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Numerical Phenomenology: Virtual Testing of the Hierarchical Structure of a Bundle of Strands

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Abstract: In this paper we study numerically the mechanical behaviour of wire ropes, particularly the influence of the geometrical configuration on the overall stiffness of the cables. Modelling the behaviour of a cable is a difficult problem, given the complexity of the geometrical layout, contact phenomena occurring among wires and possible yielding of the material. For this reason we pursue a "hierarchical beam approach", to substitute recursively, at each cabling stage, the bundle of wires with an equivalent single strand, having the characteristics computed from the previous level. We consider the first two levels of the bundle hierarchy and investigate the case of longitudinal stretching, as a representative application of the method for the problem at hand. To this aim, we perform a certain number of numerical experiments on a bundle of wires, by varying their twist pitches. In this way we compose a set of data to train suitable Artificial Neural Networks, so that, given the twist pitches and the applied longitudinal displacement in input, the ANNs give us the longitudinal reaction force, the bundle axial rotation or the overall axial stiffness. These results can be used "directly" to search for geometrical configurations that offer a significant improvement in stiffness, assuming that a higher stiffness will reduce strand bending and wires breakage. Furthermore, they can be used to obtain the characteristics of the single, equivalent beam that we need for our approach.

Keywords: Multiscale Modelling, Hierarchical Structures, Artificial Neural Network, Wire Rope Stiffness, Superconducting Strands.

1 Introduction

Wire ropes are largely used in engineering applications, ranging from suspended bridge, cranes, electrical cables, electromagnets and superconducting coils. The

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basic element of a wire rope is a single thin metallic *wire*. A certain number of wires are twisted together like helix or laid around a *core* to obtain a *strand* and the rope is constructed by twisting some strands together or laying them around a core-strand. If present, the main purpose of the core is to provide proper support for the strands under normal bending and loading conditions. A property common to structural elements such as ropes, cords, cables is their ability to resist relatively large axial load. In the case of superconducting (SC) magnets, also bending and torsional loads are particularly high, so that the coil must be carefully designed to withstand magnetic pressure and Lorentz forces that could otherwise cause wire fracture or crushing of insulation between adjacent turns. Actually for the SC coils the cabling pattern consists of more than two stages. ITER (the International Thermonuclear Experimental Reactor, now under construction) cable layout is based on a five-stage, multi-twisted configuration illustrated in Figure 1. It consists of 1422 chrome-coated strands, all stages are right-hand lay with twist pitches presently defined as in Table 1, Option I (left column). Furthermore, two other twist pitch combinations, called *Option II* and *TFPRO-OSTII,* are under experimental investigation. They are summarized in Table 1, middle and right column.

During the last decade an extensive Research and Development (R&D) program has been performed to demonstrate the feasibility of ITER magnet system [Sborchia, C. (2000)], [Mitchell, N.; Salpietro, E. (2001)]. Experimental tests have provided valuable information to finalize the design of the ITER magnetic system. However the behaviour of Nb_3Sn strand cables was not as good as expected on the basis of the characteristics evaluated for the uncabled wires [Ulbricht, A.; Duchateau, J.L.; Fietz, W.H.; Ciazynski, D.; Fillunger, H.; Fink, S.; Heller, R.; Maix, R.; Nicollet, S.; Raff, S.; et al..(2005)], [Zanino, R.; Mitchell, N.; Savoldi Richard, L. (2003)], [Zanino, R.; Boso, D.P.; Lefik, M.; et al. (2008)]. This lack in Nb_3Sn performance is due to various factors, among which the strain state of the wires due to bending and contact phenomena inside the cable [Boso, D.P.; Lefik, M.; Schrefler, B.A. (2006, IEEE)], [Boso, D.P.; Lefik, M.; Schrefler, B.A. (2005)] (in Nb_3Sn the superconducting properties depend upon temperature, magnetic field and strain field). Therefore the conductor degradation seems to be linked also to the loads on the wires within the cable, and the extent to which the wires are supported by each other, *i.e.* the cabling pattern.

The main goal of this paper is to study the mechanical behaviour of wire ropes and particularly the influence of the twist pitches on the overall behaviour of a bundle of wires. We take into consideration ITER cable layout, which is based on a triplet as first cabling stage. This is a preliminary work, and we limit our investigation to the first two levels of the cable hierarchy. The first two cabling stages of the three configurations of Table 1 are studied, as well as other twist pitch combinations, to better understand the influence of the first cabling patterns on the stiffness of a cable.

The motivation of this analysis consists in searching for geometrical configurations that offer a significant improvement in stiffness compared to the reference (Option I in Table 1), assuming that a higher stiffness will reduce strand bending and wires breakage.

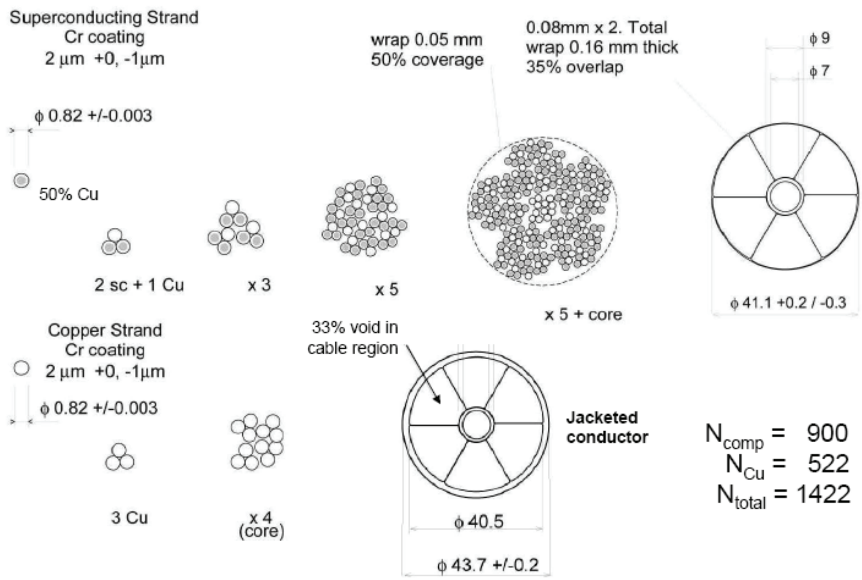

Figure 1: ITER cable layout.

Modelling the behaviour of a cable is a difficult problem [Nemov, A.S.; Boso, D.P.; Voynov, I.B.; Borovkov, A.I.; Schrefler, B.A. (2009)], [Bellina, F.; Boso, D.; Schrefler, B.A.; et al. (2002)], given the complexity of the geometrical layout, contact phenomena occurring among wires and possible yielding of the wire, to cite the main points.

The main idea of this work is to make use of a suitably trained Artificial Neural Network (ANN), to identify the longitudinal stiffness. The necessary database to train the network is obtained by performing a sufficient number of numerical experiments by means of the finite element (FE) method as explained in Section 3.

In our FE models, the wires are discretized by beam type elements, with two nodes per element and six degrees of freedom per node. Non linear behaviour of the material, large displacements and strain are taken into consideration. The possible

Table 1: Twist pitch details for the reference (Option I) and alternative (Option II and TFPROII-OST2) configurations for ITER cables (Courtesy of D. Bessette, ITER Cadarache).

	Option I	Option II	TFPROII-OST2
Cable pattern	$(3 \times 3 \times 5 \times 5 + \text{core}) \times 6$		
Stage 1	45 mm	80 mm	116 mm
Stage 2	85 mm	140 mm	182 mm
Stage 3	125 mm	190 mm	245 mm
Stage 4	250 mm	300 mm	415 mm
Core 3×4	45×85	80×140	116×182
Stage 5	450 mm	420 mm	440 mm

contact is checked pointwise on nodal positions (node-to-node contact) by means of gap elements. This is clearly a simplification of the mechanics of contacts among the wires, since in this way we disregard the local deformation in the contact areas and the related three-dimensional characteristics of stress and strain fields. However, for the type of analysis we want to perform, it is a good interpretation of real phenomena and allows for solving several numerical tests and compose the ANN training database rather quickly.

As explained, an ITER cable has five cabling stages, and it can be regarded as a hierarchical structure. The final goal of this research is to substitute, at each level, the bundle of wires with an equivalent single strand, having the characteristics computed on the bundle of the previous level. For example, at the second cable stage, three triplets are twisted together. We want to schematize this stage with one equivalent wire, having the mechanical behaviour of the nine-wire cable. A recursive substitution of this type will allow for modelling higher cabling stages with a low number of degrees of freedom. However, this is not an easy task, since the stiffness matrix of the equivalent beam element has to incorporate the dependency on the geometry (twist pitches), the level of strain and contact phenomena. This is the beginning of the research activity, here we take into consideration the effects of the first two twist pitches on the longitudinal behaviour of a sub-cable.

The idea of the hierarchical beam has already been presented in one of our recent papers [Boso, D.P.; Lefik, M.J.; Schrefler, B.A. (2007)]. It is worth to mention that in this work our main concern is to identify the influence of the twist pitch on the mechanical behaviour of the wire bundle, while in [Boso, D.P.; Lefik, M.J.; Schrefler, B.A. (2007)] the geometry was given. In that publication we solved an inverse problem to identify the coupling terms between axial force and twisting moment. For a set of trial values of coupling terms, given the kinematical load (axial displacement, axial rotation), the corresponding set of reaction forces (axial force, twisting moment) was obtained with a single equivalent straight beam. An ANN was trained with these sets of data (axial displacement, axial rotation, axial force, twisting moment at the input nodes, coupling terms at the output ones) and then used in recall mode to get the searched elements of the stiffness matrix of the equivalent single beam. A more detailed description of that problem can be found in the mentioned paper [Boso, D.P.; Lefik, M.J.; Schrefler, B.A. (2007)].

2 Description of the Artificial Neural Network Technique

For a non-linear composite or for a complex hierarchical heterogeneity, an adequate description of the effective behaviour is usually difficult to obtain on a purely theoretical way. Furthermore it seems that phenomenological observations cannot be dealt with by classical interpolative formulae, nomograms or abaci.

Artificial neural networks provide an alternative, non-symbolic approach to this problem. A neural network can be considered as a non-linear operator that transforms a set of suitably interpreted variables into another set of numerical data. It is composed of a collection of simple processing units (called *nodes* or *artificial neurones*) that are organized in *layers* and mutually interconnected with variable weights. This system of units is organised to transform an input signal into an output signal. Both input and output signals are suitably defined according to their physical interpretation. In our case they are a sequence of corresponding values, e.g. twist pitches and applied displacement are attributed to the input nodes of the ANN and at the output nodes we expect the value of the longitudinal reaction force. In this way we construct a functional dependence of the values at the output nodes as a function of the independent values at the input nodes. This is obtained by a correct choice of coefficients (synaptic weights) that scale the signal transmitted between each pair of nodes belonging to different layers of the ANN. The weights of interconnections are modified by an iterative procedure to force the desired output signal to be the response of a given input pattern. This process is called *training* and it is continued until the error between the neural network output and the desired output is minimised for a whole set of pairs: given input - known output. For this phase a proper set of corresponding input-output data (*training set*) has to be known and it is used partly to define weights and biases (*learning set*) and the remaining part (*test set*) to check the error of the network response. ANNs are trained by means of the error back propagation algorithm. According to this method, the weights of connections between nodes of the ANN are shaped iteratively by successive corrections, proportional to the error, which is transmitted through the link. As a result of the training, the relationship between input data and output data is approximated in such a manner that all given data are approximated with a given tolerance and the data not used for the network training are successfully interpolated. Once the ANN is trained, it can be used in *recall mode* to obtain the output of the problem at hand. Interested readers are referred to [Hertz, J.; Krogh, A.; Palmer, G.R. (1991)], or [Hu, Y.H.; Hwang J-N. (Eds.), (2002)] for details concerning the activity of units.

In this direct approach, ANNs can be used as a tool of storage of data and a very good interpolator. According to our experience [Lefik, M.J.; Boso, D.P.; Schrefler, B.A. (2009, CMAME)], [Lefik, M.J.; Schrefler, B.A. (2003)], the ANN approximation discovers the real, inner dependence between two sets of data much better than a theoretical approach and simulates very well a complex behaviour superposing influences of various physical factors and features. Non-symbolic model is constructed as follow: neural network is trained first to reflect correctly the set of observed, experimental or numerical data. Then the networks automatic generalisation capability (interpolation between some data sets) enable us to predict e.g. the longitudinal stiffness as a function of the twist pitches and applied displacement. The network simulation can be checked against the real (numerical in our case) experimental results at this step. If the network prediction is satisfactory, the model is ready, if not, some new experimental or numerical data have to be added to the existing training set and the network has to be taught again. According to this approach the symbolic, mathematical description of the problem is replaced by the sufficiently trained neural network (See e.g. [Liu, D. S.; Tsai, C.Y. (2009)]).

In this paper artificial neural networks with two or three hidden layers proved to be sufficient. The scheme of the ANN used is presented in Figure 2. The following equation is written for j-th output of a network composed of three layers of nodes (layer number enclosed by parentheses). Weights are labelled with the number of their related layer by superscript, b are biases:

$$o_j = \sum_s w_{js}^{(3)} g_s \left(\sum_r w_{sr}^{(2)} g_r \left(\sum_i w_{ri}^{(1)} + b_r^{(1)} \right) + b_s^{(2)} \right) + b_j^{(3)} \tag{1}$$

The transfer of the input signal $\boldsymbol{i}$ into the output signal $\boldsymbol{o}$ can be prescribed by eq. (1) that defines a typical activity of a node in a ANN. Three actions are executed by each neurone through the network:

- Summation of incoming signals from all connected nodes, weighted by the weights of connections w_{tq};
- Transformation of the sum by a so called activation function of one variable x → g(x), usually in the form of non-decreasing "cutting off" sigmoid (in eq. (1) parentheses enclose a value of the scalar argument x of the function g(x));

- The computed result (activation of the node i) is again weighted by the weight of connection w_{ij} and sent to node j. This is repeated for every connected node.

ANNs can be regarded as universal, non-linear approximation of any continuous function of many variables **x,** $f(\mathbf{x})$. Expression (2_1) symbolizes the action of the artificial neural network "@" the input x.

$$\mathbf{o} = ANN@\mathbf{x} \quad f(\mathbf{x}) - o(\mathbf{x}) < \varepsilon \tag{2}$$

In Figure 2 we show an example of such a structure, for which a physical interpretation of nodes at input and output is given. The number of nodes (i, r, s in (1)) and the number of layers can be found such that the norm of the approximation (2_2) is less than a given small number ε. This kind of network was discussed in [Lefik, M.J.; Schrefler, B.A. (2003)], [Lefik, M.J.; Schrefler, B.A. (2002)], [Gawin, D.; Lefik, M.J.; Schrefler, B.A. (2001)]. Weights w_{tq} and biases b_t in (1) can be understood as degrees of freedom of the approximation process (2). We will try to find the best approximation with the smallest possible number of degrees of freedom.

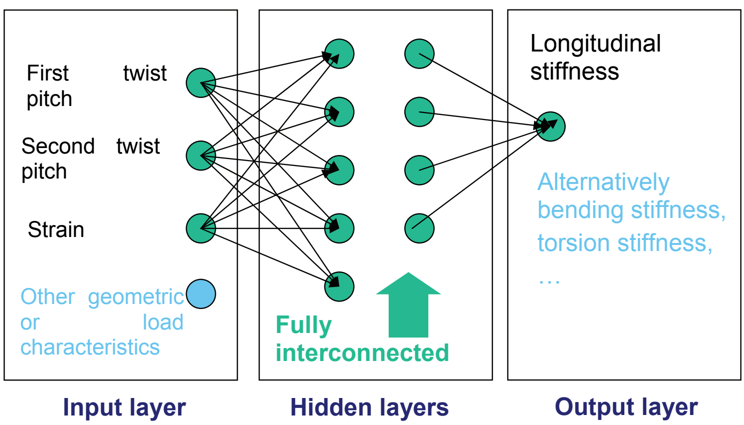

Figure 2: Scheme of the Artificial Neural Network used to approximate the longitudinal stiffness, given the twist pitches and the applied displacement. The same type of network is used to identify the longitudinal reaction forces and axial rotations.

As it was mentioned earlier, by means of Artificial Neural Networks we are interested in approximating the reactions and the rotations at ends of the analysed sample and its longitudinal stiffness as a function of the twist pitches and applied displacements. In this way a prediction of the best geometrical layout for a given engineering application in cabling manufacturing will be possible.

3 The Training Set: Virtual Testing Method

The available experimental or numerical data have to be a sufficient source of information to describe the functional dependence between the scalar, vector or tensor fields of interest. In this case we compose the input-output data set to train the network by performing a certain number of finite element analyses, i.e. we perform a *numerical testing* of the structure. This approach is well known in the framework of homogenisation methods: numerical experiments are carried out on a representative volume element (RVE) of the composite. Usually deformations are kinematically imposed and the effective properties are obtained from the relation between average strain - average stress measures, computed from the FE solution [Miehe, C.; Schröder, J.; Schotte, J. (1999)], [Pellegrino, C.; Galvanetto, U.; Schrefler, B.A. (1999)], [Boso, D.; Pellegrino, C; Galvanetto, U.; Schrefler, B.A. (2000)], [Hain, M.; Wriggers, P. (2008)]. This method is also known as *virtual testing*. In this study we perform something similar: by using a FE discretization of a bundle of wires with given twist pitches, we apply a longitudinal displacement and compute the longitudinal reaction force and the axial rotation developed. These quantities can be easily combined to calculate the equivalent axial stiffness of the bundle as a function of the mean longitudinal strain. The network can be trained by performing a sufficient number of such numerical tests, by varying the twist pitches. We underline that ANN representation cannot be used outside its numerical environment since its parameters (weights and biases) have no physical meaning. After the training process, the ANN is used in recall mode to identify the reaction force, the axial rotation or the axial stiffness for a given longitudinal displacement and twist pitch combination.

In all tests the strands are supposed to be homogeneous, isotropic with a non linear constitutive law of elasto-plastic type. Actually, superconducting strands exhibit an orthotropic behaviour (transversally isotropic) after yielding [Boso, D.P.; Lefik, M.J.; Schrefler, B.A. (2006, Cryogenics)], [Boso, D.P.; Lefik, M.J. (2009)], [Kanouté, P.; Boso, D.P.; Chaboche, J.L.; Schrefler, B.A. (2009)], [Lefik, M.J.; Boso, D.P.; Schrefler, B.A. (2009, ZAMM)], but it has a negligible influence on the phenomena analysed here. We have taken into consideration the stress – strain curve measured in the FBI facility of FZK/ITP (Karlsruhe, Germany) [Weiss, K.P. (2004)]. The considered properties are: Young modulus E = 117.7 GPa, Poisson's ratio $\nu = 0.3$, yield stress $\sigma_Y = 129$ MPa, ultimate strength $\sigma_{ult} = 324.1$ MPa. The problem is always solved by considering a non linear geometrical behaviour, that is including large displacements and large strain, and associative plasticity with isotropic hardening (Von Mises yield criterion).

4 Numerical Experiments and ANN Training

In this work we investigate the case of longitudinal stretching, as a representative application of the method for the problem at hand. Concerning the first cable stage, several numerical tests were performed on a triplet. We report the results obtained with four different cases, which are representative of a set of situations from a short (25 mm) to a long (160 mm) twist pitch. The three real cases (Option I, Option II and TFPROII-OST2 of table 1) fall within the considered range. At one end, all six degrees of freedom of each node are bounded, while at the other end they are free and longitudinal displacement is applied to each strand, parallel to the triplet axis. The results of the finite element analyses are presented in Figure 3. It is clear that the twist pitch has no influence on the longitudinal behaviour of the triplet, the four curves are overlapping.

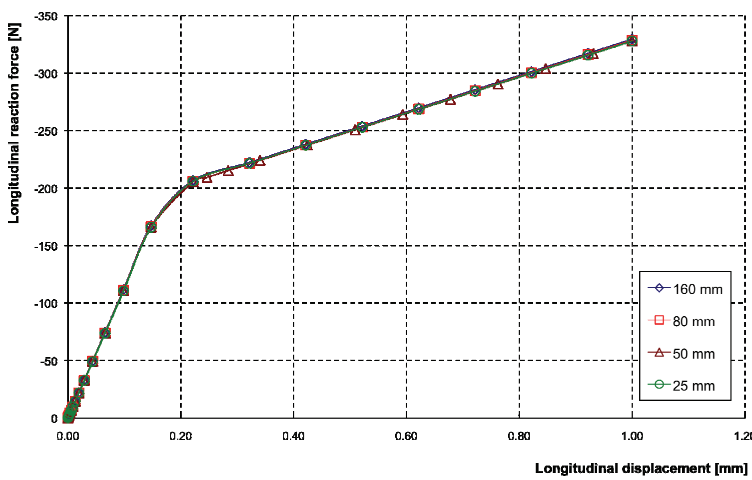

Figure 3: Longitudinal force vs. applied longitudinal displacement for four different twist pitches of a triplet.

Considering the second cable stage, a 3x3 bundle of strands is investigated. It shows a non linear behaviour from the beginning of the loading path. To understand the reason why, four cases are compared in Figure 4: 3x3 twisted and parallel strands, both for the elastic and elastic-plastic material case.

In the case of parallel strands (light blue and orange line) the behaviour is linear from the beginning, becoming non-linear because of the material yielding at a certain point (light blue line, at a displacement of about 0.2 mm). For the nine twisted strands (red and blue line), the behaviour is non linear also in the case of elastic

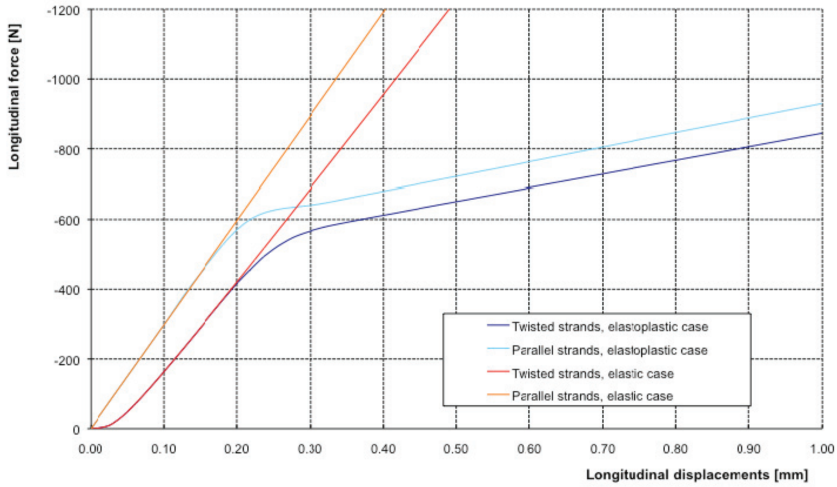

Figure 4: Longitudinal reaction force as a function of the longitudinal displacement, for twisted and parallel strands (elastic and elastoplastic case).

material (red line). This means that at the beginning of the loading process the strands are re-arranging inside the bundle (cable compaction), and then the longitudinal stiffness increases. At a certain point the stiffness decreases again for the plastic case (blue line, at a displacement of about 0.28 mm).

To construct the database to train the ANN, several numerical examples were performed, first by keeping constant the triplet twist pitch (Tp^{I}in the following) and varying the second one (Tp^{II}in the following) and then vice versa. Table 2 summarizes the considered cases and Figure 5 – Figure 6 show the numerical results obtained for some combinations of twist pitches.

Table 2: Twist pitch combination considered for the second cable stage [mm].

Tp^{I}	Tp^{II}	Tp^{II}	Tp^{II}	Tp^{II}	Tp^{II}	Tp^{II}	Tp^{II}	Tp^{II}
27	35	45	85	116	120	140	182	
45	45	60	85	116	140	182		
80	80	100	120	140	182			
116	120	130	140	160	182			
∞	∞	(9 parallel strands)						

From the numerical experiments we have noted that when the first twist pitch is short (27 and 45 mm) the influence of the second one is rather significant, while for

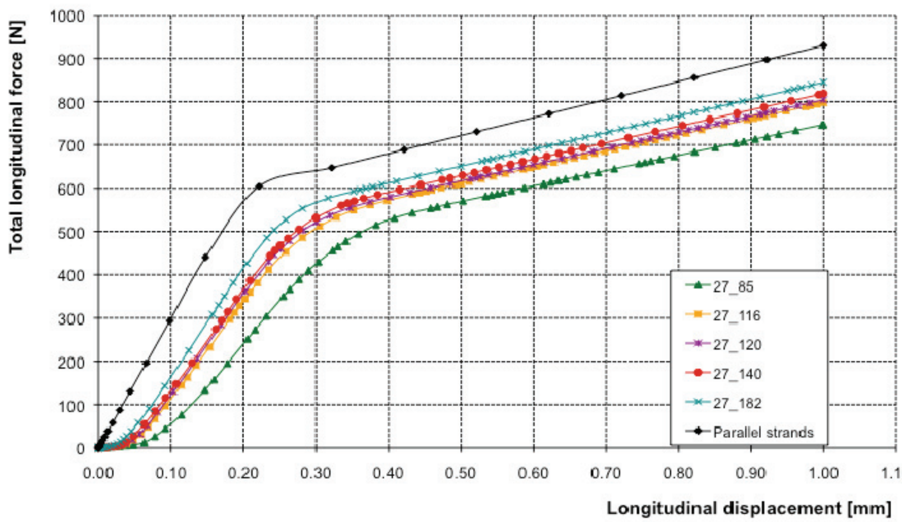

Figure 5: Longitudinal force as a function of the longitudinal displacement, for $Tp^I = 45$ mm and some values of Tp^{II}.

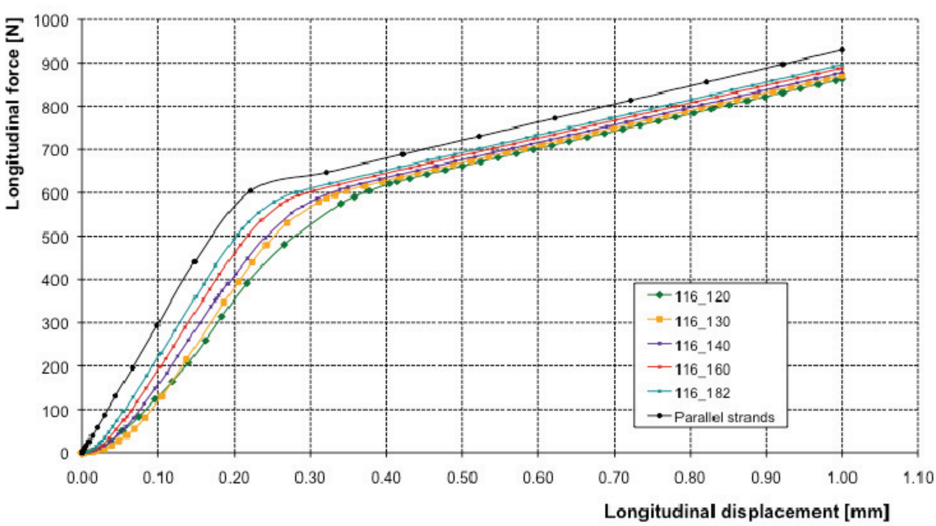

Figure 6: Longitudinal force as a function of the longitudinal displacement for $Tp^I = 116$ mm and some values of Tp^{II}.

higher values of the triplet twist pitch (Tp^{I}), the influence of the second one (Tp^{II}) is less significant (Figure 6). In any case we can state that longer twist pitches provide a higher longitudinal stiffness for the bundle of strands.

A suitable artificial neural network is trained to trace this dependence. The training database is composed by the numerical tests of the 3x3 bundle described above. The corresponding input-output sets are:

Longitudinal force = ANN@(T_p^I, T_p^{II}, applied displacement)
Axial rotation = ANN@(T_p^I, T_p^{II}, applied displacement)
Longitudinal stiffness= ANN@(T_p^I, T_p^{II}, applied displacement)

Therefore, the ANN input layer is always composed of three nodes representing the values of the twist pitch of the first and second level of our hierarchical structure (T_p^I and T_p^{II} respectively) and the applied longitudinal displacement. The output layer has always one unit, which can provide the predicted values of the longitudinal force at the end of the bundle where the displacements are applied, or the axial rotation, or the computed longitudinal stiffness of the sample. Three networks are thus created and trained with their suitable teaching patterns.

5 Results and Discussion

Once the ANNs are trained, they are used in recall mode to obtain the desired output. First of all, we wanted to investigate the influence of the twist pitch values on the axial stiffness of the bundle. To obtain the longitudinal reaction at output, the network resulted very simple, with two hidden layer of 5 and 4 nodes (ANN 3541). A sketch of the topology of the network used is illustrated in Figure 7. By using it in recall mode, we have easily obtained the force-displacement curve for several twist pitch combinations. Some illustrative examples are presented in Figure 8 and Figure 9. As previously noted, we can see that with long twist pitches, their influence on the overall behaviour is less significant.

In the same way, to obtain the longitudinal stiffness at the output, a neural network 3761 was sufficient. It has a few more nodes than the previous one, but it is still very simple. The results are presented in Figure 10 and Figure 11 for the same combinations of twist pitches as in the previous cases.

Finally, to test the potentiality of the approach, we have also compared the results of a finite element analysis dealing with a discretization considering nine strands, and an analysis considering one straight strand, endowed with the average stress – average strain law obtained from the neural network results. The average stress is obtained simply by dividing the longitudinal force by the area of the strands, the average longitudinal strain is obtained by dividing the applied displacement by the length of the bundle. The finite element discretization used for the 9-strand cable

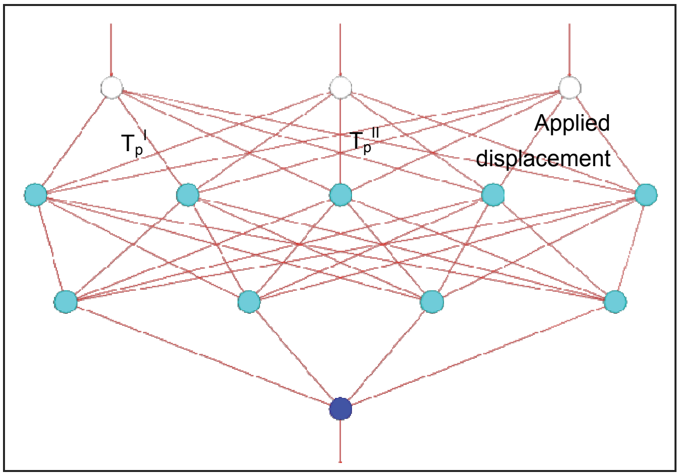

Figure 7: Topology of the network used to identify the longitudinal force: ANN 3541. Top line: input nodes (white), middle lines: hidden layers (light blue), bottom line: output node (blue).

is the same as that used to make the learning set. The wires are discretized with beam elements and contact is checked pointwise, at the nodal positions. The single equivalent strand is modelled with beam elements. The comparison between the numerical results of the two finite element models is presented in Figure 12. It can be easily seen that there is a good agreement, thus confirming that, by identifying the constitutive law for the bundle of wires via a suitable trained ANN, it is possible to define a hierarchical beam model, which can simplify the analysis of the final cable, by decreasing significantly the number of wires to be taken into consideration. The slight discrepancy at the beginning of the loading path depends upon the initial configuration of the nine-wire bundle. The more it is compacted, the less the difference will result. On the other hand, its effect disappears soon after the first load steps.

6 Concluding Remarks

We have investigated the influence of the twist pitch combination on the longitudinal stiffness of a bundle of strands. Starting from the first cabling stage (i.e. the triplet), we can state that the twist pitch has no influence on the longitudinal behaviour of the triplet itself. Concerning higher cabling stages, the twist pitch

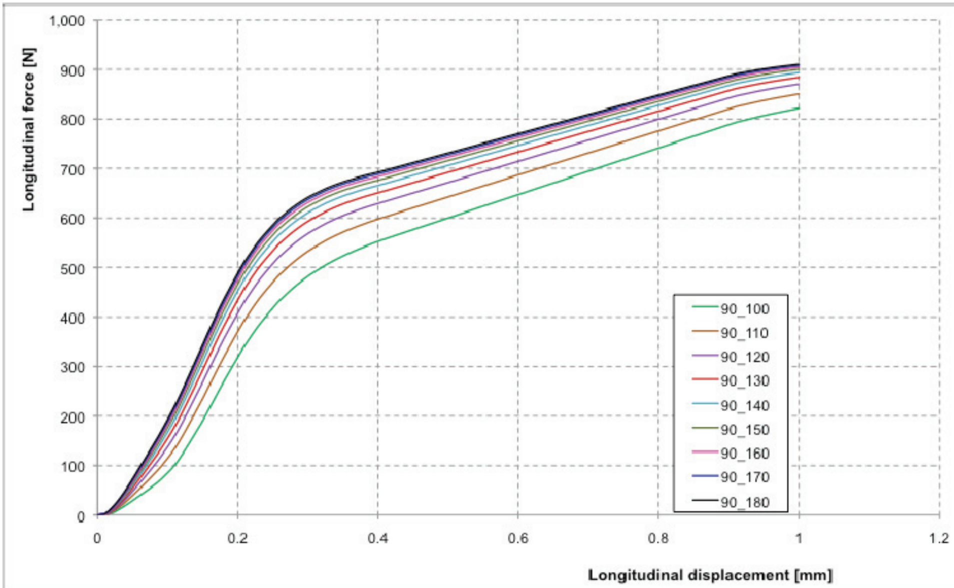

Figure 8: Longitudinal force as a function of the longitudinal displacement for Tp^{I} = 90 mm and various values of Tp^{II}.

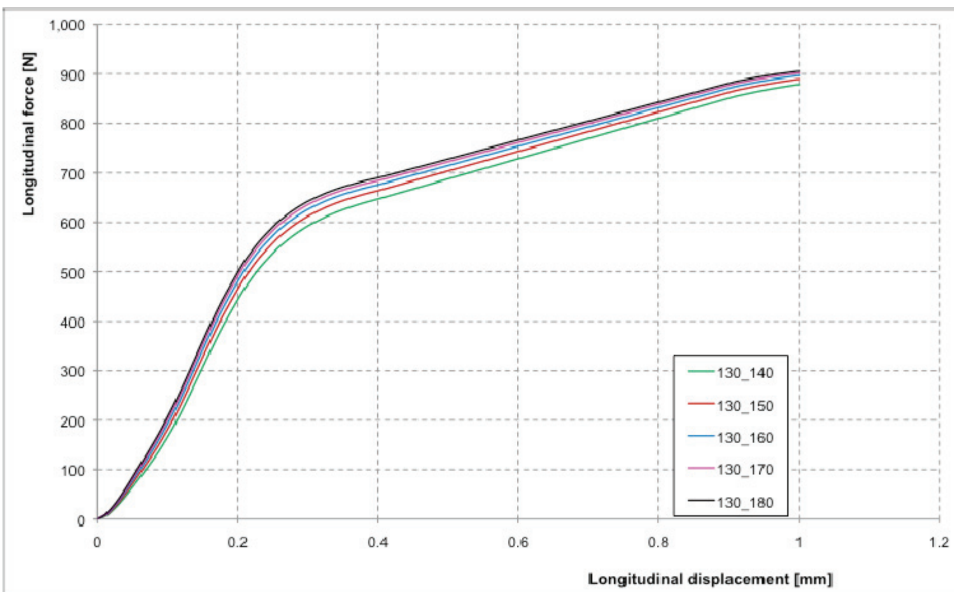

Figure 9: Longitudinal force as a function of the longitudinal displacement for Tp^{I} = 130 mm and various values of Tp^{II}.

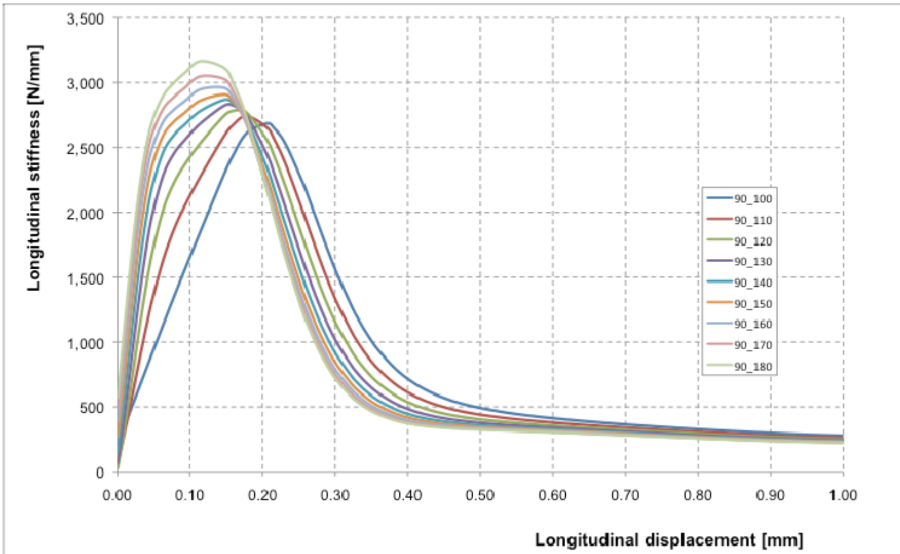

Figure 10: Longitudinal stiffness as a function of the longitudinal displacement for Tp^I = 90 mm and various values of Tp^{II}.

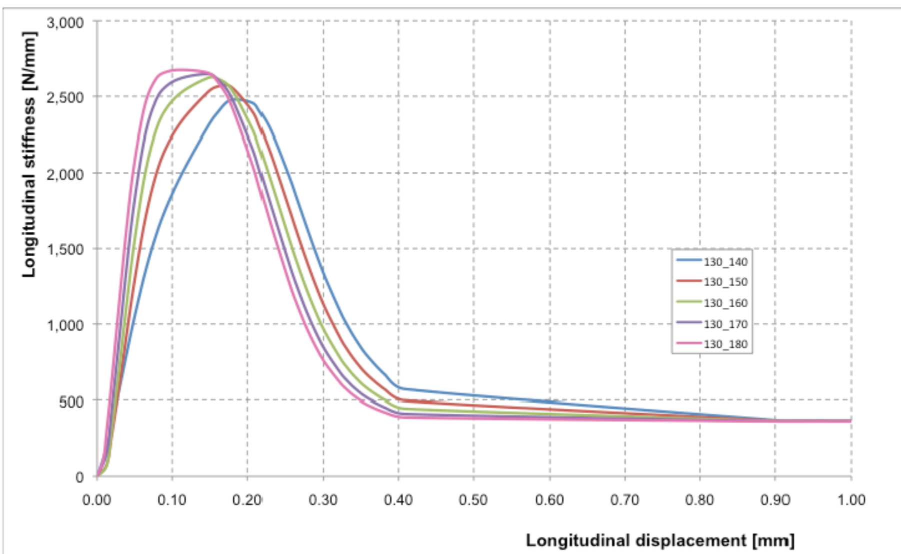

Figure 11: Longitudinal stiffness as a function of the longitudinal displacement for Tp^I = 130 mm and various values of Tp^{II}.

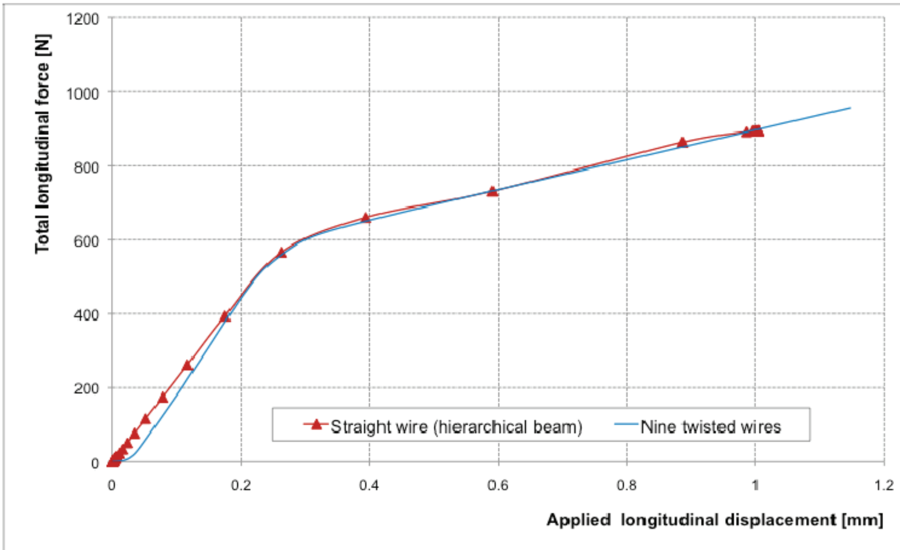

Figure 12: Comparison between the results of a nine-wired model and a single wire model.

combination has some influence on the bundle behaviour. To investigate in detail this effect, besides the three real configurations of ITER cables, we have performed a sort of sensitivity analysis by considering several 3x3 layouts. The longitudinal stiffness results higher for longer twist pitches. Even if this result is limited to the nine wire bundle, this information is already meaningful for ITER team, which has to choose the cabling patterns to test during the next experiments.

The numerical tests performed are used to compose the necessary database to teach artificial neural networks. The final goal of this work is to develop a model merging soft computation algorithms and hard computing, to have a valuable and fast predictive tool. To this aim, suitable ANNs have been trained to identify the longitudinal force, rotation or stiffness as a function of the twist pitches and applied axial displacement. Furthermore, it has been shown a comparison between a finite element analysis considering the nine strands of the second cabling stage and an equivalent single wire. The two models give practically the same results. Therefore, this preliminary work allows us to carry on the approach with an equivalent hierarchical beam, where the analyses of lower cabling stages are used to identify the characteristics of the following level. For example, this analysis allows for studying the longitudinal behaviour of a ITER petal (last but one cable stage, Figure 1) by considering 37 wires instead of 237. By identifying the complete stiffness matrix, it will be possible to study complex bundles subject to any type of loading, by using rather simple discretizations.

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