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INFERENCE OF THE TENSILE FORCE IN CABLES WITH INSULATORS USING AN ARTIFICIAL NEURAL NETWORK

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Abstract. The stability of guyed structures is highly dependent on the cables tensile force. Therefore, a versatile and reliable method for the verification of such force starting from the construction and during its service lifespan, is desirable. In the present work, an inverse method for the determination of the tensile force in cables with insulators is proposed, through the implementation of an Artificial Neural Network (ANN). Firstly, a Finite Element model is used to obtain the first natural frequency of different cable configurations. In this way it is possible to vary the tensile force, length, tilt angle, and number of insulators. The data resulting from the computational simulations is used to train the ANN. During this stage, corresponding input and output samples are introduced to the network. Once the training is completed, the ANN is capable of representing the relation between the input parameters (length, tilt angle, number of insulators and first natural frequency) and the cable tensile force. Additionally, a physical model of the cable is developed in the laboratory. A dynamic study of several configurations is performed in order to obtain the corresponding experimental natural frequencies. Finally, in order to validate the method, the parameters of the physical model configurations are introduced as the inputs of the ANN and the tensile force values are inferred. The results are compared to the actual force on the laboratory model. The resulting error is acceptable in all the cases.

1 INTRODUCTION

Guyed structures are frequently used in the Civil Engineering: from the most simple ones as advertising banners and urban power lines, to more complex structures such as slender towers which support communication antennas, high voltage transmission lines, and bridges. The rigidity of this kind of structures is highly dependent on the guys and their pretension level. Therefore, it is essential to verify the design tensile force of the cables both at the moment of the assembly of the structure and during its service lifespan. A method for determining the cables tensile force based on structural dynamics principles would be a versatile and useful tool. In this sense, some authors (Fu et al., 2004; Ren et al., 2005; Kim and Park, 2007) have addressed the study of the dynamical behaviour of bridge cables. In particular, the second paper deals with the development of an empirical formula relating natural frequencies with the tensile force. However, at the current state of development of the technique, the usage of these methods is conditioned by the high degree of uncertainty in the results and by the impossibility of application in a wide range of common use configurations. Particularly, in cables with insulators along their lengths.

Artificial Neural Networks (ANNs) are a family of models inspired by biological neural networks which are used to estimate or approximate relationships between inputs and corresponding output values, after a training process based on repeated exposition to sample patterns (supervised learning). The scope of application of the ANNs in the field of structural mechanics is wide. Ghaboussi (2010) and Yagawa and Okuda (1996) present a general review of their use in the solution of computational mechanics problems. Due to its favourable characteristics for solving minimization tasks, this kind of learning models arises as specially adequate for the resolution of inverse problems. Aydin and Kisi (2015) and Rosales et al. (2009), for instance, report the application of ANN based inverse models to identify failure in beams using experimental and computational data for training, respectively. Giorelli et al. (2015) apply the same approach for the determination of the tensile force in cables which govern the kinematics of a bio-inspired manipulator arm. In the articles published by Bandara et al. (2014) and Cheng et al. (2007), the learning samples are obtained through a computational model based on the Finite Element Method (FEM). In particular, the second paper deals with the use of an ANN for the determination of the maximum tensile force in continuum cables of a bridge structure.

In the present paper, an inverse approach is applied for the identification of the pre-stress level in cables. The use of an ANN acting as an inverse relation between the parameters of the cable and its tensile force is proposed. Taut inclined cables with one or two insulators and different tension levels are considered. The pattern samples needed for training the ANN are obtained from a FEM based model constructed *ad hoc*. The computational model allows to easily perform parametric variations of the system in order to obtain the corresponding first natural frequency of each configuration. Additionally, a physical model is constructed in the laboratory. A study of the cable undergoing free vibrations is performed. The experiment is registered using a high speed camera. Furthermore, using a video analysis software, the dynamics are reconstructed and the first natural frequency is experimentally measured. Finally, in order to validate the method, the parameters of the physical model (length, number of insulators, tilt angle and natural frequency) are introduced as inputs to the already trained ANN and the corresponding tensile forces are inferred. Several experimental configurations are studied. The network outputs are then compared to the targets and the performance of the inverse method is evaluated.

2 COMPUTATIONAL MODEL

In this section, the computational procedure is described. The model is built with the aim to provide a reliable, fast and versatile method to perform parametric variations of the system configuration. In this way, it is possible to obtain the required amount of training samples for the ANN. The model is constructed in the COMSOL Multiphysics® (2015) environment: a FEM software adequate for physics and engineering applications. The simulations are performed using the *LiveLink*^{TM} *for MATLAB*®, an extension of COMSOL which allows to integrate both programs. Thus, the results can be easily post-processed in MATLAB.

2.1 Description of the model

A scheme of a possible configuration of the studied system is depicted in Fig. 1. It consists of a pre-stressed stranded steel cable of diameter $d = 0.0015$ m, pinned at both ends. Several configurations are considered by varying certain parameters: the length L, tilt angle θ relative to the horizontal, and tensile force P. The reference length L refers to the distance between supports. As will be detailed below, a first stage of the calculation includes the action of gravity on the cable and the insulators. Thus, under self-weight, the prestressed cable extends and the true length is modified. Regarding the insulators m, they are modelled using beam elements which simulate the insulator itself, and two point masses placed at each end node of the beam (insulator), which simulate the fixing clamps. The range of values assigned to each of the mentioned parameters is reported in Table 1.

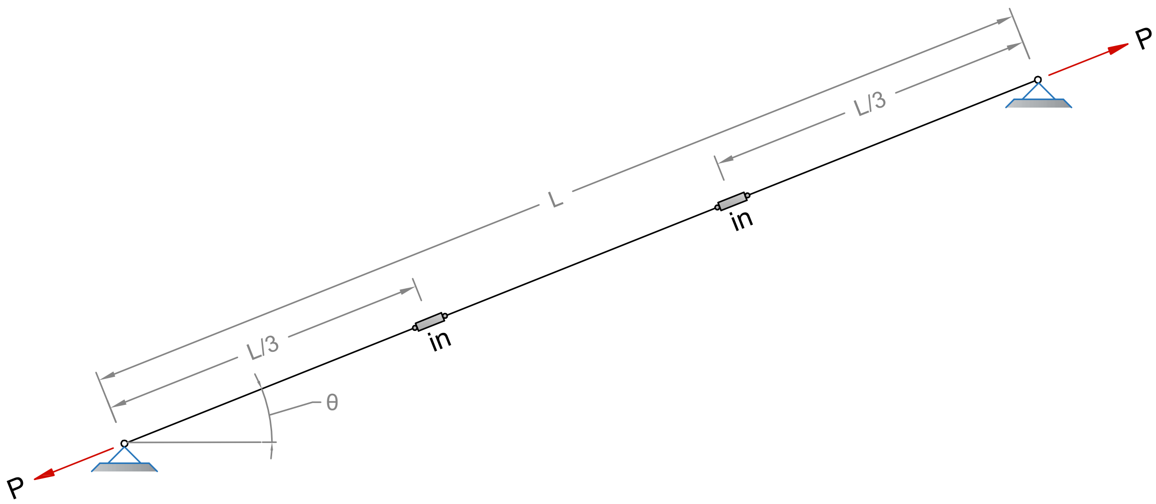


Figure 1: Taut cable with two insulators.

In the context of COMSOL, the study *Prestressed Analysis, Eigenfrequency* available for the *truss* interface using the *Structural Mechanics* module, is performed. Such study consists of two stages: in the first step the static load - self-weight and tensile force - is applied; in the second step, the eigenfrequencies of the structure under the resulting load state from step one, are computed. Truss elements with initial stress are adopted to model the cable. In addition to the characteristics informed in Table 1, it is necessary to define some geometric and material properties of the cable, namely: diameter $d = 1.5$ mm, density $\rho = 6281$ kg/m^3, Modulus of Elasticity $E = 156.96\ 10^9$ N/m^2 and Poisson ratio $\upsilon = 0.28$. Self-weight is modelled as a distributed force per unit length $w = 0.1361$ N/m. Regarding the insulators, they are modelled as Polymethyl methacrylate (PMMA) beams of length $L_{in} = 0.025$ m, rectangular cross section of sides $b_{in} = 0.011$ m and $h_{in} = 0.012$ m, density $\rho_{in} = 1190$ kg/m^3, Modulus of Elasticity $E_{in} = 3\ 10^9$ N/m^2 and Poisson ratio $\upsilon_{in} = 0.40$. Point masses of mass $m_{cl} = 0.008$ kg are placed at the ends of each insulator to simulate the fixing clamps.

As a result of the simulation, the first natural frequency of the structure is obtained.

Parameter	**Minimum**	**Maximum**	**Step**	N° of cases
Length $[m]$	1	3	0.5	5
Tensile force $[kg_f]$	1	15	2	8
Tilt angle $[degrees]$	0	60	20	4
Insulators $[n°]$	1	2	1	2

Table 1: Variation range for each of the system parameters.

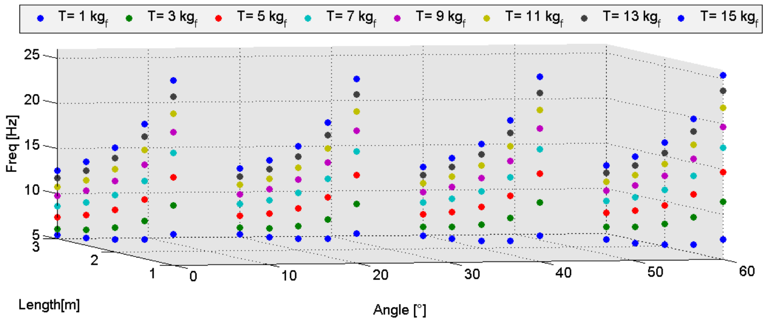
2.2 Computational results

The results of the computational simulations are depicted in Fig. 2. In graphics (a) and (b), the calculated first natural frequencies are plotted against the length and tilt angle, for cables with one and two insulators along their lengths, respectively. Additionally, each colour represents the cable tensile force and is duly referenced above each graphic. As expected, the magnitude of the natural frequencies for cables with two insulators are lower than for cables with one insulator. In graphics (c) and (d) the same data is plotted in a different way: first natural frequencies along the ordinate axis versus tilt angle and cable tensile force. This time, each colour identifies the values assigned to the cable length according to Table 1.

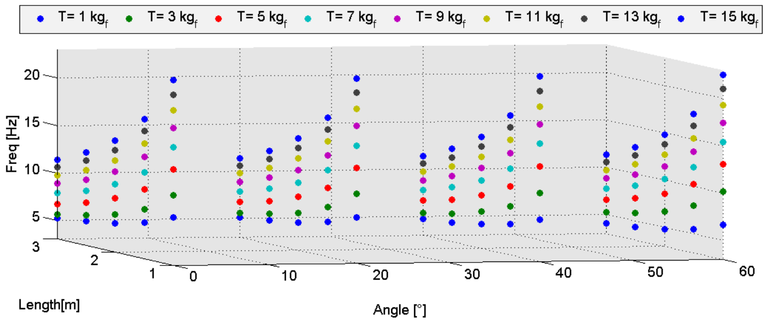
3 ARTIFICIAL NEURAL NETWORK

3.1 Description

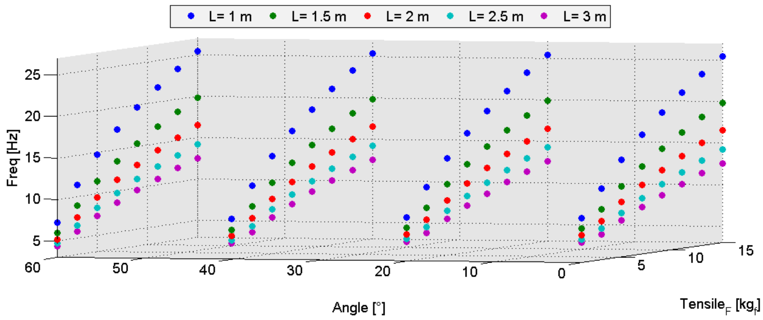
In this paper, an ANN approach is applied to solve the inverse problem of the tensile force inference in cables with insulators. ANNs are data processing algorithms inspired by the human brain (Nelles, 2001). They allow to estimate or approximate functions which are usually unknown and can depend on several inputs and outputs. Basically, ANNs consist of a number simple processing units called neurons, which are grouped in parallel substructures named layers. The neurons in the successive layers are massively interconnected through synaptic weights and biases which magnitudes are tuned using training samples by means of a learning process. In the following sections, a brief explanation of some basic concepts concerning ANNs is given. For a wider and more detailed approach on the subject, see for example Haykin (2010) or Bishop (1995).



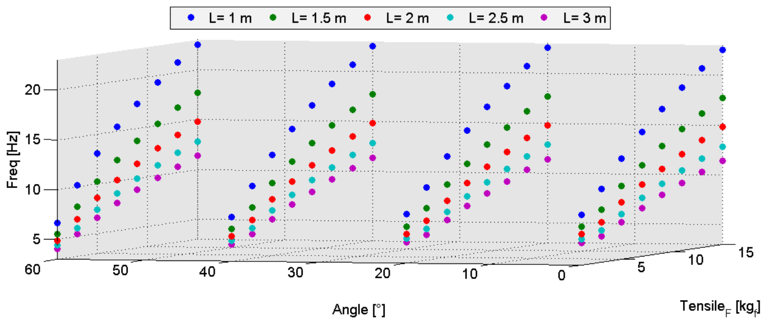
(a) *Length vs. Angle vs. Freq* (1 insulator)



(b) *Length vs. Angle vs. Freq* (2 insulators)



(c) *Angle vs. Tension vs. Freq* (1 insulator)



(d) *Angle vs. Tension vs. Freq* (2 insulators)

Figure 2: Results from the FEM simulations.

3.2 Structure

Basing on the Universal Approximation Theorem (Cybenko, 1989), a feedforward Multi Layer Perceptron (MLP), consisting of an input layer, an output layer, and a single hidden layer is adopted for this study. In a feedforward MLP the information moves in one direction only: forward, from the input layer going through the hidden to the output layer. The input layer allows the entrance of the signal $\bar{u} = [u_1, u_2, ..., u_n]$ and distributes it.

The number of neurons (also called nodes or units) in the input and output layers is given by the number of input and output variables, respectively. In the present case, the input layer consists of 4 neurons, whereas the output layer is constituted by a single neuron. However, the selection of the number of neurons in the hidden layer is not straighforward. The approach adopted in this regard is discussed in Section 3.4.

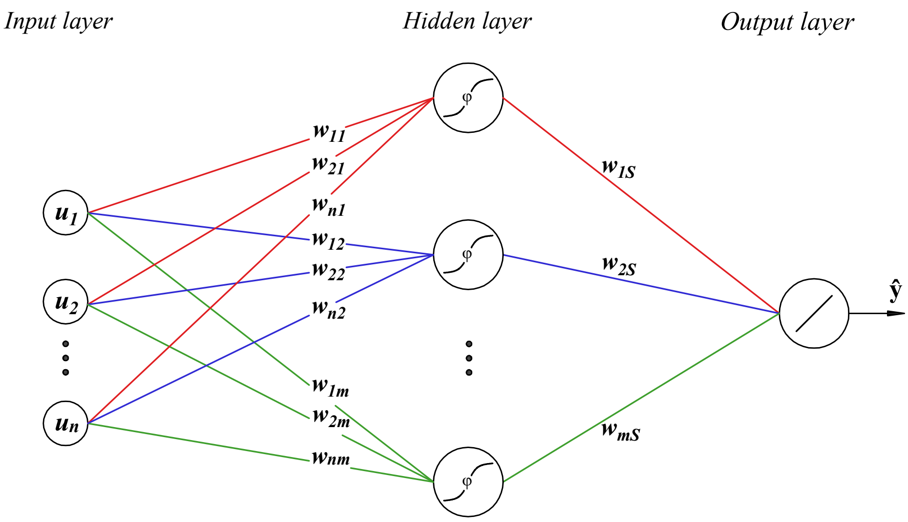


Figure 3: Multi Layer Perceptron (MLP) with one hidden layer.

Each neuron operation can be regarded as a two stages process (Fig. 4): first, the inputs are projected into the synaptic weights $\bar{w}$, and the bias term b_i is added. In the second step, the projection is transformed through an activation function (transfer function). In the hidden layer units the activation function φ is a non-linear hyperbolic-tangent sigmoid function (Eq. 1) which fulfils the conditions stated by the Universal Approximation Theorem in this regard. The use of this kind of functions improves the efficiency of the learning algorithm resulting on a faster convergence speed (Bishop, 1995). Its output v_i lies in the range (-1,1).

The activation function in the output layer neuron is linear. Its job consists in projecting the signal incoming from the hidden layer units into the corresponding weights and adding the bias. The operation results in the network output $\hat{y}$.

$$\varphi(x) = \frac{2}{(1 + e^{-2x})} - 1 \tag{1}$$

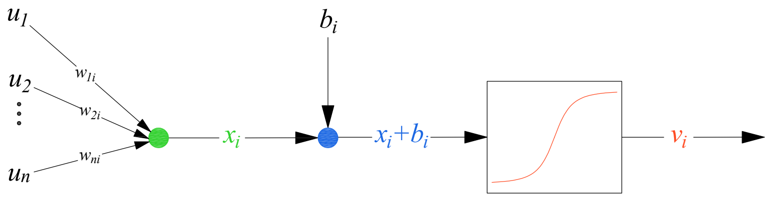


Figure 4: Operation performed by a neuron in the hidden layer.

3.3 Learning

During the learning stage, the parameters of the ANN (weights and biases) are tuned in order to minimize the cost function (*i.e.*, the function which measures the discrepancy between the desired output y and the network output $\hat{y}$). In the present paper, the learning is performed by means of the Backpropagation (BP) algorithm (Rumelhart et al., 1985), which is used in conjunction with the gradient descent optimization technique. An adaptive learning factor is applied in order to improve the performance of the steepest descent algorithm. Furthermore, with the purpose of avoiding the BP algorithm to getting stuck in local minima, a momentum term is included.

The training dataset is obtained from the FEM simulations and it consists of 320 samples (see Table 1). The input variables to the ANN are: the cable length L, tilt angle θ, number of insulators (1 or 2) and the first natural frequency f. On the other hand, the tensile force P represents the output. The dataset is split into a training set (TS)(80%) and a validation set (VS)(20%). Furthermore, in order to avoid over-fitting of the network parameters to the learning patterns, a different subset containing 80% of the TS is chosen randomly every 100 iterations. This last subset is named estimation set (ES) and is the one used for learning. The VS is employed to evaluate the performance of the network in generalization using samples which had not been used during the learning Giorelli et al. (2015).

To improve the efficiency of the learning algorithm the data is pre-processed before presenting it to the ANN: a linear mapping is applied through Eq. 2, so that the maximum and minimum value (z_{max} and z_{min}) of each input and output variable z are normalized into the interval [0,1].

$$z_{normalized} = \frac{z - z_{min}}{z_{max} - z_{min}} + z_{min} \quad (2)$$

3.4 Number of neurons in the hidden layer

In the absence of general rules for determining the optimum size of the hidden layer, the criteria adopted in this work is based on finding the ANN with the best generalization performance. In this regard, a procedure based on cross-validation is applied (Bishop, 1995). Various ANNs are trained during a fixed number of iterations N_{epochs}. The number of neurons in the hidden layer N_{nhl} is varied from N_{nhl}^{min} to N_{nhl}^{max}. The TS is used in the learning stage. Following training, the performance of the ANN is evaluated on generalization using new samples from the independent VS. The validation error corresponding to each N_{nhl} is registered. The results are compared and the ANN with the smallest validation error is chosen. The error functions used in the TS and VS are given by the mean squared errors (Eq. 3) between the desired value

$\hat{y}$ and the network output $\hat{y}$.

$$
\begin{aligned}
TS_{rms} &= \sqrt{\frac{\sum(y_{tr_i} - \hat{y}_{tr_i})^2}{N_{TS}}} \\
VS_{rms} &= \sqrt{\frac{\sum(y_{ge_i} - \hat{y}_{ge_i})^2}{N_{VS}}}
\end{aligned}
\tag{3}
$$

The synaptic weights and biases of the ANN are randomly initialized in the first iteration of the BP algorithm. Thus, very different solutions for the same problem can be reached depending on those initial values, deriving in very different training and validation errors as well. For this reason, the approach proposed by Giorelli et al. (2013) is adopted, and the procedure described above for the selection of the optimum number of hidden units is repeated N_{ts}^{max} times.

The following parameters are chosen before running the optimization algorithm: $N_{nhl}^{min} = 1$, $N_{nhl}^{max} = 20$, $N_{epochs} = 10000$, $N_{ts}^{max} = 60$. The results are reported in the histogram in Fig. 5. It shows that ANNs with number of hidden units in the range [8-10] give the smallest validation error the highest number of times ($N_{ts} = 28$). Consequently, a feedforward ANN with 9 hidden neurons is adopted for the problem in this paper.

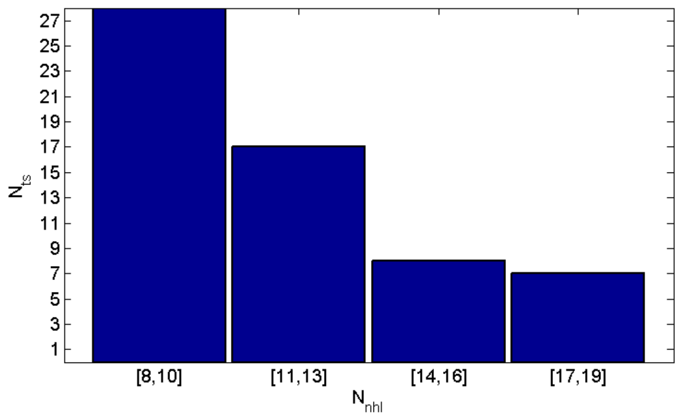


Figure 5: Hidden layer size optimization.

3.5 Training

Some parameters concerning the BP algorithm are defined before beginning the training, namely: momentum $\mu = 0.01$, initial learning rate $\nu = 0.000001$, learning rate increment $\nu_{incr} = 1.05$, learning rate decrement $\nu_{decr} = 0.75$, maximum learning rate $\nu_{max} = 2$, minimum learning rate $\nu_{min} = 0$, maximum number of iterations $MAX_{epochs} = 100000$. One of the problems that may arise during training is over-fitting (*i.e.*, the network memorize the training data, but fails to generalize when new data is input). In order to prevent this, the early stopping method is applied. In this technique the validation error is monitored every $N_{VE} = 20$ iterations during the training. When the network begins to over-fit the data, the VS error typically begins to rise. When the VS error increases for $N_{stop} = 100$ consecutive iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. The training was repeated four different times. The evolution of the VS error is plotted in Fig. 6 versus the number of iterations. The BP algorithm was never stopped by the early stopping method. However it can be observed that that after 50000 iterations the decrease rate of the error is very low. Thus, the training is finished considering that the ANN gives an adequate generalization performance. The weights and biases corresponding to the minimum VS error are adopted as the definitive ANN parameters.

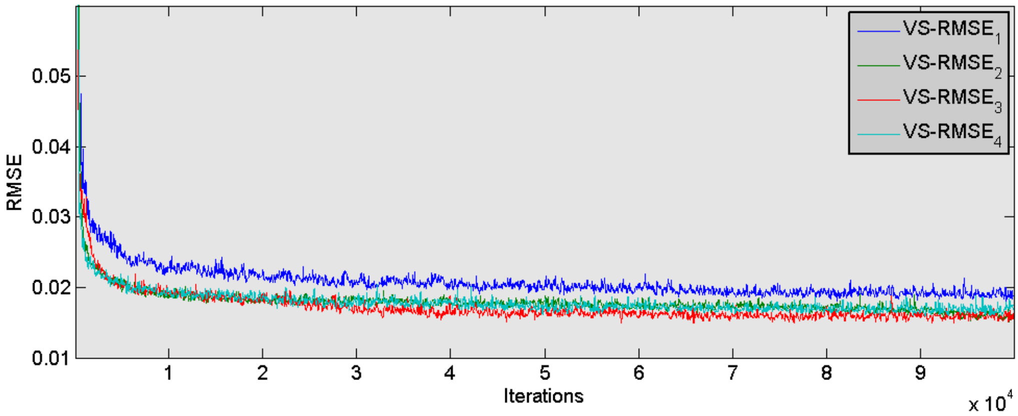


Figure 6: Evolution of the VS error for each training.

4 TEST OF THE ANN BASED INVERSE METHOD

In this section, the trained ANN is used as an inverse model to infer the cable tensile force corresponding to certain physical models. The experimental procedure and the validation results are herein reported.

4.1 Experimental setup

In the laboratory, dynamic tests were performed on different cable configurations. In all the cases the stranded steel cable diameter was $d = 1.5$ mm. The tests contemplated cables of 1 m length with one insulator and cables of 2 m length with two insulators. These configurations are identified as scenario A and B respectively. Different tilt angles and tensile forces were applied, and the corresponding first natural frequencies were measured experimentally. Table 2 depicts the parameters of each experimental configuration.

A particular experimental configuration is shown in Fig. 7. The lower end of the cable was attached to a tensioning screw whereas the upper end was fixed to an S-type load cell which registered the applied tensile force. The insulators consisted on rectangular parallelepipeds built on Polymethyl methacrylate (PMMA). Their shape and connection to the cable simulated the ceramic egg-shaped insulators used in the real scale guy wires. The desired axial load was applied by acting on the tensioning screw. In order to promote the free vibrations of the structure, the equilibrium was interrupted by a manual perturbation. A Casio Exilim EX-FS10 high speed camera was used to register the displacements of a particular point of the cable undergoing free vibrations. The records were taken at 420 frames per second during 4 seconds. Then, using the free video analysis software Tracker 4.94 (2016), the dynamics of the experiment were reconstructed and the time series displacements response was obtained. The *autotracker* functionality of the software allows to automatically track a video feature of interest. For this purpose, a red circular marker of negligible weight had previously been attached to the cable at the point which was going to be filmed. In this way, a time series of the in-plane transverse displacements of the cable was registered. The data obtained was exported and processed in Matlab were the time

Scenario A				Scenario B			
Case	Angle $[^\circ]$	Force $[kg_f]$	Freq. $[Hz]$	Case	Angle $[^\circ]$	Force $[kg_f]$	Freq. $[Hz]$
$\boldsymbol{a_1}$	28.8	4.15	14.45	$\boldsymbol{b_1}$	30.5	3.90	7.83
$\boldsymbol{a_2}$	28.8	6.14	16.88	$\boldsymbol{b_2}$	30.5	5.85	9.47
$\boldsymbol{a_3}$	28.8	8.26	19.74	$\boldsymbol{b_3}$	30.5	7.98	10.87
$\boldsymbol{a_4}$	28.8	10.01	21.50	$\boldsymbol{b_4}$	30.5	9.56	12.14
$\boldsymbol{a_5}$	28.8	12.25	23.52	$\boldsymbol{b_5}$	30.5	12.02	13.30
$\boldsymbol{a_6}$	28.8	14.28	25.16	$\boldsymbol{b_6}$	30.5	14.00	14.19
$\boldsymbol{a_7}$	43.9	3.92	13.44	$\boldsymbol{b_7}$	46.5	3.95	8.12
$\boldsymbol{a_8}$	43.9	5.86	15.96	$\boldsymbol{b_8}$	46.5	6.07	9.84
$\boldsymbol{a_9}$	43.9	7.87	18.06	$\boldsymbol{b_9}$	46.5	8.11	11.16
$\boldsymbol{a_{10}}$	43.9	9.95	19.74	$\boldsymbol{b_{10}}$	46.5	10.20	12.39
$\boldsymbol{a_{11}}$	43.9	12.40	23.10	$\boldsymbol{b_{11}}$	46.5	12.20	13.53
$\boldsymbol{a_{12}}$	43.9	14.19	24.78	$\boldsymbol{b_{12}}$	46.5	14.21	14.48
$\boldsymbol{a_{13}}$	60	3.97	14.03	$\boldsymbol{b_{13}}$	59.5	3.78	7.751
$\boldsymbol{a_{14}}$	60	6.00	17.05	$\boldsymbol{b_{14}}$	59.5	5.91	9.43
$\boldsymbol{a_{15}}$	60	8.04	19.32	$\boldsymbol{b_{15}}$	59.5	7.88	10.79
$\boldsymbol{a_{16}}$	60	9.93	21.00	$\boldsymbol{b_{16}}$	59.5	9.65	11.69
$\boldsymbol{a_{17}}$	60	11.80	23.02	$\boldsymbol{b_{17}}$	59.5	11.78	12.51
$\boldsymbol{a_{18}}$	60	13.97	24.86	$\boldsymbol{b_{18}}$	59.5	13.63	13.41

Table 2: Data for Scenario A: $L = 1$ m, 1 insulator; and Scenario B: $L = 2$ m, 2 insulators

domain representation of the signal was deconstructed into the frequency domain using the Fast Fourier Transform (FFT). The first natural frequency of the cable was determined by identifying the highest peak from the FFT. With the aim to perform a better estimation and considering the measurement uncertainties inherent to any physical experiment, the tests were repeated 5 times and the results were averaged.

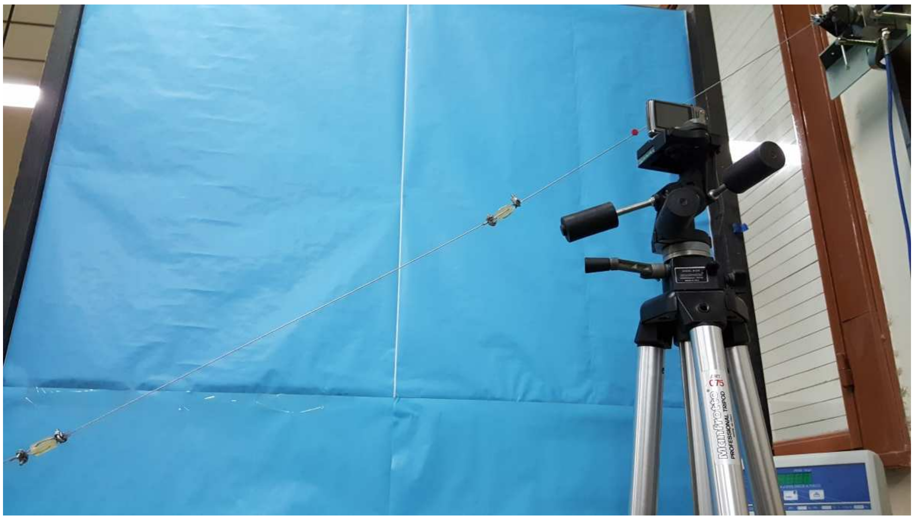
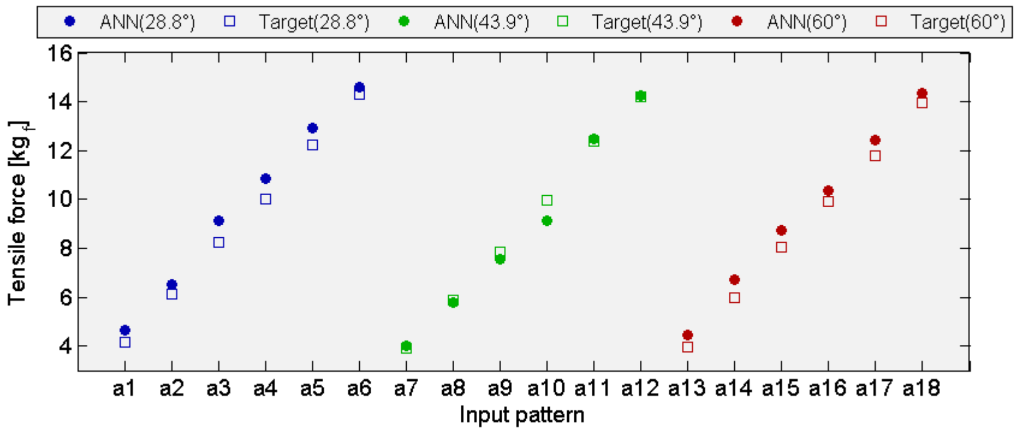


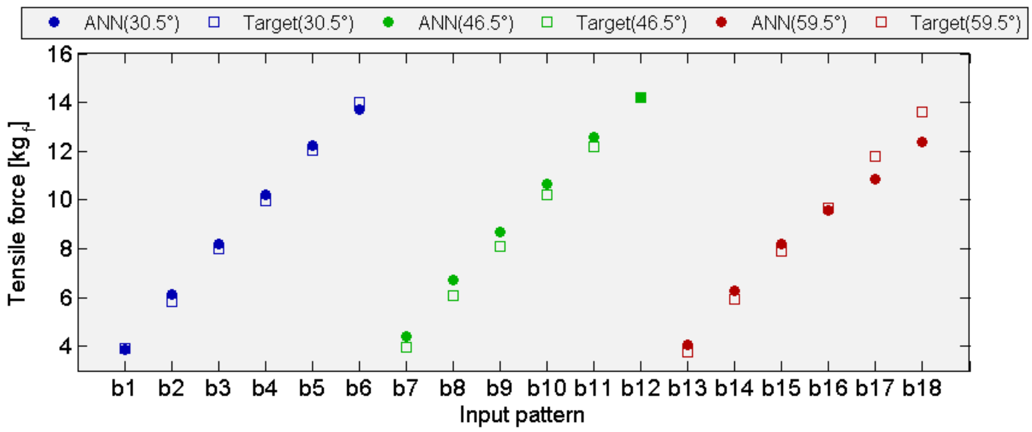
Figure 7: A particular experimental setup of the cable with two insulators.

4.2 Inference results

This paper constitutes a first step in the development of an inverse method which, based on experimental measures of the first natural frequency of the system, allows to estimate the tensile force in the cables of guyed towers. Thus, in this section, the inverse procedure is applied on a reduced scale: the input patterns to the ANN are the first natural frequency measured in the laboratory and the parameters of the physical model (see Table 2). The outputs $\hat{y}$ (filled circles) and targets t (empty squares) corresponding to each experimental configuration are depicted in Fig. 8 for the cases in scenarios A and B. The tilt angles are identified by the different colours: blue, green and red. The magnitude of the error between the ANN outputs and the targets does not seem to depend on the model parameters. Furthermore, it is observed that the inferred values lie close enough to the targets, independently from the tilt angle, tensile force or number of insulators. It can also be seen that the outputs are, in general, of higher magnitude than the targets. This discrepancy could be regarded to the fact that the frequencies measured experimentally are generally higher than those calculated using the equivalent FEM based model.



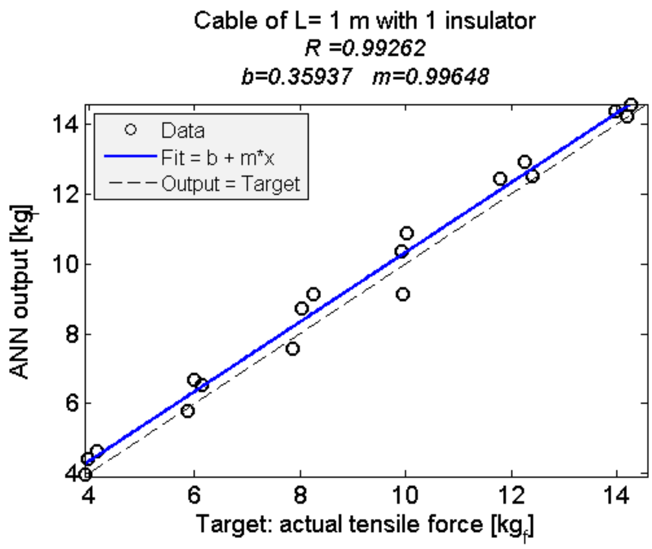
(a) Scenario A



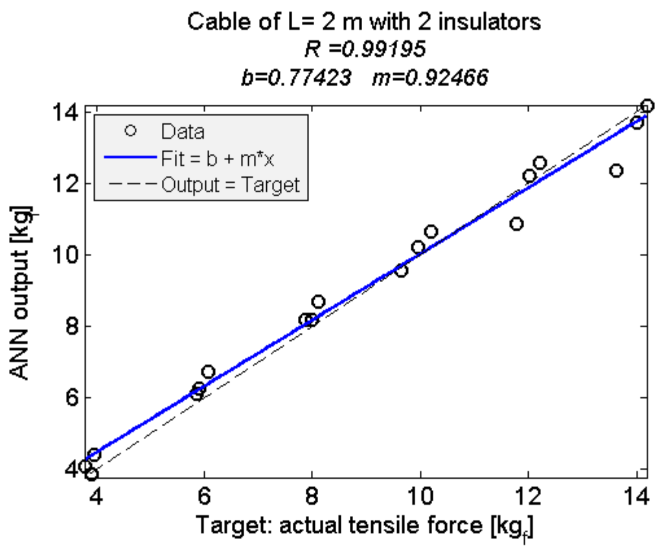
(b) Scenario B

Figure 8: Comparison of the ANN outputs and the corresponding targets for the different experimental configurations.

The accuracy of the inverse model is analysed in more detail by means of a regression analysis between the ANN output and the corresponding targets. For this purpose, the *regression()* Matlab function is used. Three parameters are obtained as result: m and b represents the slope and the y-intercept of the best linear regression respectively, whereas R represents the correlation coefficient between outputs and targets. If there were a perfect fit, then m would be 1 and b would be 0. Likewise, a value of $R = 1$ implies that a linear equation describes the relationship between outputs and targets perfectly (*i.e.*, perfect correlation). The results are depicted in Fig. 9 for the cases in scenarios A and B.



(a) Scenario A



(b) Scenario B

Figure 9: Regression analysis between ANN outputs and targets.

The targets are measured along the x-axis whereas the inferred values are measured along the y-axis. The best linear regression fit for the data is plotted as a blue line: the parameters b and m are reported, together with the regression parameter R. Additionally, the dashed line represents the curve of perfect fit where the network outputs are equal to the targets. The fit is reasonably good, with R values very close to one in each case. It is worth noting that for cables of 1 m length with one insulator (scenario A), the distance between the fit line (blue) and the line of perfect fit is very small and that value is kept almost equal for all the values of the tensile force (m is very close to one), which indicates uniformity in the error between outputs and targets. The results are less uniform for the cases in scenario B. This suggests a higher discrepancy between outputs and targets for small values of the tensile force. However, it can be seen that the error improves for higher values of the pre-stress level.

Finally, the relative error with respect to the actual tensile force (target) was calculated for each inferred value according to Eq. 4. The distribution of the relative errors for the complete set of inferred values (scenarios A and B) is shown in the histogram of Fig. 10. Additionally, the mean value, maximum value, and standard deviation are reported. This representation confirms that the error is very small most of the times ($MeanErr = 2.5\%$) and, even in the least favourable cases, its magnitude is reasonably low ($MaxErr = 11\%$).

$$error = \frac{(\hat{y} - t)}{t} \tag{4}$$

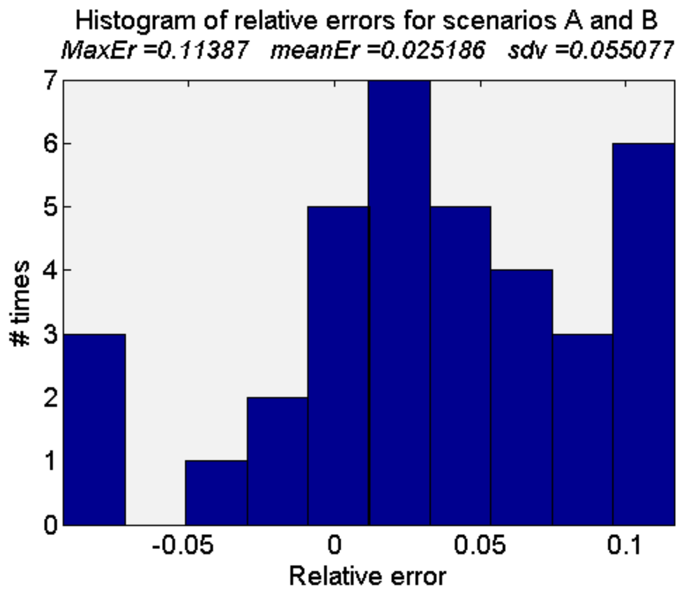


Figure 10: Histogram of the relative errors in the inferred values using the ANN based inverse model.

5 CONCLUSION

The identification of the tensile force of inclined taut cables with insulators is addressed in this paper. In particular, an ANN is proposed as an inverse model for the inference task, based on measurements of the first natural frequency of the cable. Their capacity for estimating functions which are usually unknown makes ANN particularly appropriate for this problem.

The data needed for training the ANN is obtained from computational simulations, using a FEM based model of the system.

Once the ANN is trained, it is validated using experimental data. Overall, 36 different configurations are evaluated, including cables with one and two insulators. The first natural frequency corresponding to the physical configurations was measured in the laboratory. Then, the experimental frequency and the geometrical parameters of the physical models are introduced as inputs patterns to the ANN and the corresponding estimates of the tensile force are obtained. The network outputs are compared to the true tension acting on the experimental models, and the relative errors are computed. The average error is reasonably low, and the maximum error remains within acceptable ranges.

In summary, the proposed ANN based inverse model is straightforward and provides acceptable estimates of the tensile force in different configurations of cables with insulators based on measurements of the first natural frequency. The results are promising for the application of the method in the real scale.

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