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Buckling optimization of variable stiffness cylindrical shells through artificial intelligence techniques

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ABSTRACT

Thin-walled cylindrical shells are nowadays widely used for principal structures in the aerospace field. Despite the capacity to sustain high levels of axial compressive loads they are also easily prone to fall into buckling. One of the methods currently studied to increase the value of the critical load associated with this phenomenon consists in the use of curvilinear fibers, through which it is possible to continuously change the stiffness, and consequently the local behavior of the structure. The paper describes an optimization methodology developed for the buckling optimization of thin-walled variable stiffness cylindrical shells subjected to axial load, together with a general fibers path formulation. The framework proposed involves a synergic work between the finite element method and artificial intelligence techniques. The optimal configuration shows an increase of the buckling load of about 4% together with an increase of the pre-buckling stiffness of about 6%.

1. Introduction

In the last decades, the evolution in automation and manufacturing techniques led to the birth of new advanced technologies such as Automated Fiber Placement (AFP) in which robotic is used to lay fibers tows onto a mold surface to create the laminate. In AFP, the machine head is capable of steering the fibers within the plane of the laminate allowing to change locally the stiffness of the component, creating the so-called variable stiffness (VS) composites [1]. Varying the stiffness continuously along a certain path, the designer is capable to fully exploit the directionality of the composites, increasing considerably the design space when compared to constant stiffness (CS) counterparts. The possibility to better tailor the structural behavior doesn't come for free as it is accompanied by a higher complexity of the design phase and by manufacturing limitations. The most important manufacturing limitation is related to the maximum allowable curvature of the fibers path, beyond which a drastic decrease of the performances is obtained due to fibers wrinkling. The concept of curvilinear fibers composite materials was firstly introduced by Hyer and Charette [2] with the idea of increasing the tensile load capacity of a plate with a centrally located circular hole avoiding the interruption of the fibers. Successively, many authors, attracted by this new design possibility, investigated the effect of stiffness variation with different purposes. Abdalla et al. [3] investigated the application of VS laminates with the goal of mitigating resonance problems applying the concept of lamination parameters. The same approach was also considered by Setoodeh et al. [4] for the maximization of the buckling load of a composite VS panel. Wu et al. [5] analyzed the problem of the correlation between numerical and experimental tests, taking into account different prestress conditions. Other authors, such as Vescovini and Dozio [6], considered the approximation of the structural behavior with analytical formulations. Despite the concept of variable stiffness composites attracted a lot of researchers since the start of the XXI century their applications were limited to flat panels. One of the first researcher who extended the applicability of this concept to cylindrical shells is Tatting [7]. In his work, both axisymmetric and circumferential stiffness variation were considered, and only in the second case, a satisfactory increase in performance was obtained. Blom [8] applied the VS concept to elliptical-section cylinders obtaining numerically an increase in the fundamental natural frequency of 30% and an increase of the bending critical load of 18% with compared to the quasi-isotropic counterpart. Labans and Bisagni [9] investigated the behavior of CS and VS cylinders with imperfections. Both buckling, post-buckling, vibration analysis and tests were performed obtaining good correlation.

In aerospace, like in many other fields, a lot of effort is spent trying to increase the performances of commonly used structures. Structural responses are simulated by means of well known Finite Elements (FE) software, since physical experiments are too expensive and take too much time if the objective is to find the best parameters set up during a preliminary phase. For an appropriate choice of parameters values, it

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is necessary to move the problem into an optimization framework in which parameters update is made following a specific methodology which allows finding the best design in a limited amount of time. During the optimization, the behavior of the structure associated with different combinations of the design parameters must be evaluated in order to assess the value of an objective function. This phase may require hundreds of thousands of FE simulations and consequently a high computational time. A possible solution to overcome this problem is the replacement of the high fidelity FE analysis with a properly constructed metamodel. This technique represents a model of the model since it tries to approximate the response of the numerical model of the physical system. This strategy is not completely new since many authors successfully applied it in case of CS laminates [10–13] but only few works concerning VS composites, where the number of design variables is considerably higher, are present. Rouhi et al. [14] considered the fibers path optimization of a cylinder subjected to bending moment with a multi-step metamodeling-based design optimization approach. Ye et al. [15] applied Least Squares Support Vector Regression for the optimization of a plate under compression and a cylinder in bending. Nik et al. [16] conducted a comparative study about the state-of-the-art metamodeling techniques for square panels and cylindrical shells. These papers represent the first attempts to take advantage from the introduction of Artificial Intelligence (AI) techniques inside a structural optimization problem concerning VS laminates.

Beyond the approximation of FE models AI has found several other applications related to the aerospace structural field. In the paper by Salehi and Burgueo [17], it is reported a very detailed overview of the various AI models applied for health monitoring of structures, damage detection and structural identification. In the paper by Fonte et al. [18] a recurrent neural network controller is designed for load alleviation by means of a dedicated wingtip equipped with a small control surface to be applied to a regional aircraft. Finally, in Bernelli et al. [19] the same network architecture is involved in the active suppression of the flutter.

In this paper, an optimization methodology based on bio-inspired AI techniques is presented. The methodology involves the design of an Artificial Neural Network (ANN) for the approximation of the buckling load and of the pre-buckling stiffness of a composites cylindrical shell. The net is then used for the evaluation of the fitness functions during the optimization carried out using a Particle Swarm Optimization (PSO) method. Fig. 1 shows the optimization framework developed in this paper that will be detailed in the following sections. The goal of the work is to evaluate the possibility and the quality of the structural approximation through ANNs and to further demonstrate the beneficial effects of a data-driven approach inside a structural optimization problem.

2. Modelling technique

The geometry of the cylindrical shell here considered is the same as a previous work by Labans and Bisagni [20] and consists of 705 mm of height, 300 mm of radius and 8-ply lay-up with a total thickness of 1.448 mm. The plies are made of AS4/8552 CFRP prepreg which mechanical properties are reported in Table 1.

The FE models are generated inside the commercial software Abaqus [21] and the Abaqus/CAE tasks are executed with the help of parametric Python scripts. The cylindrical shell is created in the $x-y$ plane and then rotated during the assembly so to have the x axis coincident with the cylinder axis and the cross sections in the $y-z$ plane Fig. 2.

The nodes belonging to the section at $x = 0$ are clamped while ones at $x = h$, where h is the cylinder height are free to move only along the x axis. The constraints are introduced through two reference points, one in the origin at (0, 0, 0) and the other at (h, 0, 0) which are connected with tied constraints to all the nodes of the relative cross-section. In this way, the boundary conditions can be directly applied only to the two reference points. The upper reference point is also used for the introduction of the axial load. Since the load distribution doesn't vary circumferentially, the model is built such that the fibers path can vary only in the axial direction: $\theta = \theta(x)$. In this way it is possible to assign a preferred lay-up to all the elements at a certain cross-section from the origin. The continuous variation of the fiber angle is approximated as a piece-wise constant inside each element and, along the circumference, all the elements have the same lay-up. The elements used are reduced integration S4R shell-type with a mesh size of 5 mm. The dimension of the elements has been fixed after a mesh sensitivity

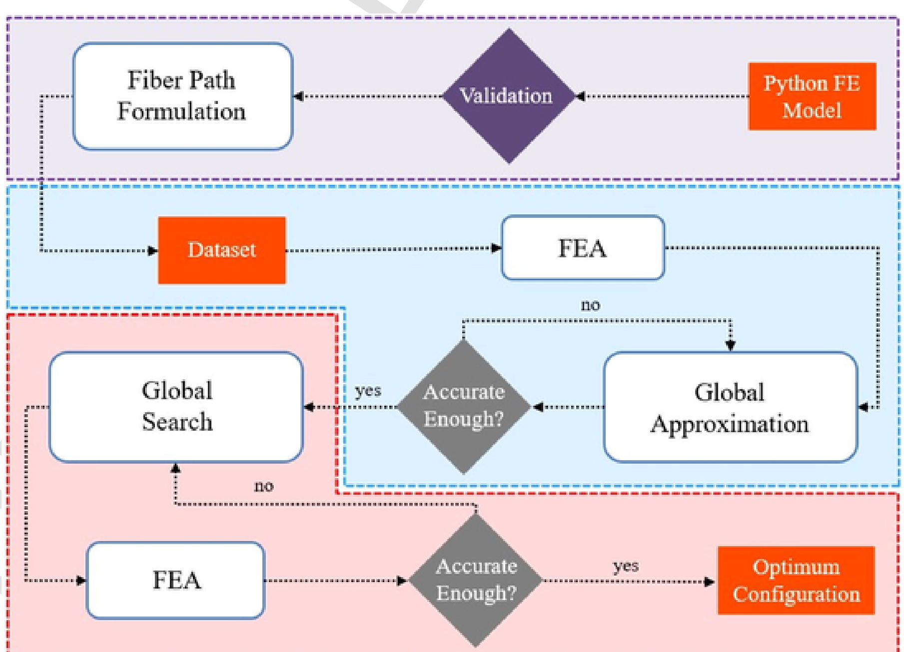

Fig. 1. Methodology flowchart.

Table 1
Material properties of AS4/8552 prepreg.

E_{11} (GPa)	E_{22} (GPa)	G_{12} (GPa)	ν_{12} (–)	ρ (kg/m ^{3})
141	10.3	4.5	0.3	1580

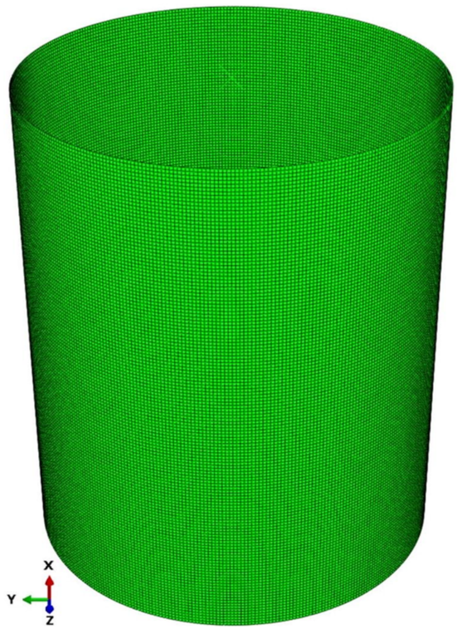

Fig. 2. FE model of the cylindrical shell.

analysis based on the convergence of the buckling load to variations of the mesh size.

2.1. Fibers path definition

The most used path definition for VS composites relies on a piecewise linear variation of the fibers angle [7] and allows discrete freedom in the path definition. The problem is that, in order to approximate a complex function, the structure must be divided into a lot of pieces at the expense of an increasing number of design variables. The other used path definitions like Lagrangian [22] or Lobatto [23] polynomials lack simplicity since involve complex mathematical formulations, do not allow for a direct interpretation of the fibers path and, in some cases, must be recovered with other techniques as the streamline analogy. The possibility of having an extensive range of paths defined through a function that requires few parameters is fundamental for an efficient optimization process. For this reason, it is here proposed a new mathematical formulation for the definition of the fibers path. The formulation is valid both for plates and for cylinders. Considering a reference system with the x-coordinate aligned with the cylinder axis and the y-coordinate tangent to the unrolled surface of the shell, the fiber path proposed is expressed as:

$$y(x) = Asin\left(\omega\frac{2\pi}{h}x + \phi\right) + \tan(\alpha)x \tag{1}$$

where A is the amplitude, ω the frequency and ϕ the phase shift of the harmonic function, h the height of the cylindrical shell and α the slope of the linear term. From the just presented equation it is possible to recover the local fiber angle:

$$\theta(x) = \arctan\left(\frac{dy}{dx}\right) \tag{2}$$

where $\theta(x)$ is the local angle between the fiber and the x axis. The expression can be divided into two terms: the first term is a trigonometric function with three parameters A, ω and ϕ that allows the fiber to follow a simple or complex path depending on the parameters combination, while the second term is the one related to the CS design space. This last term allows the formulation to overcome the limitations given by actual fiber path definitions thanks to the possibility to generate straight paths ranging from 0◦ to 90◦. In this way, the design space of the CS composites is completely taken into account and enlarged. The combination of these two terms guarantee a high design space but easily shrinkable since each parameter has a direct and known effect on the fiber shape as shown in Fig. 3. Moreover, the approximation capacity can be increased by increasing the trigonometric terms inside the path definition of Eq. (1).

Beside the large design space offered by this formulation, it gives also the possibility to easily introduce manufacturing constraints related to the fibers curvature. If the curvature of a path exceeds the limit value allowable by the specific AFP machine considered, the fibers at the inner side of the curvature will buckle during the placement of the tow. This constraint is fundamental in order to generate only admissible stacking sequences, free of defects due to fibers wrinkling. The curvature of the path is expressed as:

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

where y' and y'' are respectively the first and the second derivative of the path w.r.t the x-coordinate.

2.2. Domain of interest

One important aspect of the design optimization methodology here presented is the definition of the design space. It is fundamental to properly bound the range of variation of the variables in order to construct a global approximation model without wasting time with simulations outside the space of interest, decreasing the local approximation capability. Moreover, the optimization phase requires the knowledge of the boundaries inside which looking for the optimal configuration. For this purpose, and since the value of the curvature is imposed by the AFP machine, it was decided to use the frequency of the path formulation (Eq. (1)) as a dependent variable. After setting the values of A, ϕ, α and κ, the maximum value of ω which guarantee no wrinkling is calculated as:

$$\omega(A, \alpha, \kappa) = \sqrt{\frac{\kappa\left(1 + \tan^2(\alpha)\right)^{\frac{3}{2}}}{\frac{4\pi^2}{h^2}A}} \tag{4}$$

In this way, the upper boundary of the frequency varies according to the values of the other variables. Instead of considering the actual maximum curvature allowable by AFP machines, in this paper it is decided to use a higher value, mainly for two reasons:

1. The capacities of manufacturing machines in the field of fiber steering are continuously growing, so a further increase in manufacturing freedom is expected in the future years.
2. It is more challenging to build a metamodel onto a system with more freedom in terms of its inputs variability and response. A low value of the curvature restricts the response of the structure to be very close to a classical CS composite.

Considering in this study only symmetric and balanced configurations, as in [7], the number of design parameters is 8, as two fiber paths are considered in order to completely define the composite lay-

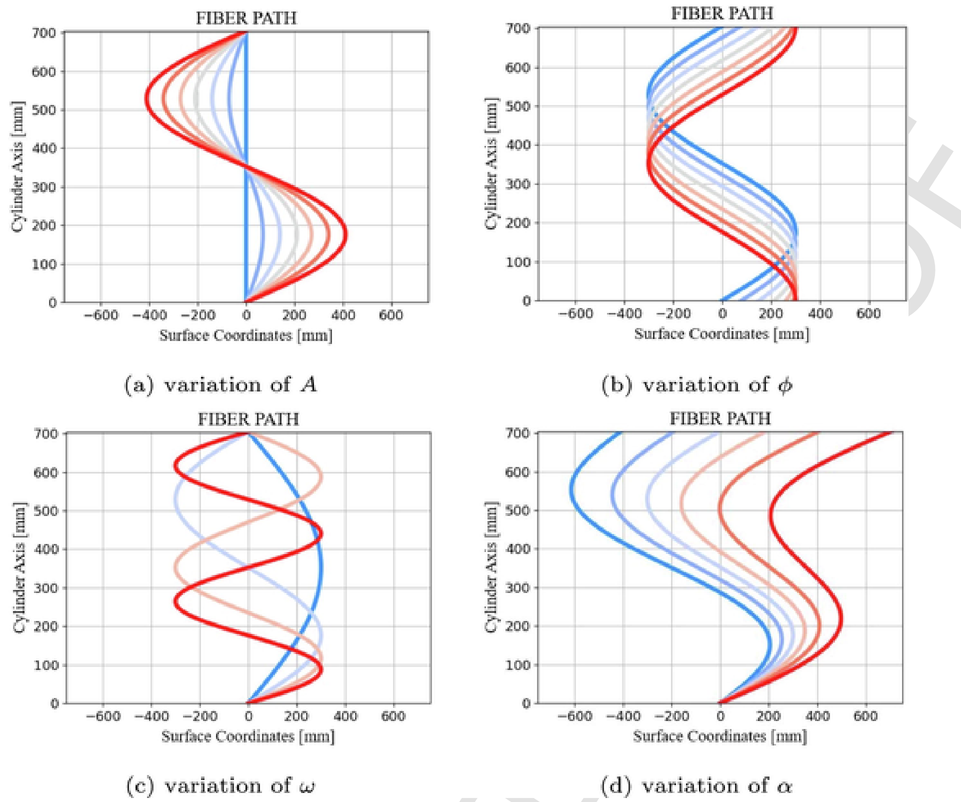

Fig. 3. Effect of the fiber path parameters.

up given by $[\pm\theta_1, \pm\theta_2]_s$. In Table 2 the boundaries of the fiber parameters, chosen after a sensitivity analysis, and the value of the maximum curvature allowed are reported. The fiber parameters are bounded so as to avoid wasting resources by simulating configurations that are certainly not optimal.

3. Metamodeling

One AI technique that is getting more and more successful in these years is the global approximation through artificial neural networks (ANNs) [24]. ANNs derive from observations of brain processes from an engineering point of view. They are nothing but the result of the attempt to simulate the accumulation of experience inside a machine with the aim of solving complicated tasks exploiting parallelization of simple operations. The fundamental unit of an ANN is the mathematical model of a neuron, which is able to perform a linear combination with a bias followed by a nonlinear function, as shown in Fig. 4. From the figure it is possible to see the design parameters of the ANN, namely w and b. The former are weights applied to the inputs of the neuron while the latter is the bias.

The complete architecture of the net is obtained by connecting a certain number of this simple unit according to different schemes. Here the feedforward scheme is adopted in which the neurons are grouped in layers and each neuron of each layer is fully connected with the neurons of the adjacent layers. Three kinds of layer exist: the input layer which contains the input parameters, the hidden layers which transform the inputs space into another dimension and the output

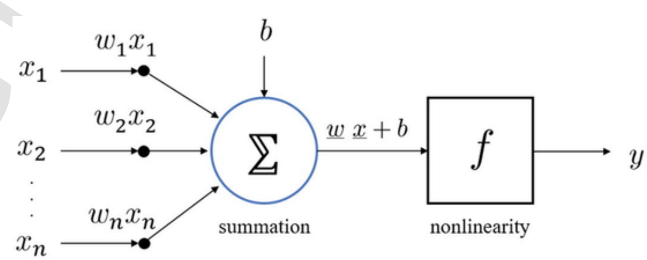

Fig. 4. Mathematical model of a neuron.

layer which provides the requested outputs. By discovering the nonlinear relation that exists between the input features and the outputs, the network is able to produce a global approximation of specific quantities. In this way, the net can replace FE simulations reducing the time required to compute the structural response. The process, through which the net is trained to approximate the structural behavior, is called learning. During this phase a certain number of input/output pairs, which constitute the dataset, are passed through to the network and its parameters are modified until a satisfactory level of approximation accuracy is obtained.

Table 2
Parameters boundaries and maximum curvature allowed.

A (mm)	ϕ (°)	ω (rad/s)	α (°)	κ_{max} (1/mm)
[10, 100]	[0, 90]	[0, 2]	[0, 45]	1/200

3.1. Dataset generation

In order to decide which combinations of input parameters could be used to train the model and so, which FE simulations perform, the Latin Hypercube Sampling (LHS) method is adopted. This method allows to generate a near-random sample of the design parameters inside the multidimensional design space. The total number of simulations performed are 135 eigenvalue buckling analysis to determine the buckling load and 135 linear static analysis to determine the stiffness. Buckling load and stiffness, together with the fiber parameters, represent the 135 inputs/outputs pairs that are used to learn this multi-task regression. Of these simulations, 81 are involved to train the network to learn the relationship between the inputs and the outputs, 27 to evaluate the approximation quality of the network and modify its architecture during the training, while the remaining 27 to state the final performances of the metamodel. The first group of samples is called training set, the second validation or dev set and the third test set. Since it is very important that all these three sets are able to represent the design space, they are generated independently and using the same LHS method. During this phase the manufacturing constraint regarding the maximum curvature is taken into account. First of all, the sample values for the parameters A, ϕ and α, are generated and then the values of ω are sampled randomly between the minimum and the maximum allowable for each sample calculated with Eq. (4). Another important aspect taken into account during the generation of the dataset is the correlation between the input variables. If the correlation between the variables is too strong, the quality of the approximation can decrease significantly. The Spearman Rank Correlation Coefficient (SRCC) is introduced for this aim. The dataset generation process is repeated different times and the training set with the lowest values of the correlation index is used. In Fig. 5 the SRCC between the design variables considered is reported. The value inside each square box represents the correlation between the corresponding variables on the x and y axes.

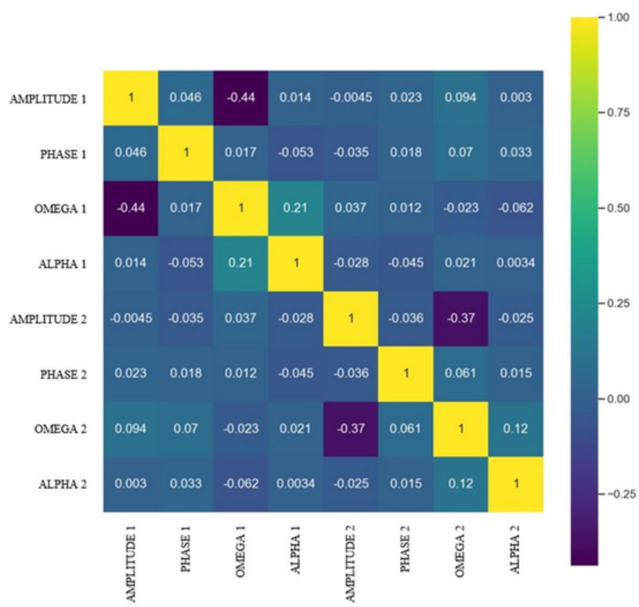

Fig. 5. Spearman Rank Correlation Coefficient.

According to [25], a value of the correlation coefficient of 0.1 indicates weak correlation, a value of 0.3 indicates moderate correlation, while a value of 0.5 indicates a strong correlation. As expected there is a fairly strong correlation between ω and A and a moderate correlation between ω and α since the values of the frequency are obtained on the basis of the maximum curvature.

3.2. Training

During the training, the parameters of the network are modified backpropagating the approximation error. For regression problems the error is computed as the Mean Squared Error (MSE). More precisely, in this case the MSE is calculated both for the buckling load and for the stiffness, and then added up. Together with the network parameters, during the training, also other variables of the architecture called hyperparameters are modified. The hyperparameters are for example the number of neurons, the number of hydden layers, the parameters initialization methods and others which have a direct effect on the approximation capability of the ANN defining the class of the estimator. In this work the optimization of the network architecture is achieved by a first global search for a group of hyperparameter in order to narrow their design space, followed by a deep local search. The hyperparameters are grouped and optimized as follow:

- Number of hydden layers and number of nodes
- Parameters initializations, batch size and optimizers
- Regularization methods and epochs

The batch size represents how many samples are shown to the network at a time to calculate and propagate the error. Once all the samples of the training set are passed to the network, an epoch is concluded, where the number of epochs represents how many times an entire set is presented to network to update the parameters. The initialization methods are techniques used to initialize the values of the parameters according to specific statistical distribution or to obtain a specific value of their variance. The optimizers are the methods used to update the parameters. In this study the most common ones are considered and are all variants of the basic gradient descent. The regularization methods are introduced to increase the generalization capacity of the network and to make the learning process less sensitive to overfitting. In Fig. 6 the flowchart describing the procedure of the dataset generation and of the training is reported.

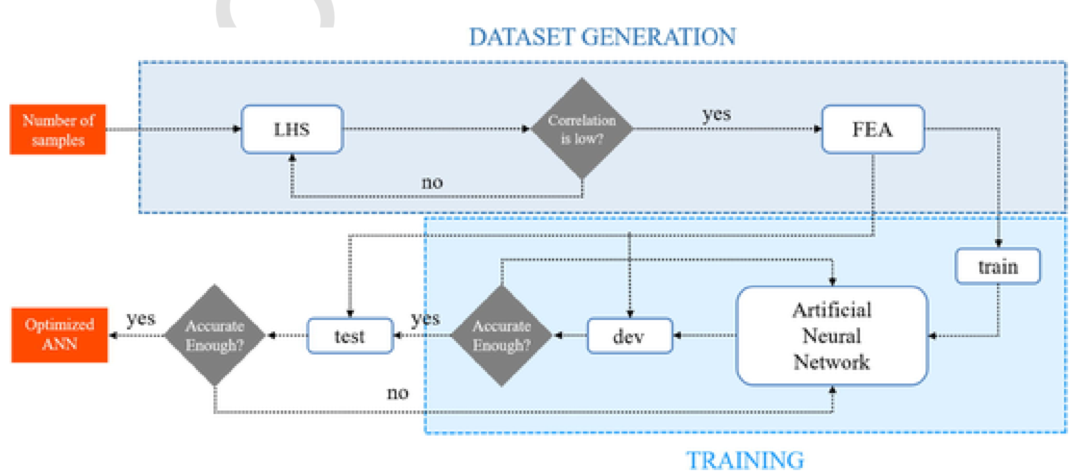

Fig. 6. Flowchart of metamodel generation.

3.3. Network optimization

In order to properly decide which the best network architecture is, it is necessary to define specific metrics of accuracy. This necessity comes from the impossibility of the MSE to take into account fundamental aspects as the variance inside the training set. In this research three metrics are considered and evaluated during the training process in order to assess the performance of the network. Let consider that y_i represents the correct response associated to the sample i,$\hat{y}_i$ represents the estimated output of the network at the same sample and $\bar{y}_i$ is the mean of all the outputs of the considered batch. The first metric considered is the *R Square Error* (R^2) which indicates the overall accuracy of the metamodel. Higher its value is, more accurate the prediction is. Considering a batch size composed by *N* samples the R^2 is defined as:

$$R^2 = 1 - \frac{MSE}{variance} \tag{5}$$

More R^2 is close to 1 and more is the variability of the output that is taken into account. The second metric considered is the *Relative Average Absolute Error* (RAAE) which is another indicator of the global accuracy of the metamodel since represents the average absolute difference between the predicted output and the correct one weighted by the standard deviation (STD). Small RAAE is and more accurate the model is:

$$RAAE = \frac{\sum_{i=1}^{N} |y_i - \hat{y}_i|}{N \times STD} \tag{6}$$

The last metric considered is the *Relative Maximum Absolute Error* (RMAE) which is a local indicator of the accuracy, since an higher RMAE value indicates that the accuracy of the model is low in one or more regions of the design space:

$$RMAE = \frac{\max_i(|y_i - \hat{y}_i|)}{STD} \tag{7}$$

After it is found the final configuration of the optimized neural network that consists of:

- number of nodes: 32
- number of hydden layers: 3
- initializers: zeros for bias and "Glorot uniform" for weights
- optimizer: Nadam with learning rate of 0.001
- batch size: 32
- epochs: 50000
- L_2 regularization: 1e−5

In Table 3 the values of the considered accuracy metrics, evaluated onto the test set, are reported.

These values are then compared with other metamodels applied to similar problems found in literature: the R2 metric is close to the values of the other methods while the other two metrics are particularly improved. Considering the RMAE this means that a neural network allows approximate very well the local behavior of the system inside the design space.

Table 3
Accuracy metrics on test set.

R^2	RAAE	RMAE
0.722	0.099	0.378

4. Design optimization

In this section, the method adopted to optimize the 8 input parameters with the goal of maximizing the buckling load is presented. The design variables are subjected to the constraint regarding the maximum curvature allowable and have a specific range of variation in which the optimal configuration has to be found. The optimization problem can be stated as:

$$\begin{aligned} &\min_x \quad \frac{1}{F_{buckling}(x)} s.t. \quad to \quad \kappa \\ &- \kappa_{\max} < 0 x_{n_{\min}} \leqslant x_n \leqslant x_{n_{\max}} \quad n = 1, \dots, 8 \end{aligned} \tag{8}$$

The problem is addressed with a population-based, metaheuristic and derivative-free method. PSO was proposed by Eberhart and Kennedy [26] and derives by the observation of a sociobiologist about the beneficial effects of experience exchange between members of a group. The idea is to fill the design space, randomly, with a certain number of particles that move into the space according to Newton's law. The dimension of the design space is equal to the number of the design variables and the position of each particle represents a possible solution of the optimization. This method is very easy to implement and compared to the Genetic Algorithm, which is the actual most used metaheuristic method, allows for a fast convergence with practically the same quality [27]. In PSO, at each iteration, the particles move subjected to three forces: the inertia, the cognitive force and the social force. The inertia force, as for a real physical particle, is a force that opposes changes in the current state and leads the particle to move in the same direction of the previous iterations. The cognitive and the social forces derive from the introduction of the concept of experience: every particle is able to remember the position associated to the best value of the fitness function of which he has experienced but is also aware of the position associated to the higher value of the fitness function found by the swarm. The cognitive term forces the particle towards its experienced best solution, while the social term forces the particle towards the global best. The basic equations of the algorithm are:

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)\Delta t \tag{9}$$

$$v_{ij}(t+1) = \rho v_{ij}(t) + \frac{c_1 r_1 (p_{ij}(t) - x_{ij})}{\Delta t} + \frac{c_2 r_2 (p_{gj}(t) - x_{ij})}{\Delta t} \tag{10}$$

where:

x_{ij} is the actual position of the particle *i*,
v_{ij} is the velocity of the particle *i*,
ρ, c_1, c_2 are the inertia weight, the cognitive term, and the social term respectively,
p_{ij}, p_{gj} are the individual best and the swarm best position,
r_1, r_2 are disturbances introduced as random values taken from a uniform distribution between 0 and 1.

In the implemented algorithm the time step Δt is fixed equal to 1.

4.1. Boundaries handling and violated constraints

PSO is a stochastic method in which each particle moves, subjected to different forces, around the design space. It is impossible to directly give to these particles an advanced knowledge on the feasibility of the moving direction. For this reason particles tend to move outside the boundaries, especially during the first iterations. In case of VS composites, the problem is even a little bit more complicated due to the dependence of the maximum value of the angular frequency in relation to the values of amplitude and linear term. This leads to having a varying maximum boundary for one design variable of each ply. Together with the imposition of the respect of the domain, it is also necessary to impose into the optimizer the fulfillment of the functional constraint about the maximum curvature. The strategy adopted to manage the constraint is to apply a sequential approach. In the first step the position of all the particles is corrected in the dimensions of the amplitudes, phase shifts, and linear terms and then, after having evaluated the maximum allowable radii of curvature also the frequencies are corrected. In this way the constraint regarding the curvature is translated into a correction of the frequency in a second step. The bound-handling scheme here considered is the reflection, according to which, if a particle is about to violate a constraint, it is reflected at a velocity equal in magnitude but with opposite direction respect to the actual one.

4.2. Optimizer parameters

Before being able to optimize the design variables it is necessary to properly choose the optimizer parameters: ρ, c_1, c_2, number of iterations and number of particles. Among these five parameters the first three are the most important, since govern the way in which the search of the minimum is performed, and are strictly related to the stability of the optimizer. In order to have a high exploitation ability at the beginning of the process, and more exploration ability at the end of the search, a dynamic inertia weight is considered. The inertia weight is linearly decreased from 0.9 to 0.4. The cognitive and the social terms are taken both equal to 2 in order to modify the behavior of the swarm during the optimization only with the inertia. The dimension of the swarm is fixed as a rule of thumb to 10 times the number of variables, and a good number of iterations is found to be 200. In Table 4 the times associated to a single global search are reported. From the table is really clear the advantage offered by the network in the optimization process since it makes the evaluation of the objective function the less expensive part of the process.

5. Results and discussion

Due to the intrinsic stochastic nature of the PSO, the optimization is repeated 10 times and in all the cases the solution converges to a similar configuration as visible in Fig. 7. The red line represents the envelope of the higher buckling load obtained during the optimization which configuration will be considered in the following.

Once the optimal configuration is obtained the results given by the ANN are validated by means of FE simulations. This step is necessary in order to check if the optimal configuration given by the network is effectively optimal. As done in literature, the buckling load and the pre-buckling stiffness obtained with FE are then compared with the values of a quasi-isotropic (QI) configuration given by a $[0, 45, -45, 90]_s$ stacking sequence. It is important to remark that for the cylinder under investigation no imperfections are included, so the real optimum configuration will be reasonably different from the one here presented. The values of the two configurations are reported in Table 5.

As it is possible to see the VS composite cylinder exhibits a 4% higher buckling load together with an increase of about 6% in the stiffness. The improvement with respect to the QI configuration is not so high. This is due to the fact that the optimization procedure is performed considering only symmetric and balanced stacking sequences, so imposes a relevant constraint on the structural behavior. A larger increase in performance is expected removing this constraint and considering all the plies as independent. In Fig. 8 half of the symmetric lay-up is reported, where each ply is represented by the shape of only one fiber.

The vertical axis corresponds to the x-coordinate, parallel to the cylinder axis, while the horizontal axis is the tangent to the unrolled surface. The external plies have fibers nearly at 0° with sinusoidal shape, while the internal ones are straight at ±45°. The first buckling mode of the optimal design is reported in Fig. 9. With respect to the QI mode shape the region at higher radial displacements moves toward the clamped edge. A particular aspect, also highlighted in literature, is that the shape manifested is very similar to a superposition of both the paths defined by θ_1 and θ_2.

In addition to the increase in performance, what is important to point out is the demonstration of the effectiveness of a design procedure based on ANNs and PSO. Considering a machine with Intel(R) Core(TM) i7-6700HQ CPU@2.60 GHz and 8 GB of RAM the CPU times required to compute the buckling load and the stiffness with FE

Table 4
Total times PSO assisted ANN.

Total (s)	ANN evaluations (s)	Constraints & updates (s)
450	80	370

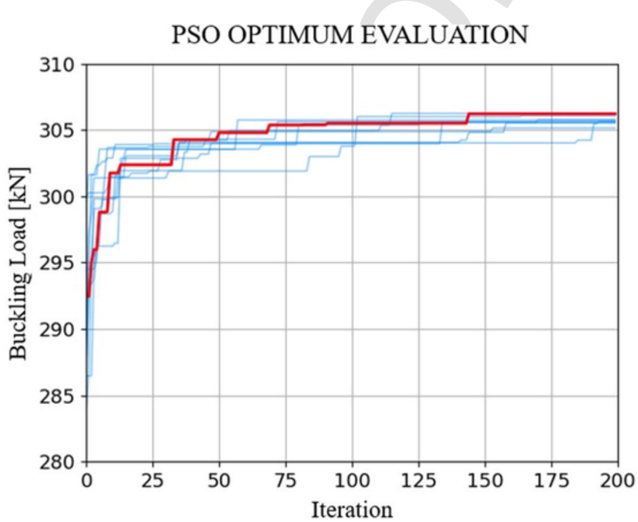

Fig. 7. Maximum buckling loads envelopes.

Table 5
VS and QI comparison.

	QI	VS
$F_{buckling}$ [kN]	300.39	312.51
K [kN/mm]	209.19	222.83

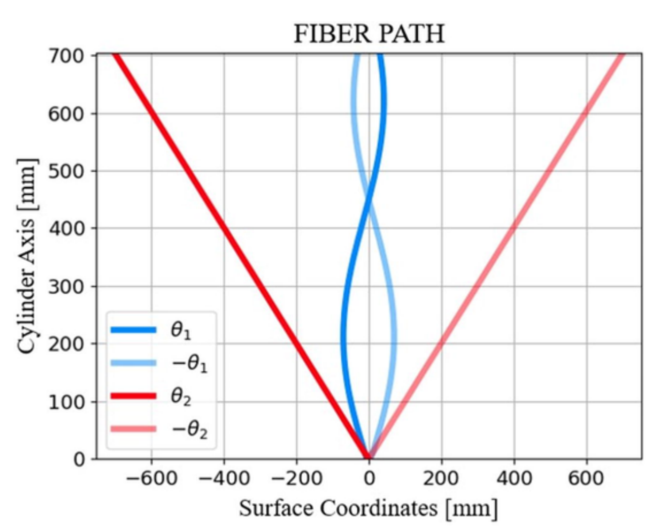

Fig. 8. Fibers shape of the optimized configuration.

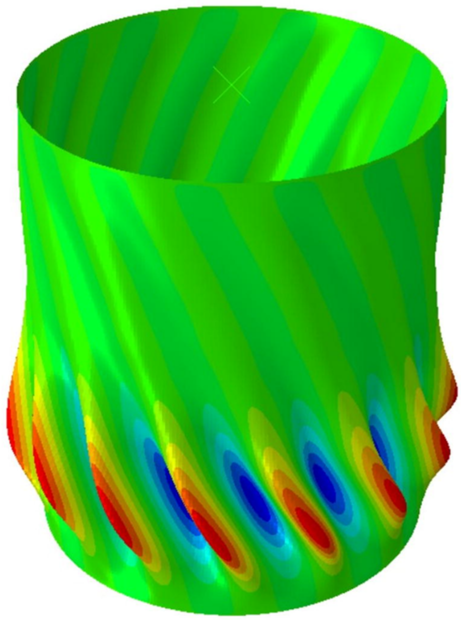

Fig. 9. First buckling mode of the optimized configuration.

simulations are respectively 420 s and 30 s, while with the ANN the two quantities are approximated in 0.2 s at once. The time required to compute the optimal configuration with the adopted methodology is about 14 days, where also the training time of the network is included. It is possible to have a comparison by multiplying the number of fitness function evaluations by the time of FE analysis, including also the times required by the PSO to evaluate the constraints and update the particles position. The time saving computed in this way is about two months and half. The advantages offered by this methodology can be summarised in three points:

1. The FE model is decoupled from the optimization phase.
2. The ANN allows to approximate multiple quantities at the same time.
3. It is possible to approximate the structural behavior of multiple configurations in the same time with a minimum increase of computational cost w.r.t. the simulation of a single configuration.

This last point is particularly important since the capability of the network's nodes to perform matrix multiplication allows to parallelize the simulations.

6. Concluding remarks

In this paper, the optimization of a variable stiffness cylindrical shell for maximum buckling load has been investigated. To this end, a methodology based on artificial intelligence techniques is proposed. A new general and easy fiber path formulation for the definition of the fibers shape was presented first. The formulation couples a trigonometric function and a linear term and allows to enlarge the design space associated with classical composite materials. The approximation of the structural behavior and the buckling optimization were performed combining a neural network system and a particle swarm optimizer. Finally, an optimization module based on PSO approach has been implemented. The results of the optimization procedure were compared to the results of a quasi-isotropic configuration showing an improvement of the buckling load of 4% together with an increase of the stiffness of 6%. This limited increasing of the buckling load is due to the fact that the optimization procedure is performed considering only symmetric and balanced stacking sequences, for which the QI configuration is almost optimal. More, at this stage of the investigation the effects of the geometrical imperfections as well the influence of the clamping is completely neglected. Indeed, it is well know the considerable effect on the buckling load but the main scope of this paper is the validation of the proposed procedure and not the realization of an optimal cylinder in presence of imperfections or other variabilities. The metamodel, based on the use of ANNs appeared as reliable despite the reasonably limited number of analysis cases used during the training phase. The use of metamodels during the optimization framework produced an impressive impact from the computational costs of the entire process. On the other hand, the PSO technique appears as reliable and easy to implement.

The first medium-term development is represented by the application of the proposed methodology to the same problem removing the constraint on the lay-up and to extend the procedure in order to allow also the optimization of a cylinder with cutouts. The second, more complex development, aims at the extension of the proposed approach to more complex structures including holes and other local geometry variation coupled to a more detailed manufacturing constraints.

Data availability statement

The raw/processed data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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