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Minimum-weight design for three dimensional woven composite stiffened panels using neural networks and genetic algorithms

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Abstract

The paper describes a modeling strategy for multi-scale analysis and optimization of stiffened panels, made of three-dimensional woven composites. Artificial neural network techniques are utilized to generate an approximate response for the optimum structural design in order to increase efficiency and applicability. The artificial neural networks are integrated with genetic algorithms to optimize mixed discrete-continuous design variables for the three dimensional woven composite structures. The proposed procedure is then applied to the multi-objective optimal design of a stiffened panel subject to buckling and post-buckling requirements.

Keywords: 3D woven composites; stiffened panels; genetic algorithms; multi-scale analysis; optimal design.

1. Introduction

Stiffened panels are extensively used in the aeronautical field, and are often subjected to buckling phenomena under a certain level of compression load. The buckling load does not represent the maximum load that the structure can carry, and indeed, on the contrary, failure may not occur until the applied load is several times the buckling load [1, 2]. Consequently, the post-buckling strength capacity has significant potential for further weight saving.

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For this reason a large number of researchers [3-9] focused their attention on optimization procedures concerning buckling load maximization or weight minimization under buckling and post-buckling constraints.

Bisagni and Lanzi developed a global approximation strategy for a post-buckling optimization procedure for laminated composite stiffened panel combining neural network and Genetic Algorithms (GA) to reduce the cost and computation time [3]. Rikards et al. [10] developed an optimization approach based on building surrogate models and genetic algorithms. Kang and Kim [6] implemented a parallel computing scheme using GA, considering buckling and post-buckling behaviors, to obtain minimum-weight design. Bisagni and Vescovini [11] prosed an optimization strategy of a fuselage composite stiffened panel relied on a semi-analytical approach for the analysis and on GA for the optimization. Todoroki and Ishikawa [12] described a new strategy for Design Of Experiment (DOE) to obtain a response surface of buckling load of laminated composites, and then implemented the stacking sequence optimizations with GA using the response surface approximation.

Three common main characteristics can be identified in literature for the optimization of composite stiffened panels. Most of the researchers make use of meta or surrogate models to approximate the response of the stiffened panels in order to reduce the computational resources needed for the optimization. The solution of the optimization problem of composite stiffened panels is generally obtained with genetic algorithms. Most of the examples reported in literatures investigated laminated composite stiffened panels, while few investigations consider the weaving optimization of 3D woven composite stiffened panels.

The internal architecture of 3D woven composites is more complicated compared to laminated composites, but also more benefits could be obtained. Besides, the weaving parameters and routes of 3D woven composites can significantly influence the mechanical performances [9-14]. A large number of researches were performed to predict the mechanical properties of 3D woven composite via experimental [13, 14], numerical [13, 15, 16] and analytical approaches [14, 16]. The limited analytical solutions for composite structures, especially for complex topological and geometrical woven composites, prevent their use in the design optimization. Numerical approaches are a good choice for optimizing existing fabrics and for creating new textile model, but the optimization based on numerical approaches can result computationally expensive for analyzing complex structures. Besides, the time dedicated to the geometry preparation and mesh generation, to the definition of the weaving architecture and the application of the appropriate boundary conditions, must be added too.

The surrogate and approximated modeling techniques are a promising solution because , when the approximated models are properly built, these models mimic the behavior of the numerical analysis accurately and, at the same time, are computationally cheaper. For this reason the optimization strategy is generally based on combining a global approximated technique with genetic algorithms [3, 6, 10, 12, 17, 18].

Typically, the optimization problems of composite stiffened panels are characterized by the combination of continuous and discrete design variable, e.g. the number and kind of stringers, the selection of material, the number of strands in weaving architectures and the number of plays. The genetic algorithms are a reliable tool to address discrete variables optimization problem [19]. They use implicit enumeration procedures, based on Darwin's theory of survival of the fittest [20]. The main advantage of this approach is that no derivative information is needed. Three operators including reproduction, crossover and mutation are usually adopted and these three steps are carried out for successive generations of the population until no further improvement in the fitness is attainable.

In the present paper, GA are combined with neural networks to solve the continuous and discrete optimization of the 3D weaving composite stiffened panels. At first, the paper focuses on the development of multi-scale analysis models for 3D weaving composite stiffened panels, starting from the fibre, through the models of yarn and textile, till the complete model of the structure. This is done by a dedicated Python script able to manage both discrete and continuous variables and to create all the requested models for the successive analysis and optimization phases. The DOE technique, coupled with the finite element code ABAQUS, is then used to reduce the number of sample points to create an accurate approximate model based on Neural Networks capable of reproducing the structural responses. Finally, the neural network-based approximate model is integrated with the GA module to setup and solve the optimization problem of stiffened panels, aiming at the minimum weight structure in presence of buckling and post-buckling requirements. Details of the implemented procedures together with an application example are reported in the following sections.

2. Multi-scale modeling of 3D woven composites

Textile composites are based on the combination of a resin system with a reinforcement, that is usually composed of thousands of fibres bundled into yarns which can be woven, braided or knitted into two dimensions (2D) or three dimension (3D) textiles. In particular, three-dimensional composites utilize fibre preforms constructed from yarns or tows arranged into complex three-dimensional structures. While they date back to 1960s, the increased global interest in recent years in 3D fabrics for resin, metal and ceramic matrix composites has led to the current expansion of their application from secondary to primary load-bearing applications in various engineering structures.

The modeling technique here adopted is based on a multi-scale simulation process including micro, meso and macro scale, as shown in Figure . In order to predict macro scale behavior of 3D woven composite, it is necessary to know the weaving fabric characteristic and the yarn's profile.

The micro-scale modelling involves the study of the orientation and mechanical properties of the constituent yarn. The meso-scale modelling is based on the concept of homogenization and evaluates the mechanical properties of a fabric Representative Volume Element (RVE), which is typically used to determine the effective stiffness of textile fabrics. The macro-scale modelling deals with predicting the mechanical behaviors of completed textile structure under complex deformation state, assuming the fabric to be a continuous medium. The homogenization techniques provide the response of a RVE (global level) given the properties or response of the structure constituents (lower level). Since textile materials are heterogeneous and periodic, a RVE is adopted to account for the microstructure, which results in significantly reducing the size of the problem of numerical modelling. The reason for emphasizing the concept of the RVE is that it appears to provide a valuable discriminator between continuum (macroscopic) theories and microscopic theories: for scales larger than the RVE one can use continuum mechanics and reproduce properties of the material as a whole [21]. The modelling hierarchical strategy adopted for textile composite in this work integrates the three different modelling stages (see Figure 1). Homogenizing techniques are then applied to link the different scale analyses.

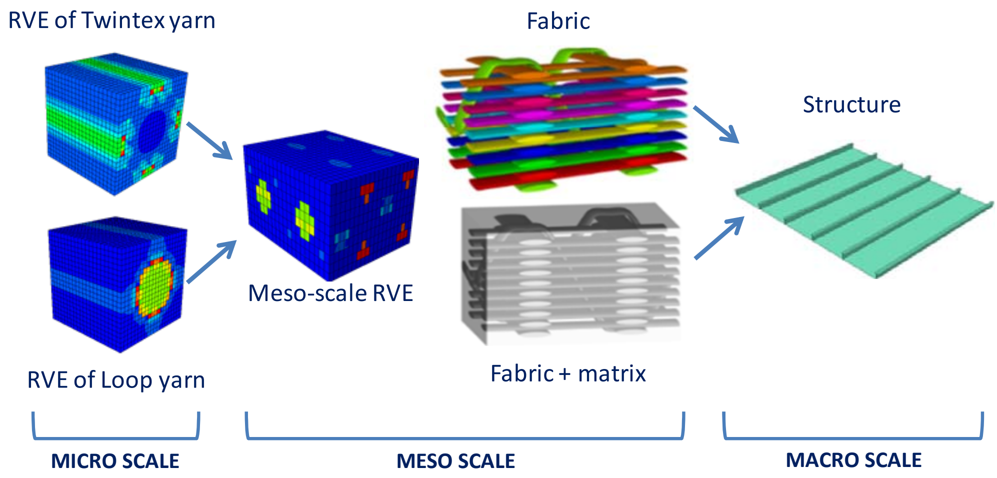

Figure 1: The proposed multi-scale modeling approach.

A square-arrangement RVE is used to represent the unidirectional material behavior of the Twintex 1398, the material adopted in this study, and loop yarn, as shown in Figure 1. It is assumed that the fibers are arranged in an even distribution with the measured volume fraction and same-average-filament diameter. Based on the hypothesis of square packing array, fiber and matrix are assumed to be in a perfect bonding condition. Fiber within the yarn cross-section can be packed into rectangular packing arrays; the circular shape is used to describe the fiber cross-section in yarn.

The effective elastic properties of RVE with right periodic boundary condition can be calculated through ABAQUS simulating six independent load cases. The basic principle and calculating process of RVEs effective elastic properties are obtained applying generalized concentrated forces with dimension of force per length, to the different degrees of freedom of RVE [22]. It corresponds to apply macroscopic stresses to the unit cell and the macroscopic stresses are related to these concentrated forces from a simple energy equivalence consideration. For example, if a force F_x is applied to the degree of freedom ε_x^0 of a unit cell while all the other extra degrees of freedom are free from constraints, the work done by the force is:

$$W = \frac{1}{2} F_x \varepsilon_x^0 \tag{1}$$

The strain energy can be written as

$$E = \frac{1}{2} \int_0^V \sigma_x^0 \, \varepsilon_x^0 \, dV = \frac{1}{2} \sigma_x^0 \varepsilon_x^0 \tag{2}$$

where V is the volume of the unite cell. Equating W to E yields a relationship between the concentrated force and the macroscopic stress applied:

$$\sigma_x^0 = F_x/V \, , \sigma_y^0 = F_y/V \, , \sigma_z^0 = F_z/V, \tag{3}$$

$$\tau_{yz}^0 = F_{yz}/V \, , \tau_{zx}^0 = F_{zx}/V \, , \tau_{xy}^0 = F_{xy}/V, \tag{4}$$

Once obtained the macroscopic stresses, the elastic properties are then easily recovered.

The multi-scale modeling procedure, sketched in Figure 2, has been developed combining already available codes with ad-hoc developed pieces of software. The open source software TexGen, developed by University of Nottingham for modelling the geometry of textile structures [23], was used to pre-process input files for ABAQUS/CAE. Combining ABAQUS with TexGen was proven as a useful strategy to deal with textile composite modeling and structural analysis problems, since they both have an application programming interface (API) accessible through the Python programming language, allowing for an easy methodology to link the two codes. Hence, a Python script can be executed within ABAQUS/CAE interface, which is able to call TexGen library function written in Python language without real-time intervention from the user. The methodology here developed, even if tested here only to the case of a stiffened panel, was intended to be applicable to any arbitrary architecture of RVE and structure, thorough a standardized procedure ranging from the geometry and mesh generation, the definition of the weaving architecture and the application of the appropriate boundary conditions. Python scripts, in particular, allow the creation and modification of the geometry and properties of the ABAQUS model, the submission of ABAQUS analysis jobs, as well as the output post-processing [24, 25], becoming so a very efficient tool to develop parameterized models to be analyzed with ABAQUS.

In the present study, the architecture of the micro and meso RVE, the stringer size, the thickness of the skin and the number of the stringers were changed according to the actual input design variables. Besides, the dedicated Python code not only integrated the multi-scale analysis [25], the data extraction and the communication, but also automatically repeated this analysis process according to the optimization needs. This point is of particular importance for GA optimization.

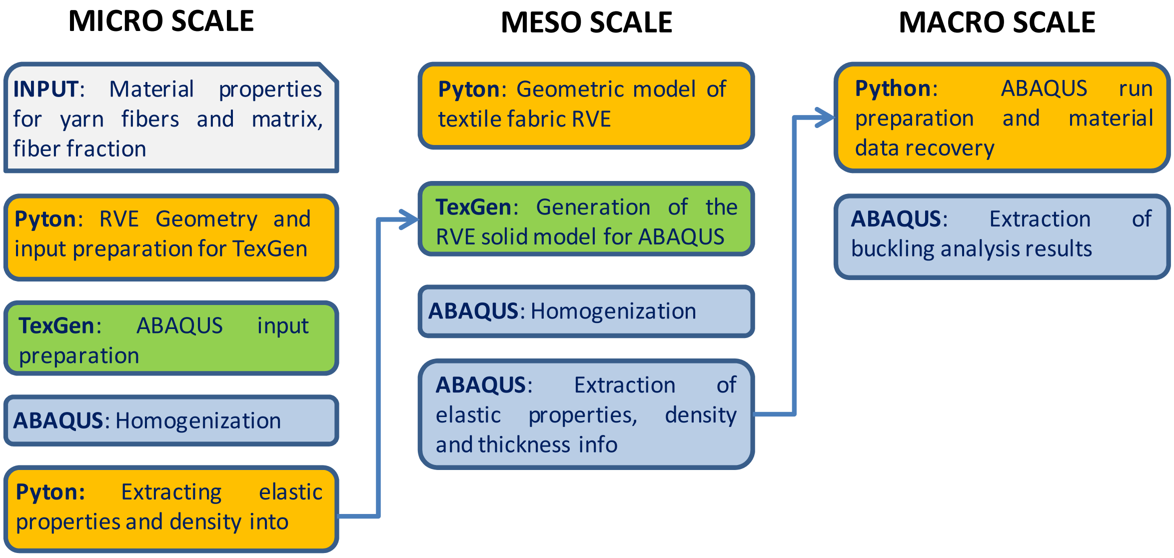

Figure 2: Overview of the proposed multi-scale approach for 3D woven composites.

3. Definition of the optimization problem

3.1. Description of the stiffened panel and the design domain

The considered structure is a compression loaded stiffened composite panel, having the width of 700 *mm* and length of 840 *mm*, with a variable number of T-shaped stringers, as shown in Figure (left). The upper and lower edges of the panel are simply supported while the longitudinal edges are free. The panel is made by Twintex®1398 and by loop yarn, whose properties are shown in

.

Based on the material data available and on the fiber fraction, the elastic constants of Twintex 1938 and of loop yarns, keeping the width and height of weft and warp yarn, as well as of the loop yarn fixed and equal to 2 *mm* and 0.3 *mm*, respectively, can be computed. The constants are summarized in

.

Table 1. Properties of Twintex 1398 and loop yarn

TW TR PP82 NUTURAL 1398		Loop Yarn	
GF [% by weight]	82	GF [% by weight]	50
PP [% by weight]	18	PP [% by weight]	50
Linear density [ypp]	345.83	Linear density [ypp]	3701
Linear density [kg/m]	0.001398	Linear density [kg/m]	0.00134
Fibre area [mm^2]	0.4443	Fibre area [mm^2]	0.0264
Matrix area [mm^2]	0.2796	Matrix area [mm^2]	0.0733
Total area [mm^2]	0.7239	Total area [mm^2]	0.0997
Fibre Volume fraction [%]	61.4	Fibre Volume fraction [%]	26.4

Table 2. Elastic constants of Twintex®1938 and loop yarns

	Twintex®1398	Loop yarn
Volume fraction of fibre	61.4%	26.4%
Density ρ [kg/mm^3]	1.93E-6	1.35E-6
E_{11} [MPa]	45170	21140
E_{22} [MPa]	8298	2737
G_{12} [MPa]	2318	886
G_{23} [MPa]	1549	750
ν_{12}	0.26	0.31
ν_{23}	0.23	0.45

The analysis and optimization of the panel is based on the identification of seven mixed discrete-continuous geometric design variables shown in Figure : x_1 is the spacing between weft and loop yarns; x_2 is the spacing between two close warp yarns; x_3 is the number of weft yarn layers in the skin; x_4 is the number of weft yarn layers in the stringers; x_5 and x_6 are the stringers width and height, respectively; and x_7 is the number of stringers. The design domain is reported in Table 3, together with the initial values of the design variables.

Table 3. Optimization domain of design variables

	Design parameter	Domain
Spacing between weft and loop yarns [mm]	x_1	[0 1]
Spacing between warp and loop yarns [mm]	x_2	[0 1]
Number of weft yarn layers in skin	x_3	{4,5……10}
Number of weft yarn layers in stringer	x_4	{10,11……20}
Stringer width [mm]	x_5	[10 30]
Stringer height [mm]	x_6	[10 30]
Number of stringers	x_7	{3,4,5,6}

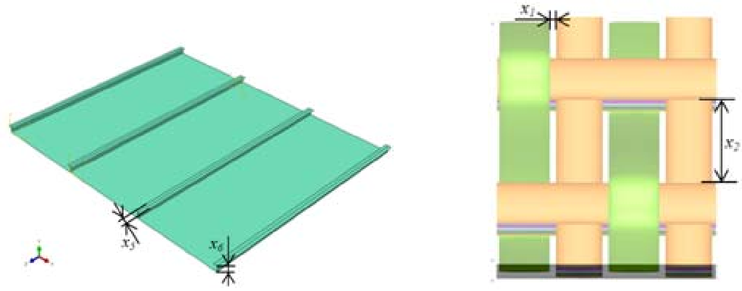

Figure 3: The stiffened panel and the design variables.

3.2. Objective function

The objective function is usually formulated according to the optimization problem by combining structural and manufacturing performances. In the present study, the mass of the considered composite stiffened panel is used as objective function. It is directly obtained from the panel geometry and the density of the representative volume elements, and can be expressed as:

$$M = 800 \times 700 \times t_{skin} \times \rho_{skin} +$$

$$+N_{\mathrm{stringer}} \times 700 \times (W_{\mathrm{stringer}} + H_{\mathrm{stringer}}) \times t_{stringer} \times \rho_{stringer} \tag{5}$$

where:

$$t_{skin} = t_{RVE\_skin} \tag{6}$$

$$t_{stringer} = t_{RVE\_stringer} \tag{7}$$

$$\rho_{skin} = (\rho_{loop} \times V_{loop} + \rho_{Tw} \times V_{Tw} + \rho_{matrix} \times V_{matrix})/V_{RVE\_skin} \tag{8}$$

$$\rho_{stringer} = (\rho_{loop} \times V_{loop} + \rho_{Tw} \times V_{Tw} + \rho_{matrix} \times V_{matrix})/V_{RVE\_stringer} \tag{9}$$

$$V_{RVE\_skin} = V_{Loop} + V_{Tw} + V_{matrix} \tag{10}$$

N_{stringer} is the number of stringers, W_{stringer} and H_{stringer} are width and height of each stringer, $t_{RVE\_stringer}$, ρ_{loop}, V_{loop}, ρ_{Tw}, V_{Tw}, ρ_{matrix}, V_{matrix} depend on RVE weaving architecture of the skin and stringers.

One of the difficulty in using GAs for optimization is due to the fact that they solve unconstrained problems. So, a specific strategy based on penalty functions has been introduced to solve the constrained optimization problem here considered.

The method here adopted [26] proposes to use a tournament selection operator, where two solutions are compared at a time, and the following criteria are always enforced:

1. Any feasible solution is preferred to any infeasible solution.
2. Among two feasible solutions, the one having better objective function value is preferred.
3. Among two infeasible solutions, the one having smaller constraint violation is preferred.

The fitness function $F(x)$ is defined as equation (11), where infeasible solutions are compared based on only their constraint violation values $\langle g_j(x) \rangle$:

$$F(x) = \begin{cases} f(x) & if\ g_j(x) \geq 0\ \forall j = 1,2,\cdots,m, \\ f_{max} + \sum_{j=1}^{m} \langle g_j(x) \rangle & otherwise. \end{cases} \tag{11}$$

The parameter f_{max} is the objective function value of the worst feasible solution in the population. Thus, the fitness of an infeasible solution not only depends on the amount of constraint violation, but also on the population of solutions at hand. However, the fitness of a feasible solution is always fixed and is equal to its objective function value.

3.3. Buckling and post-buckling constraints

A sketch of a typical load-shortening curve of the analyzed category of stiffened panels in the post-buckling field under axial compression is shown in Figure 3.

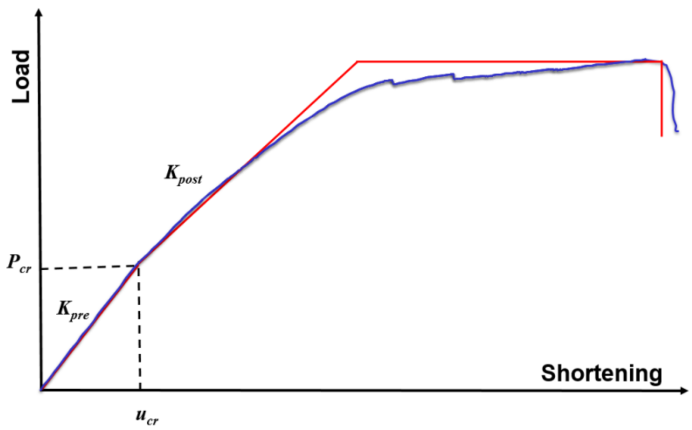

Figure 4: Typical load-shortening curve of a stiffened panel.

It presents two relevant regions. The first one is the linear part where the load is smaller than the buckling load P_{cr},. The corresponding displacement is identified with u_{cr}. The second part corresponds to the post-buckling region.

For simplicity, the load-shortening curve can be piecewise linearized using two lines, where the slopes K_{pre} and K_{post} characterize the pre- and post-buckling stiffness, respectively. Before performing the optimization design, the minimum allowable design values $\overline{P_{cr}}$, $\overline{K_{pre}}$ and $\overline{K_{post}}$ have to be defined according to the design structural requirements.

4. Optimization strategy

The optimization of stiffened panels made of 3D woven composite material combines the difficulty of multi-scale analysis with the high fidelity non-linear simulation requested by buckling and post-buckling analysis, which leads to an increasing computational analysis time. Besides, the optimization problem involves the simultaneous presence of mixed continuous and discrete variables, that suggests the use of a non-gradient-based method as GA to perform optimization design. The main drawback is that GA require a large number of iterations compared with gradient-based algorithms. Consequently, it becomes extremely time-consuming performing optimization using genetic algorithm together with high fidelity non-linear finite element analyses. The surrogate and approximated modeling techniques become necessary. The approximation technique here adopted is based on Neural Networks (NN) that appears as a reliable choice in combination with GA to perform structural optimization. When the NN-based system is properly setup, the approximated model mimics the behavior of the numerical analysis accurately, and is computationally cheaper.

The optimization process can be summarized into two main parts. The first one includes the multi-scale analysis to supply data source for constructing the approximated model. This part is implemented into a dedicated Python script interfacing TexGen and ABAQUS codes. The second part integrates the Neural Networks with the GA module to build-up the approximated model and to perform the structural optimization. This second part is implemented into a dedicated Matlab module.

The main steps in the optimization procedure can be summarized as follows:

- The DOE techniques identify the number of analyses requested to set-up a reliable approximated model depending on the type and number of design variables. Using the SAS-JMP software a total of 308 cases were defined and included into a test set.
- Multi-scale finite element analysis of the composite stiffened panel is implemented, considering mixed continuous and discrete design variables in the test set. The Python module integrated the pre-processor TexGen and ABAQUS code to automatically perform the multiscale analysis and to extract the response data. They are the 3D weaving composite properties in the case of RVE, and eigenvalues and load-shortening curve in the case of the complete stiffened panel.
- The NN architecture is defined so to be able to approximate the selected structural responses.
- The optimum problem is formulated in terms of fitness and constraint functions.
- The optimization problem is solved combining GA and NN-based approximations.
- The optimization results are verified using finite element analysis performed with ABAQUS.

5. Determination of Neural Networks architecture

5.1. Neural Networks

Artificial Neural Networks (ANNs) consists of an information processing paradigm that is inspired by the way biological nervous systems are used to approximate functions that can depend on a large number of inputs and are generally unknown. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. The connections have numeric weights that can be tuned based on experience, making neural networks adaptive to inputs and capable of learning. The back propagation neural network algorithm (BPNN), in particular, is a multi-layer feed forward network trained according to error back propagation algorithm and is one of the most widely applied neural network models. BPNN can be used to learn and store a great deal of mapping relations of input-output model. The idea of the back propagation algorithm [27] is the repeated application of the chain rule to compute the influence of each weight in the network with respect to an arbitrary error function. The training begins with random weights, and the goal is to adjust them so that the error will be minimal. In present study, BPNNs are utilized to construct approximations of the structural responses of the composite stiffened panel.

The optimization strategy is then composed by two main steps:

- Build a system of neural networks that is capable to surrogate the solution of the FE model.
- Combine the neural networks with genetic algorithms to perform the global optimization.

5.2. Training and test sets

Based on the variables and ranges summarized in Table 3, a sample of cases was created for BPNN training. In order to generate the distribution of simulation parameters, Design Of Experiment (DOE) approach was used. This method is recognized to be able to generate a small yet representative sample of cases. As much as 308 cases had to be computed according to design of experiment.

All the simulation cases were run in ABAQUS 6.10 software. A single analysis needs about 10 minutes on an i7-3520M CPU Intel processor at 2.9 GHz speed, that means about two days to complete the whole process.

The training data set is used to build-up different approximated models dedicated to each structural response. The training set is divided in a pure training set, including 266 sampling points, and one verification set, based on 42 sampling points.

5.3. Architecture of the neural network system

The original input-output problem has seven input variables and three output parameters, and required the definition of four different NNs able to simulate the considered structural responses. The entire process has been implemented using the Matlab NN Toolbox that offers the complete set of tools requested for the identification of the most suitable NNs architecture and supports a variety of training algorithm and learning functions. In particular, the data scaling option has been applied because the way in which the data are presented to the network affects the learning of the network. Therefore, pre-processing data are required before passing the training patterns to the network.

Neural networks are typically organized in three layers (input layer, hidden layer and output layer). Each layer is made up of a number of interconnected nodes which contain an activation function. Each node receives an input signal that is the weighted sum of its input links and computes an activation signal sent to the next layer along the output links. The transfer functions are defined to compute activation signal, and the three typical transfer functions, i.e. Tan-sigmoid, Linear and Log-sigmoid have been applied in this study for the definition of the optimal architecture. Most ANNs contain some form of learning rule which modifies the weights of the connections according to the input patterns. Although there are many different kinds of learning rules used by neural networks, the back propagational neural networks (BPNNs) are currently the most widely used networks in engineering applications. Hence, the BBNNs are here used to deal with the weights of neural networks.

The training process in the network involves connecting a set of sample points (input data) with known outputs (target outputs). The system adjusts the weights of the internal connections to minimize errors between the network and target outputs. The ANN was trained in present study using Bayesian regularization algorithms. The training was considered to have reached convergence if the sum of squared error stabilized over certain iterations. After the NN is satisfactorily trained and tested, it is able to generalize the rules and to predict reliable outputs corresponding to unknown input data within the domain covered by the training examples.

Table 4 shows the adopted BPNN architecture for each relevant structural response together with the mean approximation error when the verification set is applied, while Figure 4 shows the correlation plots for the buckling load and the pre-buckling stiffness. The approximation error in the case of buckling load and pre-buckling stiffness is very low (less than 1%), while in the case of the post-buckling stiffness is much higher, around 17%. This is mainly due to the highly non-linear behavior of this response that strongly depends on the evolution of load-shortening path in the deep non-linear region. This aspect suggests to revise the definition of this response index in a more stable way for future applications.

After building the NN architectures and checking the accuracy, the NN system is able to surrogate the finite element analysis of 3D-woven composite stiffened panels.

Table 4. BPNN architecture

Output parameters	Nodes	Transfer functions		Approximation
		Hidden layers	Output layer	Error [%]
P_{cr}	7, 27, 4, 1	logsig, tansig, purelin	purelin	0.75
K_{pre}	7, 27, 1, 1	logsig, tansig, purelin	Purelin	0.70
K_{post}	7, 46, 1, 1	tansig, logsig, purelin	Purelin	17.0

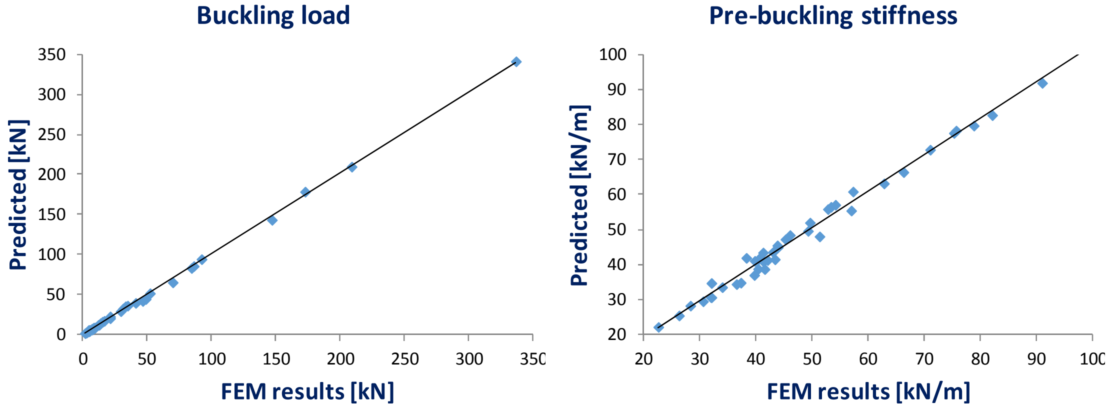

Figure 5: Correlation plots for buckling load and pre-buckling stiffness.

6. Structural optimization results and model validation

Once the approximated models have been constructed by Neural Networks, GA [20] was adopted to optimize the weaving parameters of composite stiffened panel. In the present investigation, Matlab GA toolbox was exploited to solve the minimum weight, global optimization problem.

6.1. Optimization

The objective and domain of constraints for weaving textile composite optimization problem have already been defined and is reported in Table 5. The population is initialized with 200 individuals, randomly generated in the design domain. Crossover is applied with a probability of 0.85. The probability of mutation is 0.01 for all the operators. The initial penalty of constraint parameters was set equal to 1 and penalty factor to 10. The stopping criterion is defined allowing a maximum number of 200 generations without improvement. The best fit was obtained after the evolution of 200 generations.

The best fitness value, who's trend is shown in Figure 6, was 4.11 kg, corresponding to the following design variables vector:

$$\{x_{final}\} = \{0\text{ mm}, 1\text{ mm}, 10, 12{,}15\text{ mm}, 28.20\text{ mm}, 6\}$$

Table 5. Optimization problem using NN.

Objective Function:	Minimize mass M		
Design Variables:	$0 \le x_1 \le 1$ $0 \le x_2 \le 1$ $\{x_3 \mid 4,5,6,7,8,9,10\}$ $\{x_4 \mid 10,11 \dots \dots 20\}$ $10 \le x_5 \le 30$ $10 \le x_6 \le 30$ $\{x_7 \mid 3,4,5,6\}$	Constraints:	$P_{critial}(x) > 80\ (kN)$ $K_{pre}(x) > 40\ (kN/mm\ )$ $K_{post}(x) > 20\ (kN/mm)$

6.2. Model Validation

The last step of the optimization procedure requires the validation of the optimal design configuration using Finite Element (FE) models in place of the approximated ones based on NNs. In particular, the complete multi-scale analysis has to be carried out, starting from the generation of the RVE model based on the optimal values of design variables, till the non-linear analysis using ABAQUS.

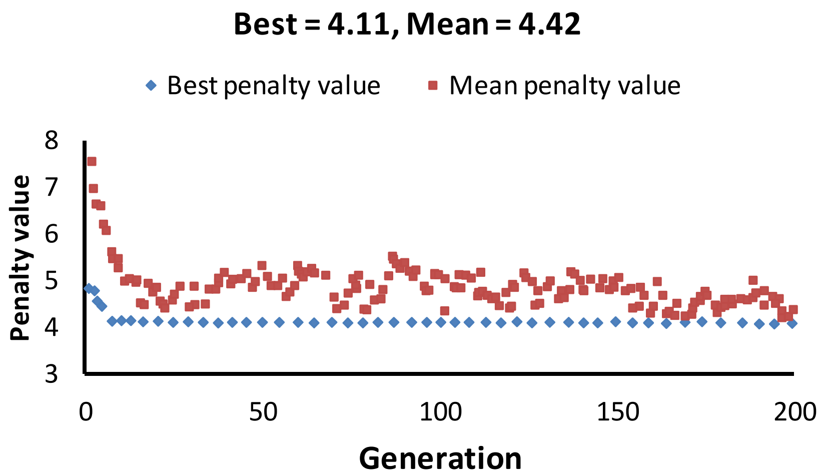

Figure 6: Optimization results.

Figure 7 and 8 show the buckling shape of the optimized stiffened panel in terms of the out-of-plane displacement and the load-shortening curve, respectively, while Table 6 reports a comparison between the approximated and the FE structural responses. Looking at the reported results, it is possible to highlight the accuracy of the obtained results, with a maximum error between the approximated and the real value less than 10% in the case of critical load, and less than 4% in the case of pre- and post-buckling stiffness. The mass saving is equal to 26% but in this case it must be pointed out that the initial design was not optimized.

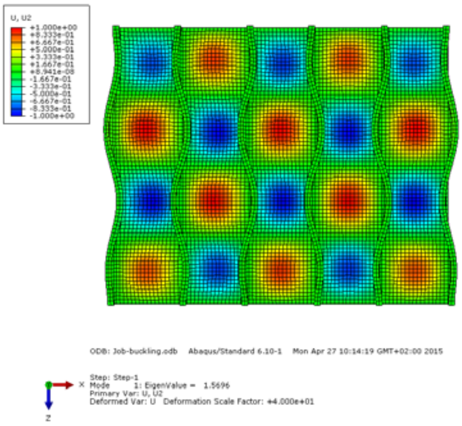

Figure 7: Eigenvalue analyses (first buckling mode)

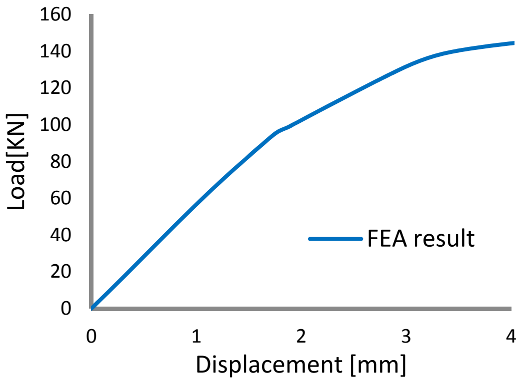

Figure 8: Load-shortening curves for optimized stiffened panel.

Table 6. Comparison NNs and FE results at the optimum design point.

	Allowables	NNs results	FE results	Error (%)
Critical load [kN]	≥80	80.4	89.20	9.8
Pre-buckling stiffness [kN/mm]	≥40	55.2	56.91	3.0
Post-buckling stiffness [kN/mm]	≥20	40.5	42.10	3.8
Mass of model [kg]	-	Initial 6.24	Final 4.59	-

7. Conclusions

The paper proposes a fast optimization strategy for the design of composite stiffened panels made of 3D woven composite. The development of an optimization procedure based on multi-scale finite element analysis, neural network and genetic algorithms resulted in a minimum weight design of a stiffened panel subject to buckling and post-buckling constraints.

A three-level hierarchical modelling approach for woven composite structures was developed to describe the fibre, the yarns, and the mechanical properties of the material at the micro scale of a Representative Volume Element, till the macro-level behaviors of the structure. Representative Volume Element and periodic boundary conditions are utilized to homogenize elastic properties of woven composite. A dedicated module written in Python language was used to interface TexGen and ABQAUS codes for the pre- and post-processing data resulting from finite element analysis.

The optimization part of the procedure here proposed was based on the combination of approximated models, obtained using Neural Networks with Genetic Algorithms.

The numerical example reported concerns the minimum mass of a stiffened panel subject to buckling constrains, involving continuous and discrete design variables related to the weaving parameters, as well as the architecture of the panel consisting in the number of stringers.

The optimal configuration was finally verified using the proposed multi-scale finite element analysis. The critical load, pre-buckling and post-buckling stiffness predicted by Neural Networks appear in good agreement with the ones obtained by finite element analysis, so validating the proposed approach based on the use of approximation techniques. Finally, the paper proves that the proposed optimization strategy is efficient and reliable for the optimization of 3D woven composite structures in the preliminary design stages.

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