applied sciences

MDPI

Article

Finite Element Model Updating for Composite Plate Structures Using Particle Swarm Optimization Algorithm

Minh Q. Tran [1], Hélder S. Sousa [1], José Matos [1], Sérgio Fernandes [1], Quyen T. Nguyen [2] and Son N. Dang [1,*]

[1] Department of Civil Engineering, ARISE, ISISE, University of Minho, 4800-058 Guimarães, Portugal
[2] 2C2T-Centro de Ciência e Tecnologia Têxtil, Universidade do Minho, 4800-058 Guimarães, Portugal
* Correspondence: sondn@civil.uminho.pt

Abstract: In the Architecture, Engineering, and Construction (AEC) industry, particularly civil engineering, the Finite Element Method (FEM) is a widely applied method for computational designs. In this regard, computational simulation has increasingly become challenging due to uncertain parameters, significantly affecting structural analysis and evaluation results, especially for composite and complex structures. Therefore, determining the exact computational parameters is crucial since the structures involve many components with different material properties, even removing some additional components affects the calculation results. This study presents a solution to increase the accuracy of the finite element (FE) model using a swarm intelligence-based approach called the particle swarm optimization (PSO) algorithm. The FE model is created based on the structure's easily observable characteristics, in which uncertainty parameters are assumed empirically and will be updated via PSO using dynamic experimental results. The results show that the finite element model achieves high accuracy, significantly improved after updating (shown by the evaluation parameters presented in the article). In this way, a precise and reliable model can be applied to reliability analysis and structural design optimization tasks. During this research project, the FE model considering the PSO algorithm was integrated into an actual bridge's structural health monitoring (SHM) system, which was the premise for creating the initial digital twin model for the advanced digital twinning technology.

Keywords: bridges; FEM; model updating; particle swarm optimization; uncertain parameters

Citation: Tran, M.Q.; Sousa, H.S.; Matos, J.; Fernandes, S.; Nguyen, Q.T.; Dang, S.N. Finite Element Model Updating for Composite Plate Structures Using Particle Swarm Optimization Algorithm. *Appl. Sci.* **2023**, *13*, 7719. https://doi.org/10.3390/app13137719

Academic Editor: Ana M. Camacho

Received: 28 May 2023
Revised: 21 June 2023
Accepted: 28 June 2023
Published: 29 June 2023

1. Introduction

Computational models or numerical models play a very important role in today's sciences. In the AEC industry, it is an effective tool for continuous structural monitoring, damage detection, life estimation, and determination of optimal servicing and maintenance strategies. New and advanced numerical modeling methods are increasingly being developed. However, the generated numerical models need to be strictly adhered to in terms of accuracy and reliability in analysis results. Therefore, the errors and uncertainties associated with model assumptions often lead to inaccuracies and uncertainties that must be quantified. This has led to the development of model update methods that aim to calibrate the numerical model. These methods are based on the actual behavior of the structure as determined through static and/or dynamic testing of the structure.

Finite element (FE) models are typically used in numerical modeling for various types of structures. An FE model simulates structural behavior, primarily based on easily surveyable parameters such as geometrical features or structural diagrams. When dealing with complex structures, minimizing the model to speed up computation and save resources is necessary. In this regard, various assumptions based on analyst views are included for simplification. Nevertheless, the model might have many uncertain parameters (material properties, section profiles, boundary conditions, and others). Consequently, the FE models will result in an approximate output, which means those FE models are helpful only when no high accuracy is required and cannot perform any further intensive work. For in-depth analysis such as structural health monitoring, design optimization, or reliability analysis, the initial FE model should have more attention paid to modeling optimization and accuracy improvements. In practice, the error between the actual structure and FE models can be reduced but never eliminated. Current efforts focus on minimizing the errors as much as possible. Updating the model improves accuracy and gives actual structure-like responses.

Several current studies have used the static behavior of the structure to update the FE model. For example, updating the beam model using random parameters under static stress [1], updating inaccurate parameters relying on the deformation of structures under static loads [2,3], and updating the FE model for the highway bridge by combining dynamic–static long-gauge strain responses [4]. In addition, some advanced FE models were proposed to deal with particular types of composite structures [5–7]. However, these solutions are currently laborious and costly, and there are too many uncertain factors, such as loads acting on the structure, measurement methods, or challenges in collecting data.

Recently, vibration identification or continuous data collection methods have been significantly developed with high accuracy [8,9]. They overcome some of the disadvantages of the static method. Based on the structure's dynamic properties, such as natural frequency, mode shapes, or modal damping ratio, a numerical model can be created which is very close to the behavior of the actual object and serves many different purposes. In this regard, several other researchers have succeeded in the implementation of FE methods. Lessons learned can be referred to for updating the FE model from in situ dynamic displacement measurement [10]; updating the cantilever bridge model manually, the frequencies should first be identified and selected as the objective function to update the model [11]; using the modal properties analyzed from the simple concrete bridge to update the model [12]. Moreover, dynamic characteristics can be used to update the FE model for different structure types [13–15]. These methods are often time-consuming to test the parameters and consume many computer resources gradually. Nevertheless, their accuracy is still not as good, requiring an optimization method to improve the technical goals. Additionally, the updated structure is mostly those simulated by a fixed material without the participation of composites.

Based on input parameters from experiments (can be static or dynamic behavior of the structure), various model update solutions have been researched and developed. The solution commonly used in structural model updates is to change the uncertainty parameters so that the analysis results are similar to the experimental results. These methods rely on trial and error in the selection of structural parameters such as geometry, material properties, and boundary conditions. With a small number of parameters for simple, less detailed structures, updating the model is quite simple. However, the usual solutions are relatively tricky when the number of parameters increases. Many researchers have started using optimization algorithms to solve this problem. They allow searching for results in a large space, while ensuring resource savings for the execution environment.

Optimizing algorithms with the FE methods also aids the engineers in fast calculation and improvement of the FE modeling, achieving the highest accuracy. For example, an optimization algorithm was used to update the FE model of the bridge structures based on sensitivity analysis [16]; an approach was proposed to update the model by combining simulated annealing and genetic algorithms (GA) [17]; the response surface method and GA were used to update a model for a simple concrete bridge [18]; and GA was also applied for updating the Canonica Bridge FE model [19]. Furthermore, various research has proposed and applied the optimization of algorithms to improve the used cuckoo search algorithm in the search mechanism of FE model parameters [20–24]. It is worth saying that optimization algorithms are a powerful mathematical tool for solving technical problems, especially in the engineering fields. They are practical and widely applicable in updating the FE model.

Optimization algorithms fall into three main categories: heuristic search methods, mathematical methods, and metaheuristic methods. In particular, the metaheuristic method is a random search method that simulates the biological evolution in nature or the social behavior of species. This method is considered to have more advantages than the other two methods. The most commonly used algorithms are genetic algorithms (GA), ant colony optimization (ACO) and particle swarm optimization (PSO). The published results [25] show that the PSO algorithm has faster convergence time in large-scale problems, especially in the problem of updating large structural models. The PSO algorithm does not require detailed mathematical description and finds the best possible value by optimizing an objective function. This helps to perform fast model updates in large structures, saving computational resources while achieving accuracy.

In this research, FE model updating regarding the central part from the core structures of the bridge, a large composite plate, is presented. The composite plate is composed of several materials working together. An initial FE model is created based on uncertain material parameters and boundary conditions. With the data processed by actual vibration measurements, the dynamic characteristics of the composites are determined, including frequency and mode shapes. These properties are the outputs of the FE model. The correlation index between the model and experimental results is minimal using the PSO optimization algorithm combined with the objective function. The results obtain the corresponding parameters of the model after being updated. These properties are needed to correct the model, creating a temporary digital replica of the structure at a specified time. Some other authors also used this approach [26,27], but the structures considered were usually simple and made of a single material, not composite materials.

This paper consists of four main parts: introduction, research methods and approaches, case study, and conclusion. After the introduction, the approach of the model update method is presented. Then, a specific case study on the real structure is performed. Finally, some conclusions were formulated during the implementation. The main contributions of this paper are (i) providing a general theory and structural model update solution; (ii) presenting solutions for collecting and processing vibration data in large structures; (iii) presenting the steps to update the model by combining the vibration measurement results with the optimization algorithm; and (iv) proving the effectiveness of the optimization algorithm (PSO) in model updating.

2. Research Methods and Approach

Considering a finite structure of degrees of freedom, the structure's partial oscillation differential equation has the form [28]

$$\boldsymbol{M}\ddot{u}(t) + \boldsymbol{K}u(t) = 0 \tag{1}$$

Here, $\boldsymbol{M}$—mass matrix of the structure and $\boldsymbol{K}$—stiffness matrix of the structure.

The two equations of oscillation of the masses have the form

$$u_i(t) = A_i \sin(\omega t + \varphi_i) \tag{2}$$

$$\ddot{u}_i(t) = -\omega^2 A_i \sin(\omega t + \varphi_i) \tag{3}$$

Substitute the equations and components into Equation (1):

$$\begin{bmatrix} m_1 & & & \\ & m_2 & & \\ & & \cdots & \\ & & & m_n \end{bmatrix} \left(-\omega^2\right) \begin{bmatrix} A_1 \\ A_2 \\ \cdots \\ A_n \end{bmatrix} + \begin{bmatrix} k_{11} & k_{12} & \cdots & k_{1n} \\ k_{21} & k_{22} & \cdots & k_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ k_{n1} & k_{n2} & \cdots & k_{nn} \end{bmatrix} \begin{bmatrix} A_1 \\ A_2 \\ \cdots \\ A_n \end{bmatrix} = 0 \tag{4}$$

or

$$\left[\begin{bmatrix} k_{11} & k_{12} & \dots & k_{1n} \\ k_{21} & k_{22} & \dots & k_{2n} \\ \dots & \dots & \dots & \dots \\ k_{n1} & k_{n2} & \dots & k_{nn} \end{bmatrix} - \omega^2 \begin{bmatrix} m_1 & & & \\ & m_2 & & \\ & & \dots & \\ & & & m_n \end{bmatrix}\right] \begin{bmatrix} 1 \\ \varphi_2 \\ \dots \\ \varphi_n \end{bmatrix} = 0 \quad (5)$$

Simplify to obtain the equation to determine the specific type of vibration:

$$\left[\boldsymbol{K} - \omega_j^2 \boldsymbol{M}\right] \boldsymbol{\Phi} = 0 \quad (6)$$

The natural frequency ($f = \omega/2\pi$) and natural vibration mode shape (φ_i) determined through Equation (5) or (6) are significant features of the structure and are often used to determine the accuracy of the FEM model. It is easy to see that, for a structure, the dynamic characteristic is unique and is influenced by $\boldsymbol{K}$ (stiffness matrix) and $\boldsymbol{M}$ (mass matrix). However, these two parameters are uncertain parameters due to material properties and boundary conditions. For structures using composite materials, the behavior of materials is simultaneously influenced by many factors. Therefore, finding an exact equivalent to the combination of the constituent materials often has to be determined through experimentation and difficulty. The number of variables in the stiffness and mass matrices is also numerous and complex. To provide an accurate model for other analysis purposes, it is necessary to have a method to calculate and select the best parameters of the model.

The essence of the problem of parameter accuracy uncertainty is choosing a set of numbers as the best solution to the mathematical or simulation problem to be solved. For a variable parameter, the search is fast and can be done manually. However, when the number of solutions is large, this seems impossible because of the significant computation. Although computers can support the calculation, it is time consuming and resource consuming.

The particle swarm optimization (PSO) algorithm was established and developed based on the ideas of swarm intelligence to find solutions for optimization problems in a particular search space [29,30]. To understand the PSO algorithm better, observe a simple example of a flock of birds foraging. The foraging space is now the entire three-dimensional space. At the beginning of the search, the whole flock flies in a specific direction, which can be very random. However, after a while of searching, some individuals in the flock began to find a place that contains food. Depending on the amount of food found, the individual sends a signal to others searching in the vicinity. This signal propagates throughout the population. Based on the information received, each individual will adjust their flight direction and speed in the order of where there is the most food. Such communication is often viewed as a phenotype of herd intelligence. This mechanism helps the whole flock of birds to find out where there is the most food in the vast search space. Figure 1 clearly illustrates the PSO algorithm when used to search for extreme value.

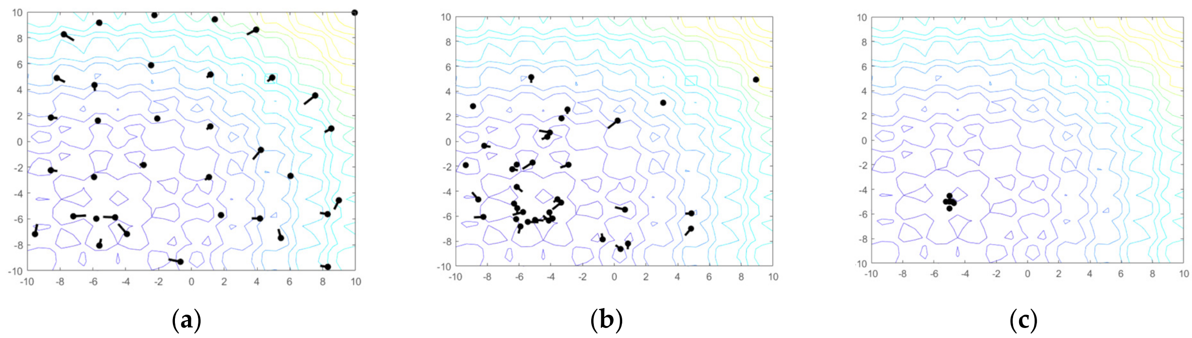

Figure 1. Illustration of the PSO algorithm: (**a**) particles in a swarm; (**b**) particles looking for "food"; and (**c**) food locations found and reported to gather particles.

In swarm optimization, each particle searches a space by itself, remembering the best value and informing others. Other instances will receive the information and decide to continue the search or report its location so that some other cases continue to act. So that values in search space will be found quickly and accurately, two important parameters are the location of an instance and the search velocity. These two parameters are expressed through the formulas for updating the position and updating the velocity of the instance [30]:

$$x^i(t+1) = x^i(t) + v^i(t+1) \tag{7}$$

$$v^i(t+1) = \mathrm{w}v^i + C_1 r_1 (p^i(t) - x^i(t)) + C_2 r_2 (G_{\mathrm{best}} - x^i(t)) \tag{8}$$

where x^i—the position of instance i at different times; v^i—the speed of individual i; w—the parameter of inertial weight; r_1 and r_2 are random values from 0 to 1; each individual has the best position at $p^i(t)$; C_1 and C_2 represent the population's cognitive coefficient; and G_{best}—the best location of the entire population. Each individual is characterized by its velocity vector and position in space.

The goal of structural model updates in FEM is to find values for uncertain variables. These values help the model have a behavior almost equivalent to the real object, which means the difference between numeric model results and experimental measurements is drastically reduced. To evaluate the similarity between the FE model and practical structure, an objective function is built based on the natural frequency and the mode shape of the structure [31]:

$$Fitness = \sum_{k=1}^{n} [1 - MAC(\varphi_k, \widetilde{\varphi}_k)] + \sum_{k=1}^{n} \frac{\omega_k^2}{\widetilde{\omega}_k^2} = \sum_{k=1}^{n} [1 - \frac{(\widetilde{\varphi}_k^T \varphi_k)^2}{(\varphi_k^T \varphi_k)(\varphi_k^T \widetilde{\varphi}_k)}] + \sum_{k=1}^{n} \frac{(\omega_k - \widetilde{\omega}_k)^2}{\widetilde{\omega}_k^2} \tag{9}$$

$$MAC = \frac{\left| \sum\limits_{k=1}^{n} (\widetilde{\varphi}_k)^T \times \varphi_k \right|}{\left\{ \sum\limits_{k=1}^{n} (\widetilde{\varphi}_k)^T \times \varphi_k \right\} \times \left\{ \sum\limits_{k=1}^{n} (\varphi_k)^T \times \varphi_k \right\}} \tag{10}$$

where n—number of modes shape considered; MAC [32]—modal assurance criterion; φ_k, $\widetilde{\varphi}_k$ are mode shapes from the FEM and experiment; ω_k; $\widetilde{\omega}_k$ are frequencies from the FEM and experiment; and T represents the transposed matrix. The PSO algorithm determines the objective function's minimum (convergence), and the implementation diagram is shown in Figure 2 below.

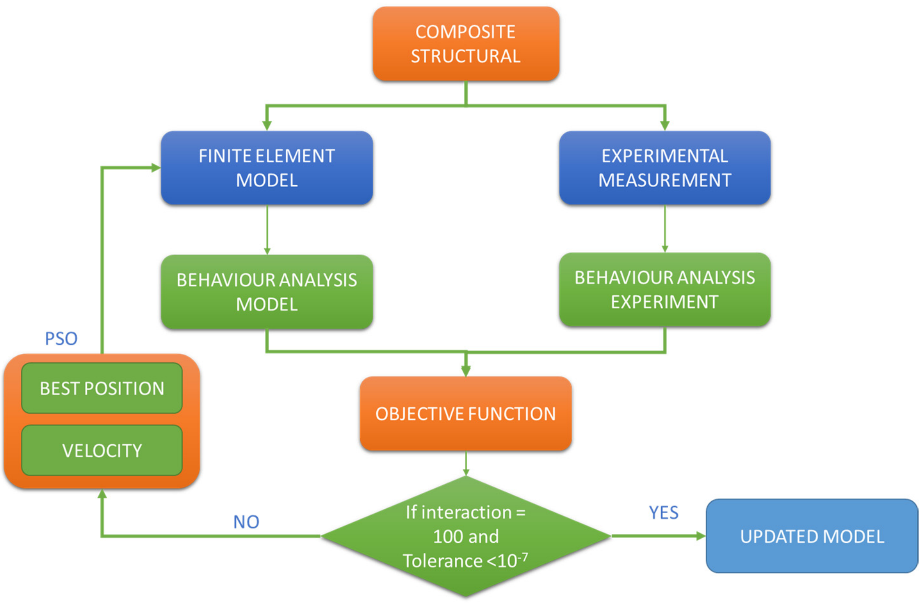

Figure 2. Methodological approach for FE model updating using PSO.

3. Case Study

3.1. Introduction to the Composite Plate Structure

The plate structure is a full-size laboratory model of the cantilever section of Thang Long Bridge—the bridge connecting the two banks of the Red River in Hanoi, Vietnam. The structure consists of 3 main parts: the upper plate structure, the I steel beam structure, and the steel box girder placed on the steel blocks. A cantilever structure is generated by attaching and fixing one plate's end to the wall. Some views and structural details of the plate composite are shown in Figures 3 and 4.

(**a**) (**b**)

Figure 3. Structural plate in the laboratory: (**a**) test setup; (**b**) structural details.

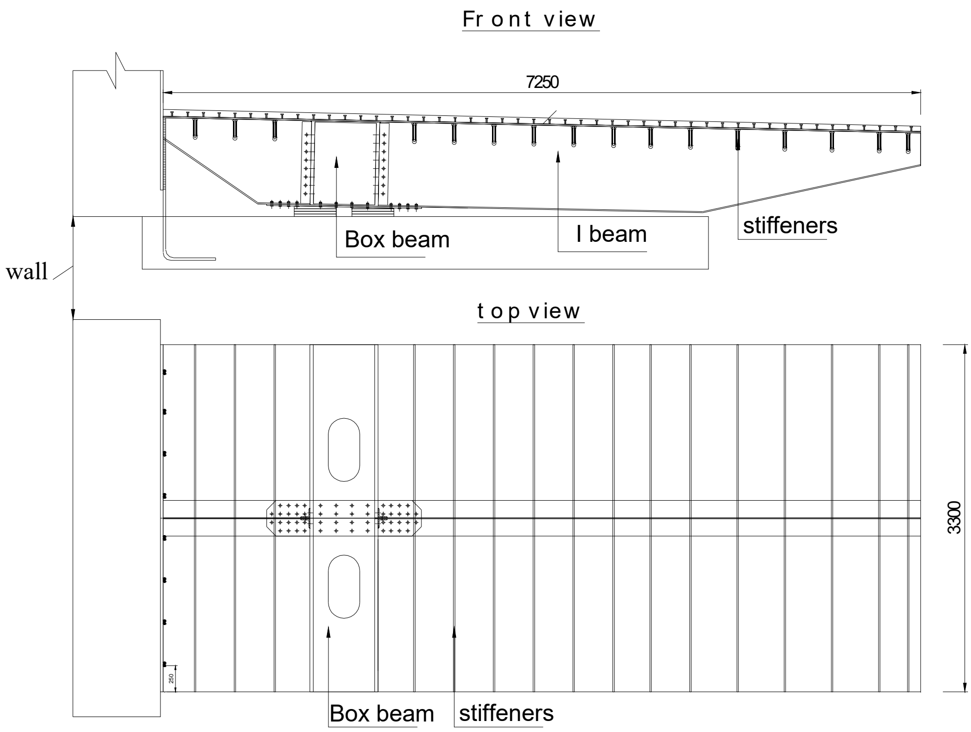

Figure 4. Design of plate structure.

The slab comprises 0.065 m thick UHPC concrete and 0.014 m thick steel plate. The two materials work together through welded studs on the steel plate's surface. An I-section beam and a box-section girder are used to support the slab, and both of these parts have a height of 0.8 m. Transverse stiffeners reinforce the entire plate structure. The overall dimensions of the slab structure are $3.3 \times 7.250 \times 0.865$ (m).

3.2. Experimental Measurement of Plate Vibration

3.2.1. Vibration Measurement

On the surface of the plate structure, eight sensor accelerometers (PCB-393B12) with high sensitivity were used to respond to signal acquisition. The sensitivities and labels of the sensors are detailed in Table 1. The natural vibrational properties of the slab are measured through excitations with a random force using a hydraulic jack placed above the structure. Since the number of sensors is limited while the DOFs to be determined are more numerous, it is necessary to divide the measuring points accordingly as reference points and roving points. The vibration measurement grid is divided into 12 measurement combinations, each consisting of a maximum of 8 sensors. Sensors at positions 3, 6, and 35 are used as reference points, and other points are moved in turn at other points in the measuring grid to obtain data from many different locations on the plate.

Table 1. Detailed parameters of sensors.

No.	Label	Sensitivity (V/g)
1	31	1.077
2	34	1.051
3	37	1.069
4	38	1.059
5	39	1.073
6	40	1.039
7	41	1.051
8	42	1.063

With each measurement setting, the data recording time is approximately 20 min (about 900–1200 s). The sampling frequency here, according to sensor details, is 1651 Hz. Figure 5 shows the grid of measuring points on the plate surface. The measurement points from this measurement grid are also the points to extract data and update the model for the digital model. Data from points one to seven are collected vertically and horizontally. Meanwhile, data at the remaining points are collected vertically. Figure 6 shows the equipment installed on the structure and the measurement process.

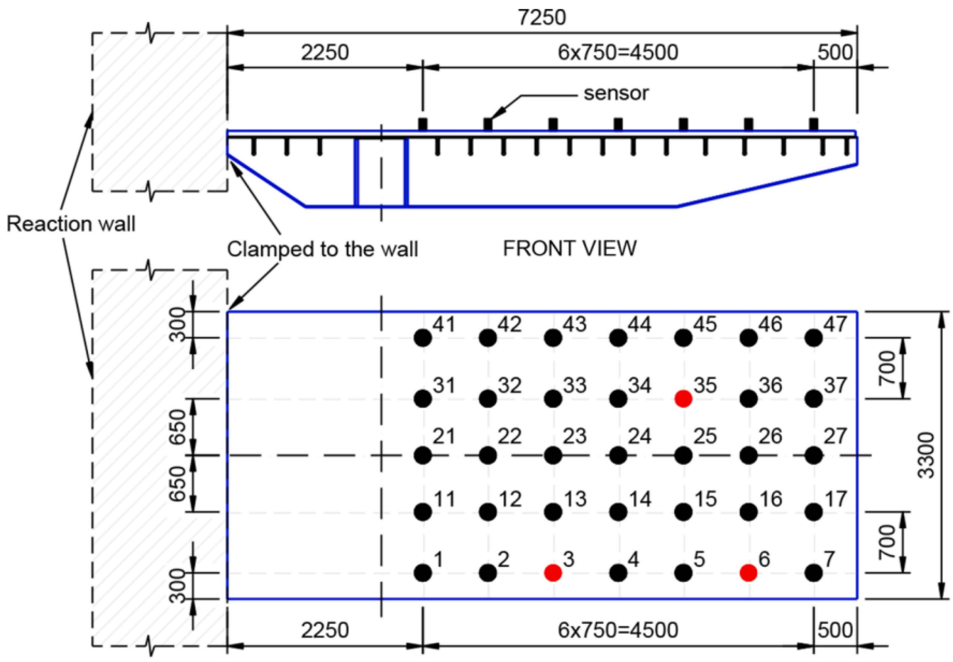

Figure 5. The measurement grid: red—reference points 3, 6, and 35; black—roving points.

(a) (b)

Figure 6. The process of measurement and sensor placement in one setup: (**a**) Data collection process; (**b**) Sensor placement in one setup.

3.2.2. Data Processing—Modal Analysis

In this step, a Matlab-based tool called MACEC was developed [33,34] to analyze the measurement data. The method for processing data is as follows (Figure 7):

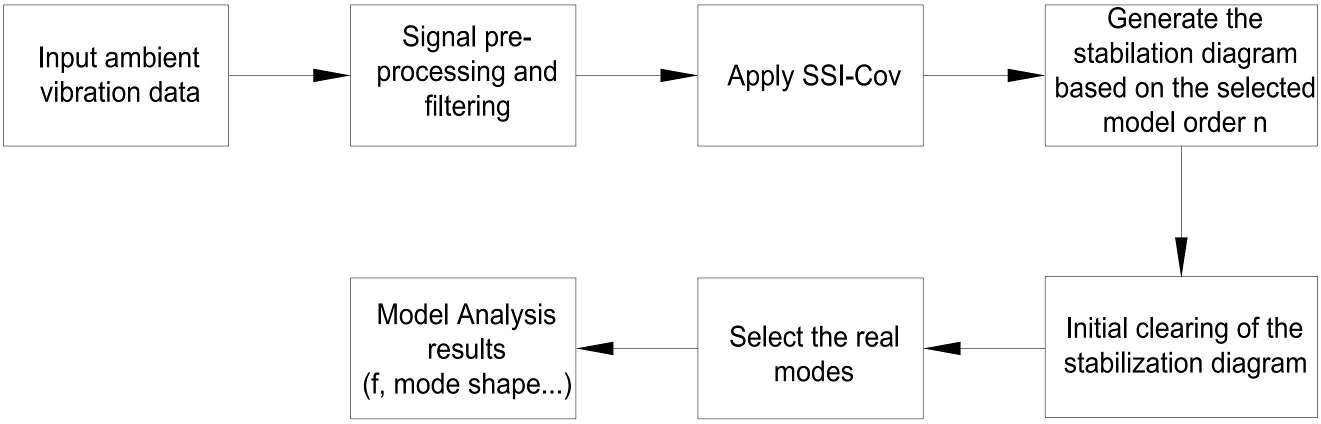

Figure 7. Process of system identification.

First, the data needs to be preprocessed. A measuring grid is created on the MACEC system. The measuring points are assigned and numbered, corresponding to the actual measuring points. Input parameters such as sensor label, sensitivity, data are assigned to each measuring point. The measured signal data is often skewed and does not coincide with the balance axis; the remove-offset function removes these components from the measurement data.

Based on input data and data obtained from preprocessing (noise removal, data classification into corresponding nodes), a model with complete data for measurement points is formed. System identification is accomplished using the covariance-based stochastic subspace identification (SSI-COV) technique [34,35]. Figure 8 demonstrates that this composite plate's frequency range of most tremendous significance is between 0 and 60 Hz. Specific criteria must be specified to obtain a clear stabilizing diagram using the state-space modeling for orders 2 to 120 in that measurement (Figure 9). Based on knowledge from numerous similar constructs, the following criteria were selected to concretize and characterize the modality: frequency stabilization (1%), damping ratio stabilization (5%), and mode shape stabilization (1%).

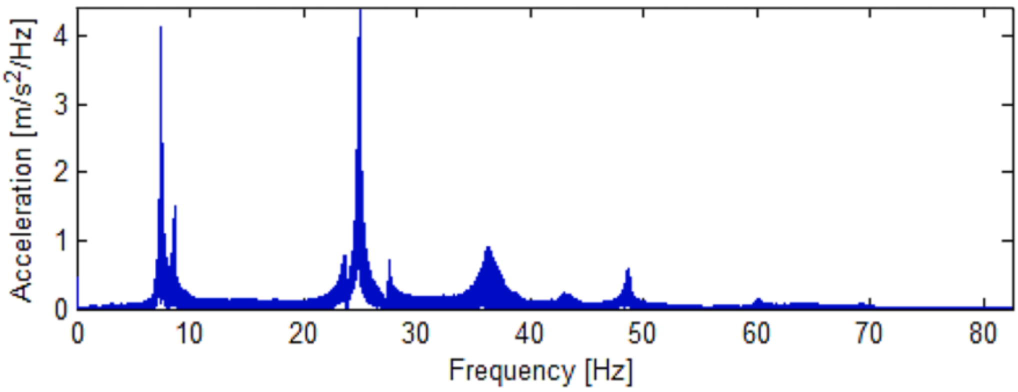

Figure 8. The signal's spectrum from the frequency domain.

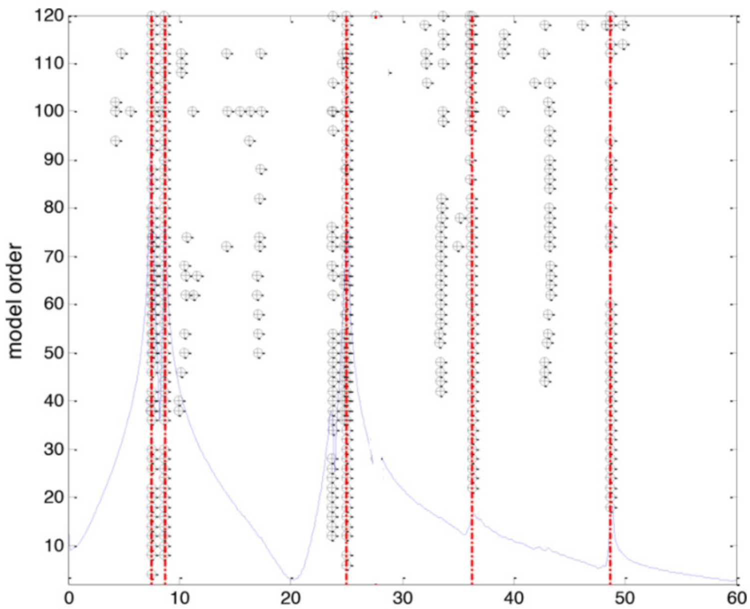

Figure 9. Stabilization diagram obtained by using SSI-COV.

Theoretically, a structure would have infinitely many vibrational shape modes. However, most of them would not contribute to the structural response evaluation. Dynamic parameters (natural frequency, damping ratio, and mode shape) are identified based on the stable poles. Usually, only the first few mode shapes of vibration are considered for the structure's dynamic behavior. Just relying on the main, low-frequency vibration patterns is enough to solve the problem of finite element model updating. According to the structure's collected response, in the stabilization diagram, the five vertical poles signify the five mode shapes of the plate structure. They consist of three torsion modes and two vertical bending modes.

The standard deviation of the natural frequency is calculated to assess the defined modes' effectiveness. Because the values of std.f are low, each setting's system recognition quality is high. Modal phase alignment (MPC) measures the mode shape's departure from actual values, MPC = 1 corresponds to the pure real mode. Every MPC value is higher than 0.998. A structure with light and/or proportional damping physics modes is likely to be realistic, so the elevated MPC result typically indicates a mode that has been precisely defined. Figure 10 shows a plot of the experiment's mode shapes:

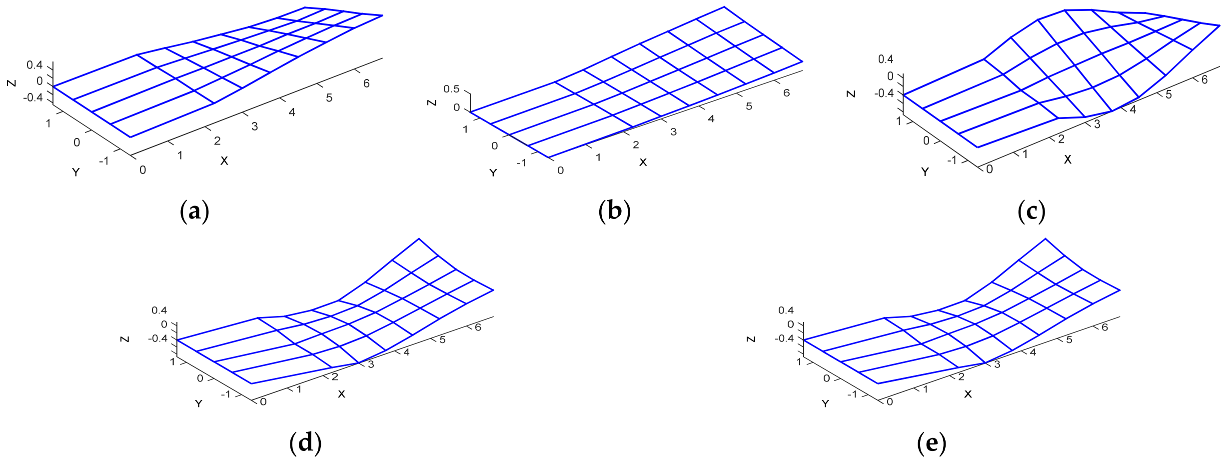

Figure 10. Five first mode shapes from the measurement: (**a**) Mode shape 1: f_1 = 7.47 Hz, 1st torsion; (**b**) Mode shape 2: f_2 = 8.62 Hz, 1st vertical bending; (**c**) Mode shape 3: f_3 = 24.99 Hz, 2nd torsion; (**d**) Mode shape 4: f_4 = 36.16 Hz, 2nd vertical bending; and (**e**) Mode shape 5: f_5 = 48.81 Hz, 3rd torsion.

Results from setups are the average values shown in Table 2:

Table 2. Measurement results of the plate structure.

Mode	f (Hz)	std.f
1	7.47	0.020
2	8.62	0.024
3	24.99	0.082
4	36.16	0.112
5	48.81	0.080

3.3. Initial Finite Element Model

An FE model is built with the Stabil toolbox [36]. This model will be produced before making experimental measurements to analyze the dynamic behavior of the actual structure so that the sensor grid can be arranged. The FE model uses 4-node shell elements (shell4) and beam elements (for box beam and I-beams) simultaneously (Figure 11).

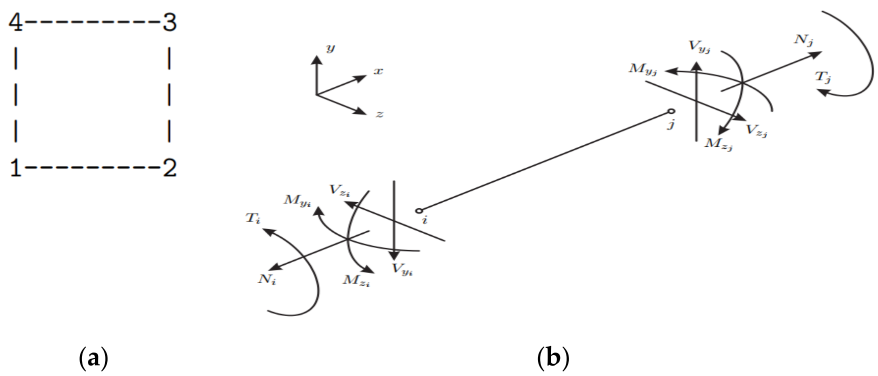

Figure 11. Type of element in FE model: (**a**) shell4; (**b**) seam.

To be easy to control and update later, the element nodes are located at the sensor positions compared to the experiment. Details of the FE model are detailed in the following list:

- There are 70 nodes and 69 elements that model the plate structure. In that, there are 54 shell4 elements and 15 beam elements. The cross-section of the components includes 5 types.

- Primary structure: The plate under consideration is made of 0.014 m thick steel plate, strengthened by transverse stiffeners. The design documents are the basis for the FE model's material properties: the Young's modulus of UHPC slab: Ec = 35 GPa, Young's modulus of steel: Es = 210 GPa, concrete density ρc = 2500 kg/m^3, steel density ρs = 7850 kg/m^3, other nonstructural taken into account as the added volume.
- Box beam and I-beam are the beam elements in the model, using the same material as the steel plate. I-beams are discontinuous: two sections of the beam with variable cross-section are built cross-section based on first-order function.
- Boundary conditions: A rigid link between the plate head and the wall is built into the model by locking all DOFs of the plate structure head. In addition, according to reality, the nodes below the box girder (nodes 12, 22, 42, and 52 in the model) are considered by "bearing" with initial kb = 1 × 1010 N/m stiffness.

  The FE model is shown in Figure 12.

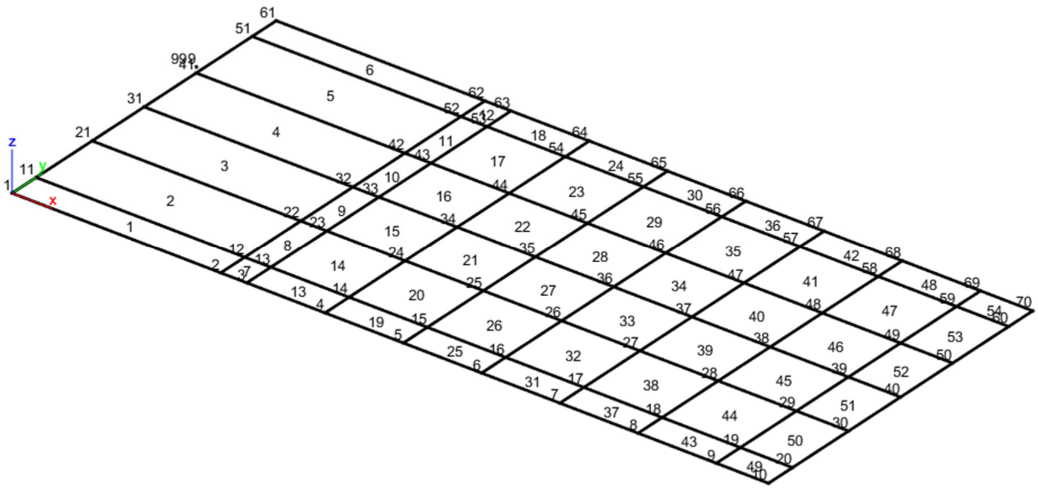

Figure 12. Finite element model of composite plate.

Utilizing the Block-Lanczos method, the FE model's dynamic analysis is carried out. Table 3 and Figure 13 present the first five mode shapes and frequencies.

Table 3. The results of the FE model's dynamic analysis.

Mode	f-Simulation (Hz)	f-Measurement (Hz)	Error (%)	MAC	Type
1	7.102	7.47	4.92	0.87	1st torsion
2	9.282	8.62	7.67	0.85	1st vertical bending
3	23.472	24.99	6.07	0.86	2nd torsion
4	38.227	36.16	5.71	0.63	bending
5	46.105	48.81	5.54	0.66	3rd torsion

Error = $|f_{simulation} - f_{measurement}| \times 100/f_{measurement}$.

The MAC values are determined through Formula (10) between the FE model results and the actual measurements. The first 3 MAC values greater than 0.85 show good agreement between each pair of mode shapes. However, the next 2 MAC values do not reach this minimum value. The correlation between the calculated and measured mode shape vectors are not guaranteed. The frequency values are also significantly different. This is a common situation for initial FE models, most of which cannot extract modes with high accuracy. Meanwhile, depending on the calculation requirements of the structure, some structures need high accuracy for structure health monitoring, to diagnose damage, and to make major predictions. Accuracy is important for maintenance or for accurate calculations to achieve the highest efficiency in military constructions and structures. There are many uncertain parameters such as material properties, stiffness parameters, etc. For this reason, it is recommended to perform a model update procedure to reduce errors.

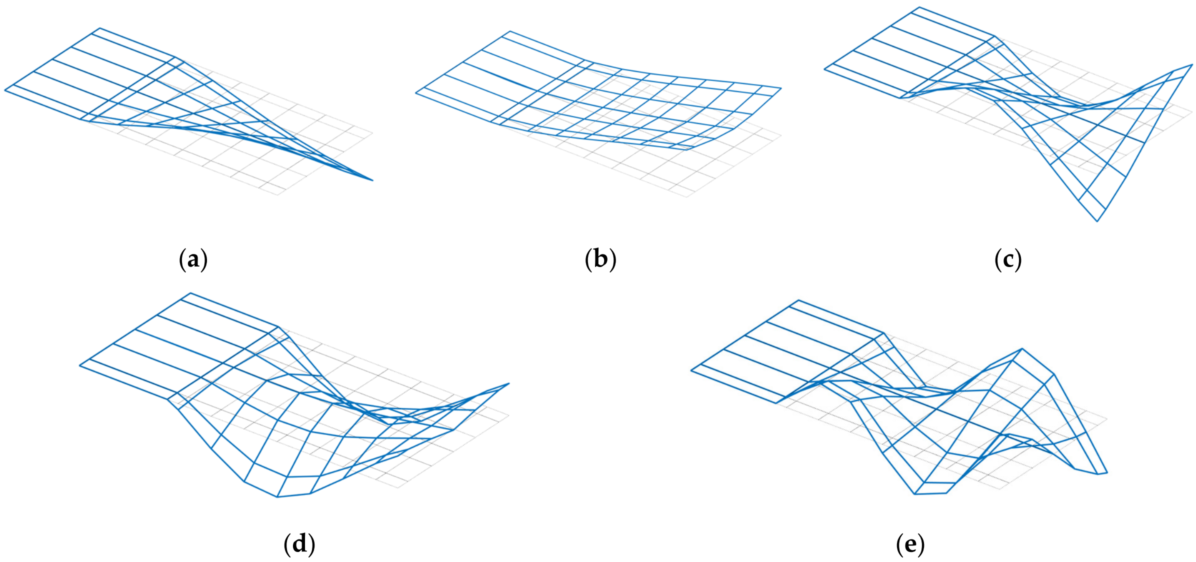

Figure 13. First five mode shapes from the simulation: (**a**) Mode shape 1: f_1 = 7.102 Hz, 1st torsion; (**b**) Mode shape 2: f_2 = 9.282 Hz, 1st vertical bending; (**c**) Mode shape 3: f_3 = 23.472 Hz, 2nd torsion; (**d**) Mode shape 4: f_4 = 38.227 Hz, 2nd vertical bending; and (**e**) Mode shape 5: f_5 = 46.105 Hz, 3rd torsion.

3.4. Update Model Parameters through the PSO Algorithm

In some actual large structures, it is pretty challenging to determine the dimensions and geometrical features of the structure so that the geometric features will be considered an uncertain parameter. However, in this case, the parameters of the geometrical dimensions can be completely accurate based on detailed measurements or design documents, so this can be considered a specific parameter to reduce the amount of computation.

Usually, the material parameters should be determined through direct tests (destructive tests). Thereby, the exact parameters will be selected. However, this is relatively expensive. For existing structures, sampling interference will affect the structure. In the case of the plate under consideration, UHPC was applied for the first time at a construction site in Vietnam. Therefore, the parameters of UHPC are entirely unknown. In addition, uncertain parameters related to steel materials and bearing stiffness are only empirical estimates. Moreover, the fact that the two materials, UHPC and steel, are combined by working together through the rivet system also influences the structural stiffness calculation results, and this part will be adjusted and updated through the parameters of UHPC and steel.

The model's uncertain parameters are described in detail in Table 4.

Table 4. Uncertainty parameters of model.

No.	Uncertainty Parameters	Initial Value	Upper Bound	Lower Bound
1	Young's modulus - *UHPC*: E_c (GPa) - *Steel* E_s (GPa)	 33.91 200	 33.91 210	 29.91 190
2	Weight density - *UHPC*: ρ_c (kg/m^3) - *Steel* ρ_s (kg/m^3)	 2500 7850	 2800 8000	 2400 7800
3	Stiffness of bearing - k_b (N/m)	 1×10^{10}	 4×10^{10}	 4×10^{7}

After obtaining the unnecessary parameters, update the model with the objective function. The update process is performed and processed on a computer with Intel(R) Core(TM) spec i5-10400F CPU @ 2.90 GHz 2.90 GHz, 8 GB RAM. In the PSO algorithm, the population is generated with 50 individuals. For the purpose of convergence, assign the value 0.3 to the inertial weight parameter (w), where social and cognitive learning coefficients are $C_1 = 2$ and $C_2 = 2$, respectively [37]. The fitness must not change by more than 10^{-7} from one iteration to the next, or the number of iterations must not exceed 100, both of which were set as ending criteria for the PSO loops. The convergence curve when using PSO is shown in Figure 14.

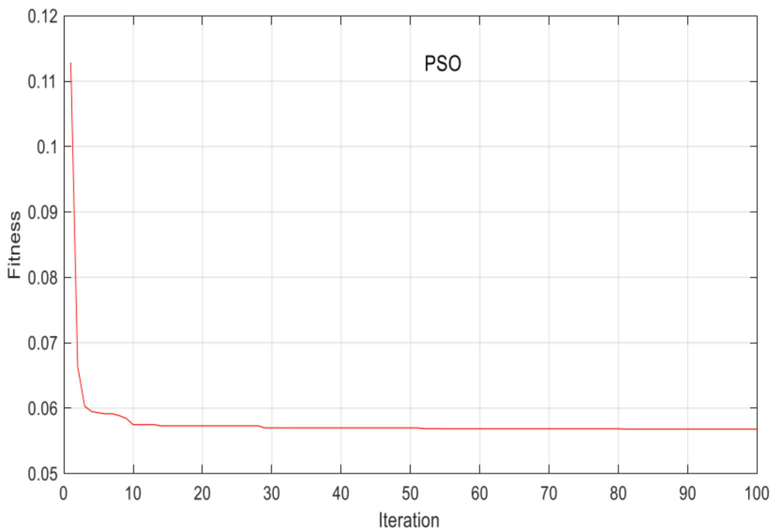

Figure 14. Fitness function convergence curve using PSO.

The updated uncertainty parameters and FE model after using the PSO are presented in Tables 5 and 6.

Table 5. Updated parameters.

No.	Uncertain Parameters	Initial Value	Updated Value
1	Young's modulus - *Concrete* E_c (GPa) - *Steel* E_s (GPa)	33.91 200	32.37 209.98
2	Weight density - *Concrete* ρ_c (kg/m^3) - *Steel* ρ_s (kg/m^3)	2500 7850	2776.8 7958.5
3	Stiffness of bearing - k_b (N/m)	1×10^{10}	1.378×10^{8}

Table 6. Analysis results of the plate after updated.

Mode	f-Simulation (Hz)	f-Measurement (Hz)	Error (%)	MAC	Type
1	7.45	7.47	0.27↓	0.96↑	1st torsion
2	8.61	8.62	0.12↓	0.92↑	1st vertical bending
3	24.91	24.99	0.32↓	0.95↑	2nd torsion
4	36.43	36.16	0.74↓	0.94↑	Bending
5	48.13	48.81	1.39↓	0.91↑	3rd torsion

Error = $|f_{simulation} - f_{measurement}| \times 100/f_{measurement}$.

The FE model's MAC values before and after updating are displayed in Figure 15. After being updated, the accuracy of the model has increased a lot. These MAC values show good agreement between the FE and the actual models.

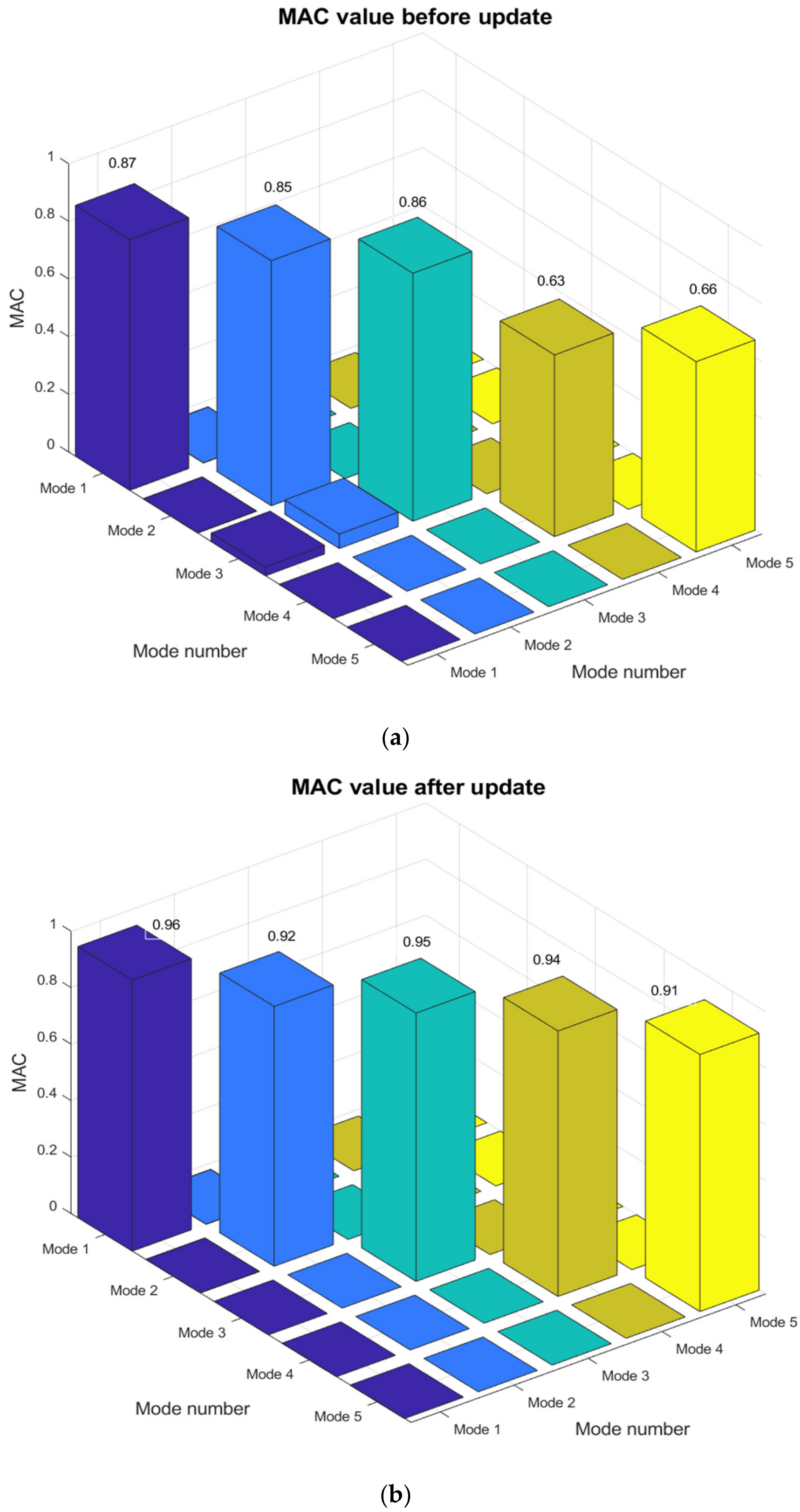

Figure 15. MAC values of mode shapes: (**a**) before model updating; (**b**) after model updating.

The first model was established based on the characteristics that are easy to investigate, and the analytical experience had a relatively high error rate compared to the experimental measurements. After updating the model, the natural frequency of errors between calculation and measurement is significantly reduced, and the model has high accuracy and reliability (Figure 16).

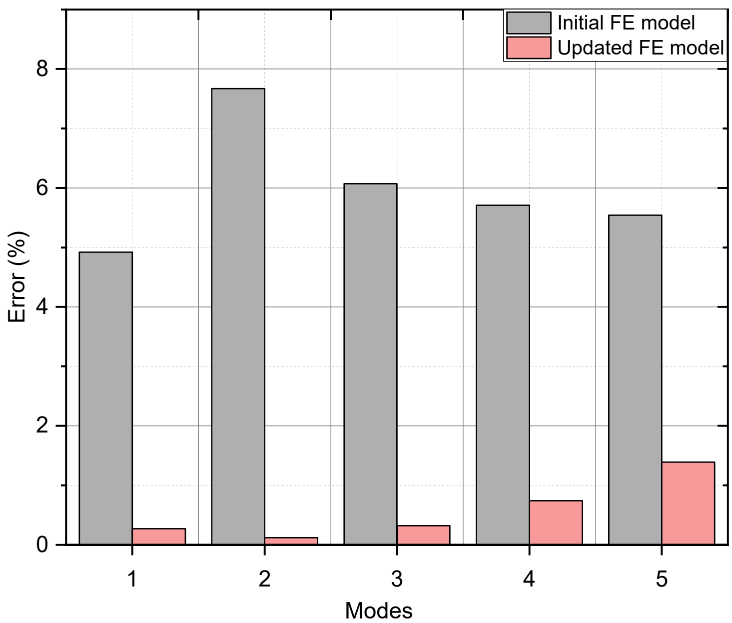

Figure 16. Comparison of error frequency difference before and after model update using PSO.

The calculation results show that, after about 30 iterations performed by PSO, the model parameters converge and give good results, minimizing the process of testing parameters in the modeling.

More than just updating the model with material specifications, other uncertain parameters can be changed if the exact parameters are unknown. This work can be of great significance for structural safety assessments. For example, when there is an updated model of a structure, when the structure fails, zoning and damage assessment will be calculated by selecting the uncertainty parameters for the structure within the damaged area. The calculation results can evaluate the deterioration of structural function and propose reasonable repair and upgrade measures.

The updated model becomes a temporary digital twin of the structure at a specified time. Based on this model, other techniques will be further researched and developed to create an interactive data stream between the real and virtual models to create a complete digital twin.

4. Conclusions

This paper describes a technique for updating the finite element model for composite plate structure using a particle swarm optimization algorithm. After the model is updated, the numerical results and experimental results exhibit a high degree of correspondence. The key findings are summed up as follows:

- PSO demonstrates how it can be used to solve engineering-related issues. It can improve the accuracy of the FE analysis while reducing the calculation process with results that are close to the actual test of the structure. Furthermore, the initial FE model can be updated by selecting and adjusting the uncertain parameters of the structure. On the other hand, this procedure is combined with experimental results; consequently, the FE model is relatively accurate compared with reality(the most significant deviation between simulation and experimental measurements was noticeably reduced from 7.67% to 0.12%).

- Regarding the digital twinning creation, a temporary twin should first be created as soon as possible at the early stage of the operational stage. This work can be done by updating the uncertainty parameters of the FE model. Using PSO aids to speed up calculations while maintaining high model correctness. For structures using composites, updating material parameters is essential because the performance of single materials may not be fully utilized in the structure.
- Updating the model can be applied to the structural damage assessment problem, localizing some damage when the structure has issues by taking the damaged area's parameters into variables for calculation. Finding these parameters will lead to accurate predictions about the deterioration of the structure, thereby suggesting measures to strengthen and repair or take measures to continue to serve the structure accordingly.
- Although good results are obtained, experiments to determine the input (target) parameters of the structure need to be carefully defined. With large structures, field experiments will be a challenge. Uncertainty depends on the experience and opinion of the authors.
- Regarding future work of this study, combining different optimization algorithms will be considered to improve the efficiency of model updating. On the other hand, new techniques will be developed to generate the data flow of the FE model, updated against the actual model's real-time data to deal with unexpected events.

Author Contributions: Conceptualization, J.M., M.Q.T. and Q.T.N.; methodology, J.M., H.S.S. and Q.T.N.; software, M.Q.T., S.F. and S.N.D.; validation, J.M. and S.N.D.; formal analysis, Q.T.N.; investigation, S.F., M.Q.T. and S.N.D.; resources, S.F.; data curation, S.N.D.; writing—original draft preparation, M.Q.T. and S.N.D.; writing—review and editing, J.M. and S.N.D.; visualization, S.F. and M.Q.T.; supervision, J.M., H.S.S. and S.N.D.; project administration, J.M. and S.N.D.; funding acquisition, J.M., S.F. and S.N.D. All authors have read and agreed to the published version of the manuscript.

Funding: This work was partly financed by FCT/MCTES through national funds (PIDDAC) under the R&D Unit Institute for Sustainability and Innovation in Structural Engineering (ISISE), under reference UIDB/04029/2020, and under the Associate Laboratory Advanced Production and Intelligent Systems ARISE under reference LA/P/0112/2020. The authors also acknowledge ANI ("Agência Nacional de Inovação") for the financial support given to the R&D Project "GOA Bridge Management System—Bridge Intelligence", with reference POCI-01-0247-FEDER-069642, cofinanced by the European Regional Development Fund (FEDER) through the Operational Competitiveness and Internationalization Program (POCI).

Acknowledgments: Minh Q. Tran was supported by the doctoral grant reference PRT/BD/154268/2022 financed by the Portuguese Foundation for Science and Technology (FCT), under the MIT Portugal Program (2022 MPP2030-FCT). Minh Q. Tran acknowledges Huan X. Nguyen (Faculty of Science and Technology, Middlesex University, London NW4 4BT, UK) and Thuc V. Ngo (Mien Tay Construction University, Institute of Science and International Cooperation, 85100 Vĩnh Long, Vietnam) for their support as cosupervisors as well as specific suggestions in terms of the "conceptualization" and "methodology" of this paper. Helder S. Sousa acknowledges the funding by FCT through the Scientific Employment Stimulus—4th Edition.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Wu, Z.; Huang, B.; Li, Y.; Pu, W. A Statistical Model Updating Method of Beam Structures with Random Parameters under Static Load. *Appl. Sci.* **2017**, *7*, 601. [CrossRef]
2. Kim, S.; Koo, K.Y.; Lee, J.-J. Bridge Finite Model Updating Approach By Static Load Input/Deflection Output Measurements: Field Experiment. In Proceedings of the 2016 Structures Congress (Structures 16), Jeju Island, Republic of Korea, 28 August–1 September 2016; Volume 16.
3. Kim, S.; Kim, N.; Park, Y.S.; Jin, S.S. A Sequential Framework for Improving Identifiability of FE Model Updating Using Static and Dynamic Data. *Sensors* **2019**, *19*, 5099. [CrossRef] [PubMed]
4. Wu, B.; Lu, H.; Chen, B.; Gao, Z. Study on Finite Element Model Updating in Highway Bridge Static Loading Test Using Spatially-Distributed Optical Fiber Sensors. *Sensors* **2017**, *17*, 1657. [CrossRef] [PubMed]

5. Quyền, N.T.; Quốc, N.T.; Trụ, N.; Gomes, A.J.P.; Ferreira, F.B.N. An Alpha Finite Element Method for Linear Static and Buckling Analysis of Textile-Like Sheet Materials. *Solid State Phenom.* **2022**, *333*, 211–217. [CrossRef]
6. Quyên, N.T.; Dourado, N.; Gomes, A.J.P.; Ferreira, F.B.N. A Cell-Based Smoothed Finite Element Method for Modal Analysis of Non-Woven Fabrics. *Comput. Mater. Contin.* **2021**, *67*, 2765–2795. [CrossRef]
7. Tohidi, S.D.; Rocha, A.M.; Dourado, N.; Rezazadeh, M.; Quyền, N.T.; Zille, A.; Hesseler, S.; Gries, T.; Dencheva, N.V.; Dencheva, Z. Influence of Transcrystalline Layer on Finite Element Mesoscale Modeling of Polyamide 6 Based Single Polymer Laminate Composites. *Compos. Struct.* **2020**, *232*, 111555. [CrossRef]
8. Minh, T.Q.; Nhung, N.T.C.; Quyet, N.H.; Helder, S.S.; Jose, C. Matos Opportunities and Challenges of Digital Twins in Structural Health Monitoring. In Proceedings of the 4th International Conference on Sustainability in Civil Engineering, Hanoi, Vietnam, 25–27 November 2022.
9. Tran, M.Q.; Sousa, H.S.; Matos, J.C. Application of AI Tools in Creating Datasets from A Real Data Component for Structural Health Monitoring. In *Data Driven Methods for Civil Structural Health Monitoring and Resilience*; CRC Press: Boca Raton, FL, USA, 2023.
10. Feng, D.; Feng, M.Q. Model Updating of Railway Bridge Using In Situ Dynamic Displacement Measurement under Trainloads. *J. Bridge Eng.* **2015**, *20*, 04015019. [CrossRef]
11. Bayraktar, A.; Altunişik, A.C.; Sevim, B.; Türker, T. Finite Element Model Updating of Kömürhan Highway Bridge Based on Experimental Measurements. *Smart Struct. Syst.* **2010**, *6*, 373–388. [CrossRef]
12. El-Borgi, S.; Choura, S.; Ventura, C.; Baccouch, M.; Cherif, F. Modal Identification and Model Updating of a Reinforced Concrete Bridge. *Smart Struct. Syst.* **2005**, *1*, 83–101. [CrossRef]
13. Ren, W.X.; Chen, H.B. Finite Element Model Updating in Structural Dynamics by Using the Response Surface Method. *Eng. Struct.* **2010**, *32*, 2455–2465. [CrossRef]
14. Asadollahi, P.; Huang, Y.; Li, J. Bayesian Finite Element Model Updating and Assessment of Cable-Stayed Bridges Using Wireless Sensor Data. *Sensors* **2018**, *18*, 3057. [CrossRef]
15. Zhang, Q.W.; Chang, T.Y.P.; Chang, C.C. Finite-Element Model Updating for the Kap Shui Mun Cable-Stayed Bridge. *J. Bridge Eng.* **2001**, *6*, 285–293. [CrossRef]
16. Huang, M.; Zhu, H. Finite Element Model Updating of Bridge Structures Based on Sensitivity Analysis and Optimization Algorithm. *Wuhan Univ. J. Nat. Sci.* **2008**, *13*, 87–92.
17. Levin, R.I.; Lieven, N.A.J. Dynamic Finite Element Model Updating Using Simulated Annealing and Genetic Algorithms. *Mech. Syst. Signal Process.* **1998**, *12*, 91–120. [CrossRef]
18. Deng, L.; Cai, C.S. Bridge Model Updating Using Response Surface Method and Genetic Algorithm. *J. Bridge Eng.* **2009**, *15*, 553–564. [CrossRef]
19. Liu, T.; Zhang, Q.; Zordan, T.; Briseghella, B. Finite Element Model Updating of Canonica Bridge Using Experimental Modal Data and Genetic Algorithm. *Struct. Eng. Int.* **2016**, *187*, 1064–1075. [CrossRef]
20. Tran-Ngoc, H.; Khatir, S.; De Roeck, G.; Bui-Tien, T.; Abdel Wahab, M. Damage Assessment in Beam-Like Structures Using Cuckoo Search Algorithm and Experimentally Measured Data. *Lect. Notes Mech. Eng.* **2020**, 380–385.
21. Nguyen, N.T.C.; Tran, M.Q.; Sousa, H.S.; Van Ngo, T.; Matos, J.C. Damage Detection of Structural Based on Indirect Vibration Measurement Results Combined with Artificial Neural Network. *J. Mater. Eng. Struct. JMES* **2022**, *9*, 403–410. Available online: http://revue.ummto.dz/index.php/JMES/article/view/3286 (accessed on 24 December 2022).
22. Zhou, Y.; Zheng, H.; Luo, Q.; Wu, J. An Improved Cuckoo Search Algorithm for Solving Planar Graph Coloring Problem. *Appl. Math. Inf. Sci. Int. J.* **2013**, *7*, 785. [CrossRef]
23. Mohapatra, P.; Chakravarty, S.; Dash, P.K. An Improved Cuckoo Search Based Extreme Learning Machine for Medical Data Classification. *Swarm Evol. Comput.* **2015**, *24*, 25–49. [CrossRef]
24. Yang, X.S.; Deb, S. Cuckoo Search via Lévy Flights. In Proceedings of the 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC), Coimbatore, India, 9–11 December 2009; pp. 210–214. [CrossRef]
25. Peng, Y.Y.; Shiuh, S.Y.; Pei, P.W.; Yi, T.W. A Hybrid Particle Swarm Optimization Algorithm for Optimal Task Assignment in Distributed Systems. *Comput. Stand. Interfaces* **2006**, *28*, 441–450. [CrossRef]
26. Boulkaibet, I.; Mthembu, L.; De Lima Neto, F.; Marwala, T. Finite Element Model Updating Using Fish School Search and Volitive Particle Swarm Optimization. *Integr. Comput. Aided Eng.* **2015**, *22*, 361–376. [CrossRef]
27. Marwala, T. Dynamic Model Updating Using Particle Swarm Optimization Method. *arXiv* **2007**, arXiv:0705.1760.
28. Anil, K. *Chopra Dynamics of Structures: Theory and Applications to Earthquake Engineering*; Pearson Education: London, UK, 2013; ISBN 978-0-13-285803-8.
29. Zeugmann, T.; Poupart, P.; Kennedy, J.; Jin, X.; Han, J.; Saitta, L.; Sebag, M.; Peters, J.; Bagnell, J.A.; Daelemans, W.; et al. Particle Swarm Optimization. *Encycl. Mach. Learn.* **2011**, 760–766. [CrossRef]
30. Kennedy, J.; Eberhart, R. Particle Swarm Optimization. In Proceedings of the ICNN'95-International Conference on Neural Networks, Perth, WA, Australia, 27 November–1 December 1995; Volume 4, pp. 1942–1948. [CrossRef]
31. Weiguo, Z.; Octavian, P. Parametric Model Updating with Frequency and MAC Combined Objective Function of Port Crane Structure Based on Operational Modal Analysis. *Open Phys.* **2019**, *17*, 69–76. [CrossRef]
32. Miroslav, P.; Michal, B.; Tomáš, H. Modal Assurance Criterion. *Procedia Eng.* **2012**, *48*, 543–548. [CrossRef]

33. Edwin, R.; Mattias, S.; Guido, D.R. *MACEC 3.4: The Matlab Toolbox for Experimental and Operational Modal Analysis*; Department of Civil Engineering, KU Leuven: Leuven, Belgium, 2021.
34. Reynders, E.; Schevenels, M.; De Roeck, G. *MACEC 3.2: A MATLAB Toolbox for Experimental and Operational Modal Analysis*; Department of Civil Engineering, KU Leuven: Leuven, Belgium, 2014.
35. Peeters, B.; De Roeck, G. Stochastic System Identification for Operational Modal Analysis: A Review. *J. Dyn. Syst. Meas. Contr.* **2001**, *123*, 659–667. [CrossRef]
36. François, S.; Schevenels, M.; Dooms, D.; Jansen, M.; Wambacq, J.; Lombaert, G.; Degrande, G.; De Roeck, G. Stabil: An Educational Matlab Toolbox for Static and Dynamic Structural Analysis. *Comput. Appl. Eng. Educ.* **2021**, *29*, 1372–1389. [CrossRef]
37. Eberthart, R.C.; Shi, Y. Particle Swarm Optimization: Developments, Applications and Resources. In Proceedings of the 2001 Congress on Evolutionary Computation, Seoul, Republic of Korea, 27–30 May 2001.