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ARTIFICIAL INTELLIGENCE TECHNIQUES IN DESIGN OPTIMIZATION OF VARIABLE STIFFNESS CYLINDRICAL SHELLS

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ABSTRACT

The main driver of aerospace structures design is the increase in performances of currently in use components. The behavior of structures is investigated by means of highly accurate finite elements (FE) analysis. The problem related to this kind of simulations is the high computational time required to obtain the structural response associated with nonlinear phenomena. This aspect is particularly significant during the preliminary phase, especially when the analysis involves an optimization procedure. One strategy to overcome this problem is the introduction of artificial intelligence techniques in the design phase. This work proposes an optimization framework based on the approximation of the structural behavior through an artificial neural network (ANN). The net is exploited during the optimization, performed with a particle swarm optimizer, in order to reduce the computational effort. FE analysis are used to train the ANN and to validate the results. The methodology is applied to the optimization of the fibers shape of variable stiffness cylindrical shells, with the goal of maximize the critical load taking into account also manufacturing constraints. The higher accuracy offered by ANN with respect to other global approximation techniques and the time saving, resulting from the developed methodology, are both highlighted.

Keywords: artificial neural networks, particle swarm optimizer, variable stiffness, buckling

1 INTRODUCTION

In the last decades the field of machine learning experienced a remarkable increase in attention and performance. The possibility to generate programs able to carry out a specific task without being explicitly programmed is particularly promising in the engineering field. This because usually when complex non-linear problems are investigated, the evolution of the system under analysis is too complicated to code or the high computational cost can make the optimization phase prohibitive. In computational mechanics the behaviour of the structure is approximated by means of finite element analyses (FEA) that, in addition to being very precise, they are also very time consuming. A solution to this problem can be found in the field of Artificial Intelligence tools. The generation of a model able to autonomously understand and approximate the behaviour of a system can help the designer to generate a reliable metamodel to be used during the optimization phase to reduce computational efforts. This strategy is not properly new since many authors already investigate the possibility to take advantage from these models in the aerospace field. Despite that, the continuous growth in computing power and the evolution of the mathematical formulations involved, generated by the considerable scientific interest in this field, makes a deep investigation indispensable to completely understand the reliability and the power of these models.

This paper provides an investigation in the state-of-the-art methods concerning Artificial Neural Networks (ANN) with the goal to assist the optimization of a Variable Stiffness (VS) cylindrical shell. VS composites are a new type of composite materials in which the fibers are no more constrained to be rectilinear but can follow specific paths. Different studies have been published regarding the optimization of these laminates, for different purposes, but the field is still quite new and requires further investigations. This is particularly true when this concept is applied to cylindrical shells, where the few works present showed the possibility to considerably improve the buckling load and reduce the problem of these structures associate to the high sensitivity to imperfections.

2 VARIABLE STIFFNESS CYLINDRICAL SHELLS

The methodology here considered is applied to the optimization of a VS cylindrical shell previously investigated by Labans and Bisagni [1]. The shell is clamped on the lower edge while the upper one is free to move only along the axial direction, where is introduced also the axial load. In this section, a brief description of the modelling techniques adopted to describe the fibers variation and to model the composite shell are presented.

2.1 Fiber path formulation

The modelling of a VS composite requires the definition of a mathematical formulation to describe the variation of the fibers angle inside the component. In the following, a new path formulation is adopted where only axial variations of the shape are allowed. Considering a reference system with the *x*-coordinate along the cylinder axis and the *y*-coordinate tangent to the unrolled surface of the shell, the fiber shape is defined by:

$$y(x) = A\sin\left(\omega\frac{2\pi}{h}x + \phi\right) + \tan(\alpha)x$$

where h is the height of the cylinder, A is the amplitude, ω is the angular velocity, ϕ is the phase shift and α is the angular coefficient of the linear function.

The expression can be splitted in two terms. The first term is the one that effectively allows to steer the fibers and is a harmonic function with a wavelength equal to the cylinder height. The second term instead, is the one that allows to completely take into account the design space of the constant stiffness composites.

2.1.1 Manufacturing constraint

During the design of the layup it is important to ensure that all the fibers paths are effectively manufacturable. When a composite material is produced with a fiber placement technology, the most important constraint is in the maximum amount of steering. The amount of steering is limited by the value of the maximum curvature κ that guarantee no wrinkling of fibers. The absolute value of the curvature of the path is given by:

$$\kappa(x) = \frac{|y''|}{|1 + y'^2|^{\frac{3}{2}}}$$

Since the maximum curvature is imposed by the manufacturing machine and since it is important to explicitly define the design space, the equation is managed in order to obtain a more useful formulation. Taking the maximum w.r.t x and ϕ and inverting the equation it is possible to obtain in closed form the maximum value of the frequency that avoid wrinkling of the fibers:

$$\omega(A, \alpha, \kappa) = \frac{h}{2\pi}\sqrt{\frac{\kappa\left(1 + \tan^2(\alpha)\right)^{\frac{3}{2}}}{A}}$$

2.2 Modelling of the variable stiffness cylindrical shell

The geometry of the structure is 705 *mm* of height, 300 *mm* of radius and 8-ply of AS4/8552 CFRP prepreg with a total thickness of 1.448 *mm*. In order to evaluate the procedure in a limited amount of time only balanced and symmetric layups are considered. The model is generated inside the commercial software Abaqus with S4R shell-type elements and a mesh dimension of approximatively 5 *mm*, fixed after a mesh sensitivity analysis.

The continuous variation of the fiber angle, and so the continuous variation of the stiffness, is modelled necessarily with a discrete variation from an element to another. Once the path of a fiber is defined, it is approximated as piecewise linear with as many pieces as the number of elements along the x axis. In this way, each element of the model has a layup made of rectilinear fibers, the layup is constant for all the elements belonging to the same cross-section and vary only along the cylinder axis.

Since it is imposed the constraint of only symmetric and balanced stacking sequences, the layup of the shell is defined by only two paths $[\pm\theta_1, \pm\theta_2]_S$. In Figure 1 a schematic procedure of the modelling technique is reported, where each ply is represented by the shape of only one fiber. The coarse mesh in the figure is used only to better understand the procedure.

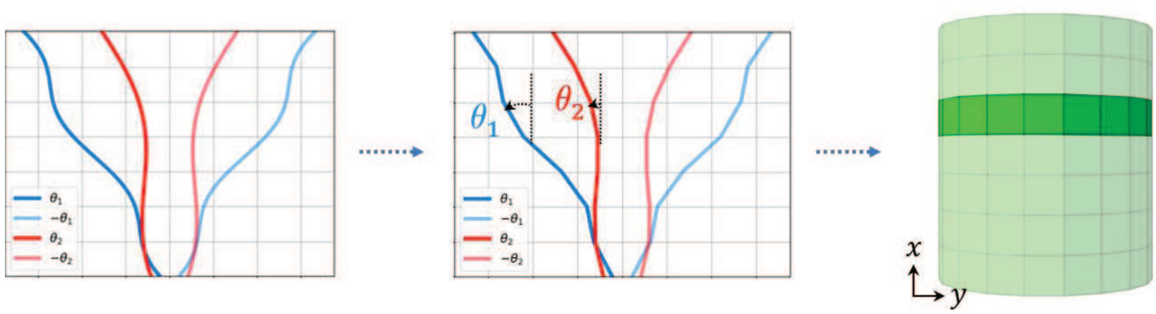


Figure 1: Variable stiffness modelling technique

3 ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANNs) are the result of observations of brain processes from an engineering point of view. Actually, ANN, can be involved to solve different types of problems. In the field of computational mechanics, the most common application is the supervised regression in which the network is used as a global approximation tool in order to approximate the structural behaviour. The basic unit of an ANN is the mathematical model of the neuron, depicted in Figure 2.

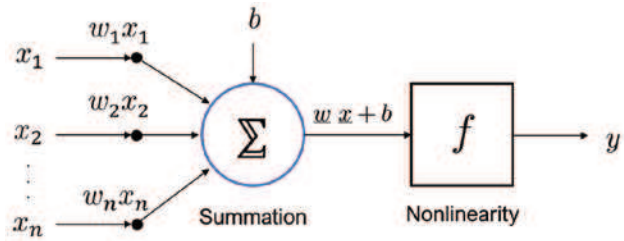


Figure 2: Mathematical model of the neuron

This unit receives a combination of inputs and elaborates them before shooting information to other neurons. Two operations are applied to the inputs, the first is a weighted linear summation with a bias and the second is an activation function, this last necessary in order to approximate non-linear structural behaviors.

The network is obtained by connecting a certain number of neurons according to different architectures. For regression problems, the simplest architecture is the feedforward multi-layer perceptron (MLP), in which neurons are grouped in layers and the signal propagates always from the first to the last as reported in Figure 3.

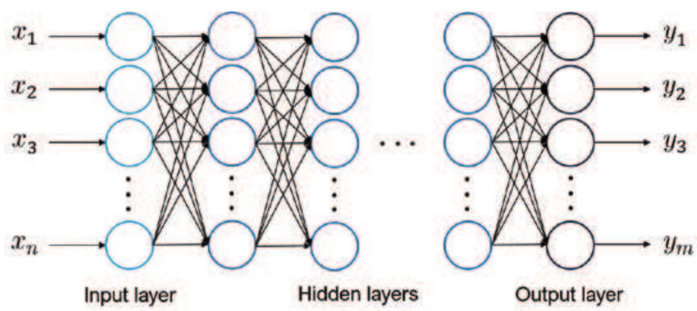


Figure 3: Feedforward multi-layer perceptron

The input layer receives the inputs of the system, the output one provides the requested outputs, and the hidden layers are those used to discover the relation that elapses between the inputs and the outputs. The network learns how to approximate the behavior of the structure by modifying autonomously its parameters, namely the weights w and the bias b through a process called learning.

4 DESIGN OF THE NEURAL NETWORK SYSTEM

The steps required to design a neural network able to approximate the structural behavior and replace finite elements (FE) simulations during the optimization are here presented. The most critical part is the Design of Experiments (DoE). Since ANN is a data driven technique, low approximation capability results from a training with a not appropriate training set. In addition to the training set other two set are generated with FEA, one used to modify the hyperparameters called validation set and one to state the performance of the ANN in an unbiased way called test set. In total 81 eigenvalues buckling analysis and linear static analysis are performed for the training set, 27 for the validation set and 27 for the test set.

4.1 Training set definition

The objective is to find the combinations of input parameters that allow to obtain the greatest information possible from the design space minimizing the number of simulations required. These two requirements arise from the inability of the network to extrapolate results outside the training domain and from the necessity to avoid a waste of computational time.

Since the domain of interest is not simply bounded by the minimum and maximum values of the inputs, due to the non-linear relationship between the design variables and the maximum allowable curvature, an ad hoc procedure is required. First of all, the values of amplitude, phase shift and linear term are sampled with the Latin Hypercube Sampling (LHS) method. The LHS allows to sample in a near-random way and without overlap. At this point, for each sample, the value of the pulsation is sampled randomly between zero and the maximum allowable value. In this way, it is ensured that all the parameters combinations are associated to configurations free of defects given by fibers wrinkling.

During the generation of the training set also the correlation between the design parameters is taken into account. Since low generalization capability is resulting when high correlation is present between the samples, the just presented procedure is repeated until a training set with low correlation is obtained.

4.2 Loss and metrics of accuracy

During the training, the network learns to approximate the structural behaviour by minimizing a certain loss function. The loss is calculated as the difference between the approximated outputs given by the ANN and the real ones obtained with FE simulations. In this specific application, the network is trained in order to perform multi-task regression, approximating both the buckling load and the pre-buckling stiffness at the same time. The loss is calculated as the Mean Squared Error (MSE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M}(\hat{y}-y)^2$$

The MSE is used to update the network parameters but is not able to capture important aspects as the variance of the error inside the design space. For this reason the quality of the approximation is evaluated with three different metrics: R-square (R^2), Relative Average Absolute Error (RAAE) and Relative Maximum Absolute Error (RMAE). These metrics are used to modify the network architecture and the hyperparameters in order to obtain the greatest generalization possible.

4.3 Training, optimization and validation of the network

The training and optimization phases are strictly related. The hyperparameters are divided in groups, for each group is executed the training and the performance of the network are evaluated with the accuracy metrics. Starting from the first group of hyperparameters, the combination that provides the greatest accuracy is considered optimal, used for the following group and so on. In this work the hyperparameters are divided in three groups:

a) Activation function, number of nodes and number of layers
b) Parameters initializations, batch size and optimizers
c) Regularization methods and epochs

The optimized network is composed by 32 nodes per layer and 3 hidden layers.

4.3.1 Statement of final performance and model comparison

Once optimized the network, its approximation capabilities must be evaluated onto a set never seen by the network during the training in order to avoid biased evaluation. In *Table 1* a comparison between the here developed neural network and other 4 metamodeling techniques analysed by Nik et all. [2] for a similar problem is reported.

Metamodel	R^2	RMAE	RAAE
Polynomial Regression (PR)	0.462	2.826	0.589
Radial Basis Function (RBF)	0.779	1.827	0.346
Kriging (KRG)	0.798	1.859	0.343
Support Vector Regression (SVR)	0.680	1.982	0.415
Artificial Neural Network	0.722	0.378	0.099

Table 1: Comparison of metamodeling techniques

From the point of view of the R^2 the best metamodel is given by KRG but with an accuracy value very close to RBF and ANN. Concerning the RMAE and RAAE the most accurate model is the ANN. R^2 and RAAE are two global accuracy metrics while the RMAE indicates the local level of accuracy. From this comparison it is possible to state that ANN has almost the same global approximation capabilities of best metamodeling techniques but is capable to better capture the local behaviour of the system.

5 NEURAL NETWORK ASSISTED OPTIMIZATION

The maximization of the buckling load is achieved through an optimization procedure based on a metaheuristic algorithm. Since the scope of the methodology here investigated is to reduce the computational times associated to the structural design optimization a fast bio-inspired metaheuristic called Particle Swarm Optimization (PSO) is considered. The neural network previously trained, is now used to approximate the value of the objective function given by the inverse of the buckling load.

5.1 Optimization results

Since PSO is intrinsically stochastic, principally due to the random initial position of particles, the optimization procedure is repeated 10 times and in all the cases the maximum buckling load obtained is very similar Figure 4.

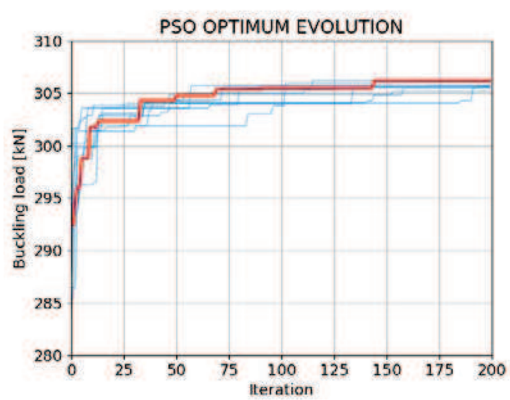


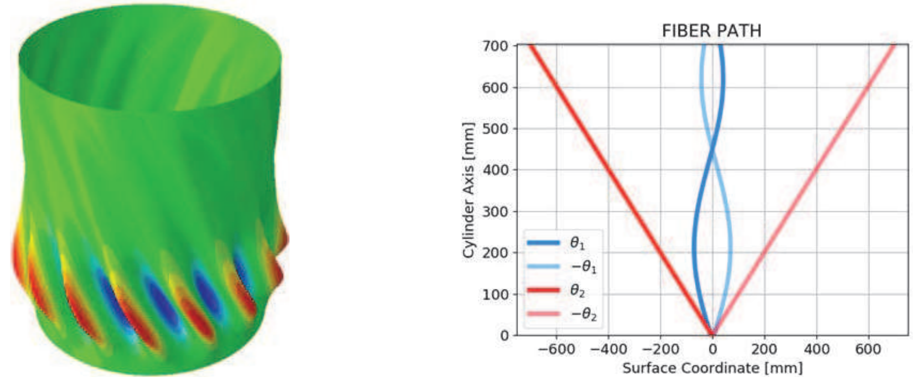
Figure 4: Evolution of the maximum buckling load

At this point it is important remember that the value of the objective function is given by the global approximation tool. In order to assess the effectiveness of the optimum configurations obtained the results are validated by means of FEA. In Table 2 the buckling load and the pre-buckling stiffness associated to best configuration after the validation are shown. As done in literature, also the values associated to the same geometry with quasi isotropic (QI) layup are reported in order to have a comparison.

	Quasi Isotropic	Variable Stiffness
Buckling load [kN]	300.39	312.51
Stiffness [kN/mm]	209.19	222.83

Table 2: Optimization results

With respect to the QI configuration an improvement of about 4% in the buckling load and of about 6% in the pre-buckling stiffness are obtained. In Figure 5 the first mode shape and the fiber shapes for half of the layup corresponding to the optimal configuration are reported. The fibers of the outer plies follow an almost complete sinusoidal function while the inner ones are at $\pm 45°$. As it is possible to see the mode shape resembles the superposition of the two fibers paths. Because of the lack of symmetry of the fibers with respect to the cross-section at $x = h/2$ the maximum radial displacements move toward the lower edge. This behavior can be explained considering that the lower edge is the one with a clamp constraint and this could help to sustain the load with a stabilizing effect.



(a) (b)

Figure 5: Optimization results. (a) first mode shape; (b) shape of the fibers

5.2 Computational times

In order to highlights the advantages offered by an optimization procedure driven by a deep learning algorithm it is important to evaluate the differences in terms computational times between this methodology and the one which makes use of only FEA. In *Table 3* the computational times required to compute the buckling load and the stiffness with Abaqus simulation and with the ANN are reported. Besides the big reduction of computational efforts offered by use of an ANN, which is also able to approximate both the quantities in the same time, it is important to point out that it allows also to parallelize the approximations. Thanks to the possibility to write in a matrix form the operations carried out by neurons, the time required to evaluate one configuration and the one required to evaluate, for example, 100 configurations is approximatively the same. It is possible to parallelize also FE analysis but with a considerable increase in complexity in doing so and, in case of neural network, this task is automatically performed with libraries such TensorFlow.

Abaqus		Neural Network
Buckling load	Stiffness	Buckling load + stiffness
420 s	30 s	0.2 s

Table 3: Comparison of computational times

It is now possible to compare the total optimization times required by the two strategies. Since only the optimization with ANN has been performed, the total time required by use of only FEA is approximated. This time is obtained by multiplying the times required by the two FE simulations for the number of particles in the swarm and for the number of iterations, and then adding the time required by the PSO for the evaluations of the constraint and for the correction of the positions. In order to correctly compare the two strategies, the time spent to train the network is also taken into considerations. In *Table 4* the two optimization times are reported. Even if buckling analysis are not so computationally expensive a saving of about 2 months and half is obtained.

Abaqus	Neural Network	Times saved
2133 h	336 h	1797 h

Table 4: Comparison of optimization times

6 CONCLUSIONS AND FUTURE WORKS

In this paper an optimization framework based on artificial intelligence techniques as been proposed and investigated. The methodology envisages the training of an artificial neural network with finite element simulations in order to learn to approximate the structural behaviour. In this way the network can substitute the expensive simulations during the search of the optimum configuration where a lot of analyses must be performed. The optimization makes use of a derivative-free bio-inspired metaheuristic algorithm called particle swarm which provides a fast convergence with a good result. The framework has been applied to the optimization of a variable stiffness cylindrical shell for maximum buckling load. An improvement of both the buckling load and the pre-buckling stiffness with a remarkable reduction of computational times with respect to the same optimization with only finite elements analysis has been obtained. The same methodology can be applied to the same problem removing the strict constraint onto the layup of the configurations and including also requirements on the post-buckling field. Further improvements are expected in this application.

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