Proceedings of the Sixth International Conference on
Soft Computing, Machine Learning and Optimisation in
Civil, Structural and Environmental Engineering
Edited by: P. Iványi, J. Lógó and B.H.V. Topping
Civil-Comp Conferences, Volume 5, Paper 2.3
Civil-Comp Press, Edinburgh, United Kingdom, 2023
doi: 10.4203/ccc.5.2.3

Multi-objective Optimisation of Dynamic Properties and Cost of a Composite Shell

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Abstract

This paper presents multi-objective optimisation of a laminated cylinder's dynamic behaviour and cost through stacking sequence, geometry, and appropriate materials choice. The optimized dynamic parameters are the width of a band in the frequency spectrum free of natural frequencies and the cost of applied materials. The multi-objective procedure involves mode shape identification, genetic algorithm-based optimisation, and deep neural networks-based surrogate model. The novel elements proposed are a detailed analysis of the number of initial finite element method calls necessary to train the neural network-based surrogate model, a study concerning different surrogate model schemes (one network or a network ensemble), error function applied during surrogate model training, and the application of high-fidelity (and time-consuming) or low-fidelity (but very fast) finite element models.

Keywords: multi-objective optimisation, surrogate models, deep neural networks, genetic algorithms, mode shapes identification

1 Introduction

In many engineering fields, composite materials are used more often, e.g., in aircraft, mechanical, environmental, or civil engineering [1]. Composites are applied as auxiliary or primary structural materials, and they have a very desired, high ratio of strength to weight and high durability. Most composite cylindrical shells are used under dynamic loading; unfortunately, their dynamic behaviour has not yet been widely investigated. Understanding this behaviour may be crucial in applying composite materials in structural engineering [2]. Another phenomenon that may be analyzed is buckling [3], associated with a process where a structure suddenly changes shape. Triggered by a varying external load, this configuration change often happens in a catastrophic way—named bifurcation buckling—which is predicted by employing an eigenvalue analysis.

The optimisation is one of the crucial stages in the design process. Optimising static and/or dynamic parameters of a composite structure (e.g., fundamental natural frequency, mass, buckling force, material cost) requires repeatedly calculating the value of the so-called objective function describing the distance of parameters being optimized from their desired values. Real-life engineering problems are typically characterized by multiple objectives conflicting with each other. For this reason, an appropriate trade-off between these objective functions should be made using multi-objective optimisation (MOO). The computing power demand and time consumption can be reduced if zero-order optimisation algorithms are applied (no derivatives of the objective functions are necessary) and modern surrogate models of a considered structure are used. Applying nature-inspired metaheuristic algorithms, such as genetic algorithms (GAs), supported by neural networks (NNs) can meet these assumptions [4–7].

The properties of a composite structure are optimized through the changes in the values of basic topological parameters (lamination parameters), through the changes in geometry, and through the appropriate selection of materials for consecutive layers. The proposed optimisation procedure involves nature-inspired optimisation algorithms [3] such as genetic algorithms [8, 9], and deep neural networks (DNNs) [7, 10] as a tool to replace time-consuming finite element method (FEM) calculations in dynamic parameters prediction. This work primarily aims to build a multi-objective optimisation framework (for maximising the frequency spectrum gaps around arbitrarily selected excitation frequencies [11] and the cost of applied materials) for composite circular shells.

The new elements proposed in the work are a detailed analysis of the number of initial FE calls necessary to train the DNN-based surrogate model, a study concerning different metamodel schemes (one DNN or a network ensemble), error function applied during DNN training, and the application of high-fidelity (and time-consuming) or low-fidelity (but very fast) FE models. However, this work presents a selection of results related to two issues: the additional re-training of the DNN surrogate model and the automatic vibration mode shape identification application.

2 The investigated models and optimisation procedure

2.1 The finite element and surrogate models

The investigated structure is a shell of the revolution created by rotating a hyperbola connecting three points. Moving the middle of these tree points leads to obtaining shells of different geometry (with different *depths*). The length of the hyperboloid (along the revolution axis) equals $L = 6.0$ m, the upper radius $R_{up} = 61.03$ cm, the lower radius $R_{down} = 1.3R_{up}$, the depth of the hyperboloid, d, varies between $d = 30$ cm and $d = 110$ cm. The thickness of the shell is equal to $t = 1.6$ cm and is divided into eight composite layers of equal thickness. The end of the shell under analysis (with $R_{down} = 1.3R_{up} = 79.34$ cm) is fixed — all its displacements are blocked.

Each shell layer can be made of a different composite material, with a different direction of the composite reinforcement fibres. Three materials are taken into account; two of them are carbon fibre-reinforced polymer (CFRP) and glass fibre-reinforced polymer (GFRP), and their material properties and costs are taken from [12]. The material costs are unitless since they show only the mutual relation of the costs of different materials. The third material is theoretical (and is here called TFRP), with the properties and cost calculated as the average of CFRP and GFRP. This material was introduced to make the optimisation problem (considered in the later part of the article) more complex, considering more options than only two distinctly different materials. All properties of the applied materials are summarized in Table 1.

	E_a	E_b	E_c	ν_{ab}	ν_{ac}	ν_{bc}	G_{ab}	G_{ac}	G_{bc}	ρ	Cost
		GPa			—			GPa		kg/m^3	—
CFRP	120	8	8	0.014	0.028	0.028	5	5	3	1536	10.20
TFTP	80	6	6	0.020	0.036	0.036	4	4	3	1428	5.78
GFRP	40	4	4	0.026	0.044	0.028	3	3	3	1320	1.36

Table 1: Material properties of three considered composite materials.

The second model is described by seventeen varying parameters subject to further optimisation. The variable parameters are as follows:

- d, depth of the structure; $30\,\mathrm{cm} \le d \le 110\,\mathrm{cm}$,
- material of each of the eight composite layers that make up the structure shell; μ_i, $i = 1, 2, \ldots, 8$, $\mu_i \in 1, 2, 3$,
- lamination angle of the eight composite layers; λ_i, $i = 1, 2, \ldots, 8$, $-90° \le \lambda_i \le +90°$ (with a step of $5°$).

The finite element model comprises square-like, multilayered shell 4-node MITC4 elements (first-order shear theory). Each layer corresponds to one composite layer with possibly different material properties and lamination angles. The base size of the elements called h, is chosen to be almost equal to $h = 5$ cm (it differs slightly in the circumferential and longitudinal directions; moreover, it also differs for different locations along the axis of the whole shell).

During the optimisation of the dynamic properties of the investigated structure, the number of calculations of dynamic properties corresponding to different values of the model parameters reaches at least several hundred or, more probably, several thousand. Applying the FEM model leads to highly time-consuming numerical simulations. A neural network-based surrogate model (or metamodel) is proposed to overcome this problem.

The task of the surrogate model is to immediately estimate, with satisfactory accuracy, the values of a selected number of the natural frequencies corresponding to particular values of the investigated model parameters. DNN is applied as a surrogate model. Various DNN-based surrogate models are considered, among them surrogate models that assess 11 natural frequencies corresponding to 11 carefully selected mode shapes.

Supervised learning is applied to create the networks building surrogate model; preparing a set of examples and presenting them to the networks is necessary to teach the network to reproduce the relationship between input and output data. It has to be firmly stated that a crucial point in DNN-based surrogate model application is a constant control of numerical effort (CPU time consumption); the overall CPU time consumed during a necessary number of FE calls—including the generation of examples for DNN-based model learning—has to be significantly smaller than CPU time consumption in case the surrogate model is not applied.

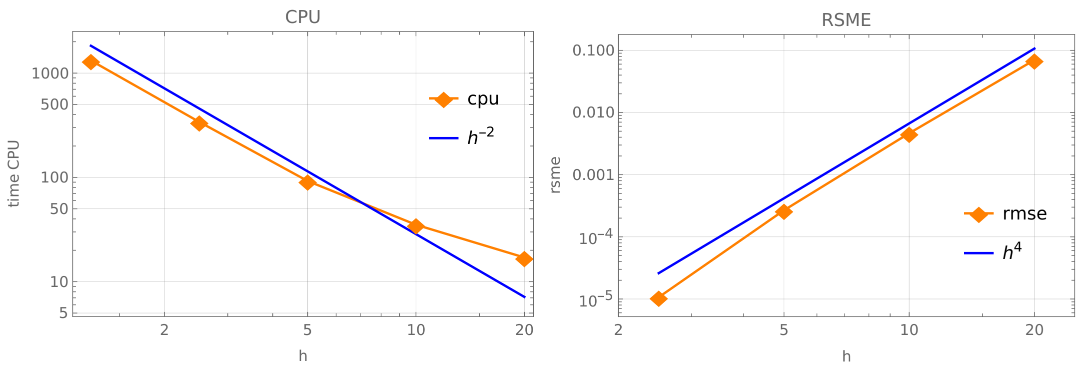

Figure 1: The analysis of time-consumption and the accuracy of multi-fidelity models; h is the size of one finite element.

The high-fidelity model is applied to build the set of patterns used to teach the surrogate model and for the final verification of the results obtained. The low-fidelity model is primarily used for preliminary verification of the results to reject the solutions the surrogate model erroneously indicates. The low-fidelity model with the element size twice as high as in the fine model is four times less time-consuming and gives results with 16 times higher error (see Figure 1); however, the decrease in accuracy is not as important as the decrease in time consumption while the model is applied for preliminary verification.

2.2 The optimisation scheme

The main optimisation is preceded by creating a surrogate model (based on DNN), which predicts—for the given set of model parameters—the structure's frequency spectrum. The optimisation scheme is presented in Figure 2. The loop shown in Figure 2 depicts the possibility of tuning the surrogate model every time the subsequent results are obtained and is called curriculum learning (CL). In what follows, CL0 means that no CL loop was applied, CLx means that x loops were made.

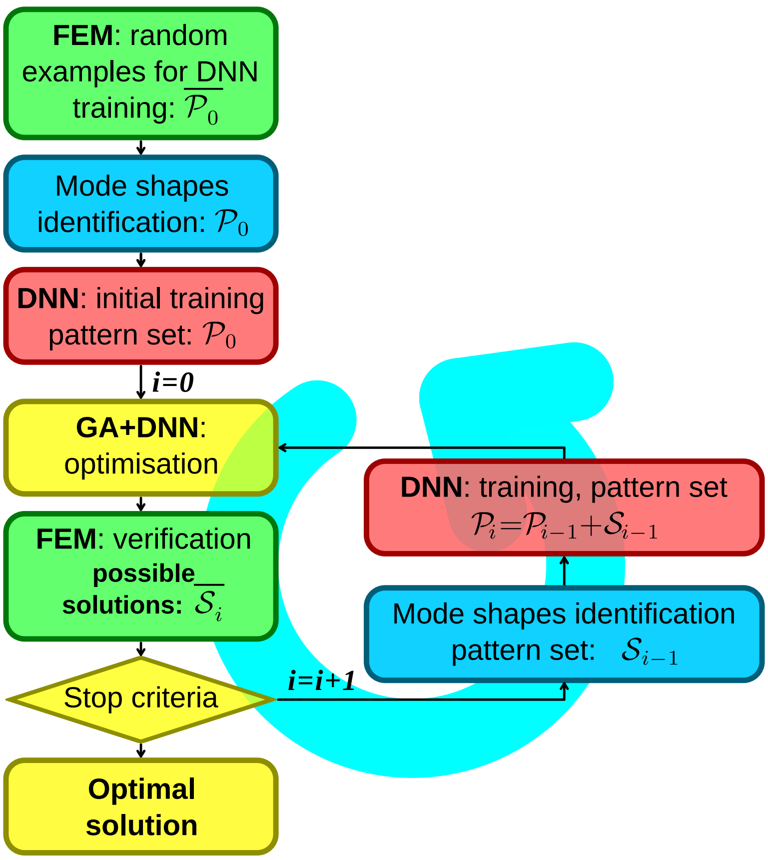

Figure 2: The applied optimisation scheme.

3 The results

Several simulations were carried out, verifying the results obtained from calculations with different assumptions. Figure 3 presents the comparison of the Pareto fronts obtained with one CL loop (called CL1) or without CL loops (CL0). Each of the four graphs in Figure 3 presents the results obtained in maximising a frequency gap around a different possible excitation frequency (50 Hz, 60 Hz, 70 Hz, and 80 Hz) together with minimisation of material costs. The advantage of applying even one CL loop is visible in each case.

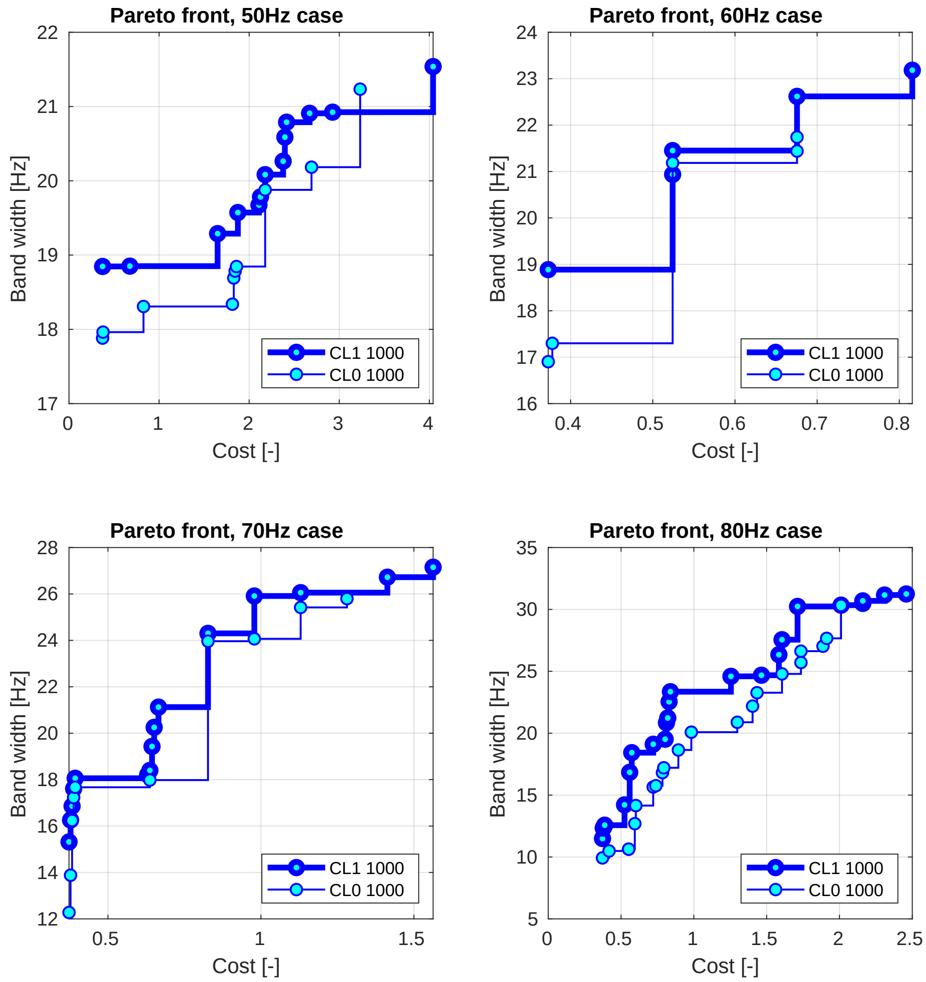

Figure 3: The Pareto optimal fronts obtained for CL0 and CL1 cases, surrogate model is trained using 1000 examples (1000 FE calls are necessary before the optimisation is fired).

Figure 4 compares the Pareto fronts obtained with prior identification of mode shapes and the application of natural frequencies corresponding to the selected mode shapes or without the identification of mode shapes and the application of the first eleven natural frequencies.

Each of the four graphs in Figure 4 presents again the results obtained in maximising a frequency gap around a different possible excitation frequency (50 Hz, 60 Hz,

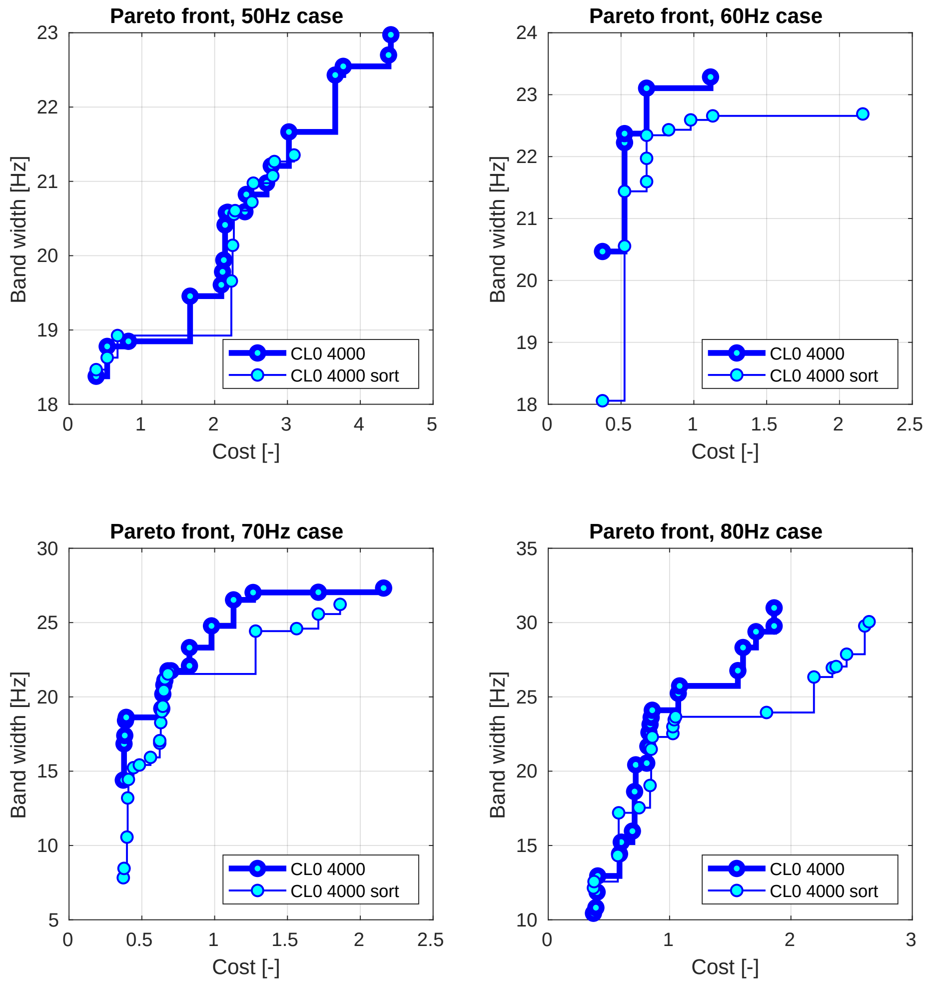

Figure 4: The Pareto optimal fronts obtained with (CL0 4000) and without mode shapes identification (CL0 4000 sort).

70 Hz, and 80 Hz), with or without mode shapes identification. Performance improvement when using mode shapes identification is evident.

4 Concluding remarks

The paper presents the optimisation of the lamination angles in subsequent composite layers, the optimisation of basic geometrical parameters, and the selection of the composite materials for the subsequent composite layers. The two competing objective functions are

- the maximisation of the frequency gap around a possible excitation frequency,
- the minimisation of material costs.

The analysis of the obtained results leads to the following conclusions:

- the application of curriculum learning loop improves the results in every tested case, the improvement is greater than in the case of application of a comparably higher number of examples (generated using FE calculations),
- the identification of mode shapes and application of the natural frequencies corresponding to identified mode shapes proved its usability, also in multi-objective optimisation cases,
- the application of FE models of different fidelity level (high- and low-fidelity models) leads to a significant reduction of numerical effort necessary to optimize the investigated structure.

Acknowledgements

This research was supported by the Polish Ministry of Education and Science grant to maintain research potential.

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