement strategy is first studied based on the FEM model with virtual springs and additional mass. The optimal results are then used for damage identification based on the frequencies. And lastly, the problem of crack depth is considered also using the optimal sensor placement results. The investigated results show the suggested method can solve the problem of optimal sensor placement in structures of low weight, where the vibrational sensor and cable set-up can affect the modal analysis results. Therefore, the study could be extended to more complex structural systems such as small three dimensional composite frames and trusses, the type of structures that makes microsatellites.

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