Localisation of the excitation position from a beam deformations using neural networks

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ABSTRACT: The monitoring system as well as the diagnosis of rotating machines defects, by vibrations analysis generated by these machines constitute recent studies.
This type of conditional maintenance, becomes interesting since the machine occupies a significant place in the production process. The currently studies are specially interested on the defect diagnosis using the neural networks which use the form detection. The excitations position on the rotating machine, informs us also about the evaluation and the position the defect on the studied machine. For example, we can mention, the unbalance, which the position on the drive shaft is very important. It is the objective assigned by the suggested study in this paper, it is the determination of the position of excitation from the rotor deformations by using the neural networks.
The study is centered on a circular beam which boundary conditions were: clamped - free, by dynamic analysis. We fixed the load intensity and frequency excitation and while varying the position of this load, we determine the different loaded beam deformations. We submit, thereafter, the system to a training according to the type of networks used, to try to recover the position of the load from the knowledge of the rotor deformations. In dynamics, the most interesting result obtained is the influence of the number of mode shapes (1st mode, 2nd mode,…) to consider for the deformation determination, on the network type and the parameters related to this network. The obtained results were satisfactory for the capacity of the method to be able to localise the excitation position from the beam deformation.

1. INTRODUCTION

The system monitoring as well as the machines defects diagnosis, by its generated vibrations and noise analysis have always a real importance. This type of maintenance (conditional maintenance) becomes interesting since the machine occupies a significant place in a production process. The studies currently undertaken related especially to the diagnosis of the defects by the use of the neural networks.
On the machine, the excitations position, also informs us about the evaluation and the position of machine defect, for example, the case of an unbalance defect. The present study interested to the determination of the excitation position from a beam deformations using the neural networks.
The study was applied to a clamped-free circular beam, by static and dynamic analysis. We fixed the intensity and the frequency excitation (in the dynamic case), and while varying the position of the force, we determine the corresponding beam bending deformations. We subject, thereafter, the network used to the training to try to find the load position from the knowledge of the beam deformations.

The application of the neural networks is very diversified, we can in particular quote their application in the electronics field (speech processing), the robotics (piloting of mobile robots) and of mechanics in its general domain.
Several studies were undertaken for their application to mechanics, In particular Monari and al. have who interested to improve quality of the point welding of sheets, where it is too difficult to obtain a better quality of welding on the same product, and with constant adjustment of the electrodes of welding. To solve this problem, the neural networks were used to predict the diameter of welding by taking account of tens of judicious parameters to have an influence on the final diameter of the welding.
The network used includes hidden layers using non-linear transfer functions (sigmoidal function) except the output neuron, whose transfer function is a linear one. The training is made using the algorithm of the backpropagation and quasi-Newton algorithm (Howard and Beale (1998)).

2. THEORICAL ANALYSIS

The network used in this application, contains a structure with two layers of neurons. The input layer used the hyperbolic tangent sigmoidal function, the output one used a linear layer. The number of the input neurons is given according to the problem complexity, it didn't mean that very complex problem requires a great number of neurons, it is enough to start with some input neurons and to increase this number if it is necessary, until obtaining an optimal network architecture. The output neurons are given according to the beam meshgrid.
The learning rule used, employed in 85 % of the identification problems, is the backpropagation of the average quadratic error between the objective output and those obtained by the network. The neuron used in this network hadn't a linear transfer function enabling him to deal with linear and non-linear problems of the relation existing between the vectors of entry and exit (figure 1).

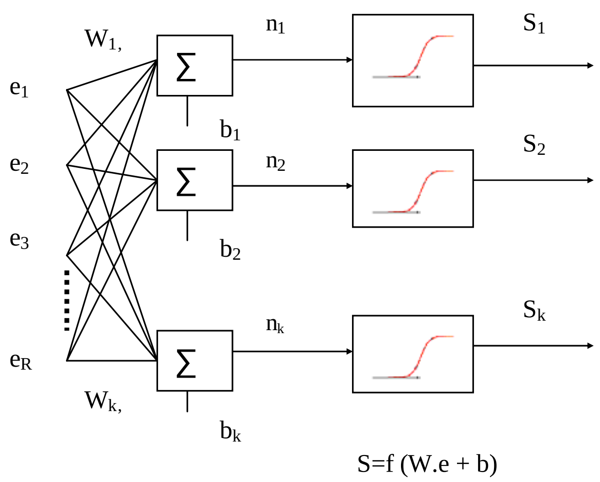

Figure 1- *Network with retropropagation layers.*

where
e_1, e_2: correspond to the network input, it characterises the excitation position on the beam, their number depends on the number of examples of training which we subject to the network.
$S_1, S_2,$ correspond to the network output, it characterises the beam points, their number depends on the number of examples of training which we subject to the network.
and $n_1, n_2, \ldots n_k$ the total input presented in the network.

All the data are gathered in the input matrix E(i,j), and an output matrix S(i,j), which constitute the whole of the data of training.
where :
i = 1...,n : n is related to the number of examples of training
j = 1...,m : m is related to the meshgrid of the beam.

$$E = \begin{pmatrix} e_{11} & e_{11} & \cdots & e_{1m} \\ e_{21} & e_{22} & \cdots & e_{21} \\ \cdots & \cdots & \cdots & \cdots \\ e_{nm} & e_{2m} & \cdots & e_{nm} \end{pmatrix} \qquad S = \begin{pmatrix} s_{11} & s_{11} & \cdots & s_{1m} \\ s_{21} & s_{22} & \cdots & s_{21} \\ \cdots & \cdots & \cdots & \cdots \\ s_{nm} & s_{2m} & \cdots & s_{nm} \end{pmatrix}$$

The network used is not buckled, with the training rule the backpropagation of errors gradient. An iteration of this rule can be described in the following way (Davaldo and Naim (1993)).

$$X_{k+1} = X_k - \alpha_k g_k$$

where X_k is the weights vector, g_k the error gradient and α_k the rate of training.

3. NUMERICAL EXPLOITATION

3.1 Model presentation

We have, such as it was quoted in the general introduction, considered a beam of circular section clamped-free. We considered the mode by mode analysis where the deflexion is given from the modal response of the mode considered. We considered the first four modes.
The network model used is the not buckled one of backpropagation of the error. The network used contained two layers : an input layer, with a nonlinear function threshold of the hyperbolic tangent type sigmoïdal, and an output layer. The network type depends on the number of outputs related to the beam meshgrid and the number of training examples.
The parameters which we vary to test the capacity of this method to locate the excitation on the beam, on the basis of the beam deflection, are the meshgrid applied on the beam and the number of training examples as well as the rigidity of the beam.

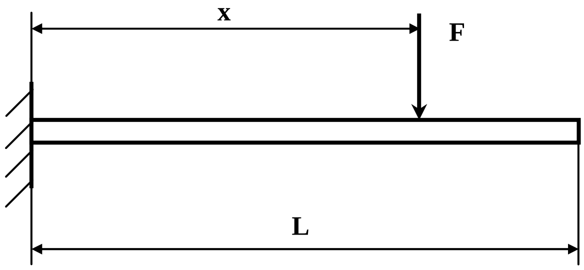

Figure 2- *Clamped-free circular beam.*

The amplitude of the force is 10 N and the geometrical and mechanical characteristics of the beam are resumed in the table 1.

Table 1- Mechanical characteristics of the beam.

Beam parameters	
Length :	1 m
Diameter :	0.1 m
Young modulus :	210 GPa
Poisson's coefficient :	0.3
Density :	7800 kg/m^3

3.2 Results

The results obtained in the static case are very satisfactory, the network with carried out the desired behaviour, indeed its answers is adapted quickly to the different deformations during the generalisation test, and the position force detection was found with only few examples of training.

Figure 3, illustrating the generalisation test using a network with 11 points grid on the beam and only three examples injected give good results. The three examples injected into this case correspond to the positions X = 0.2 m, X = 0.6 m and X = 1 m.

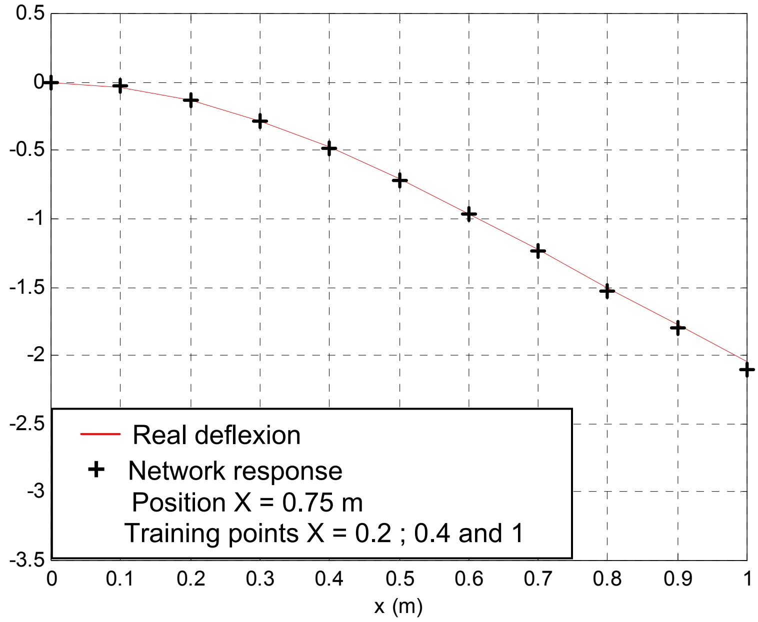

Figure 3- *Comparison between the network response and the real deflexion. 11 points meshgrid and 3 examples injected.*

The fact of increasing the meshgrid on the beam at 21 points, while thus passing to 21 network outputs, does not influence the result much, as shown in figure 4.
On the other hand, the fact of adding the number of examples injected on the network, we note a clear improvement, as illustrated on figure 5.

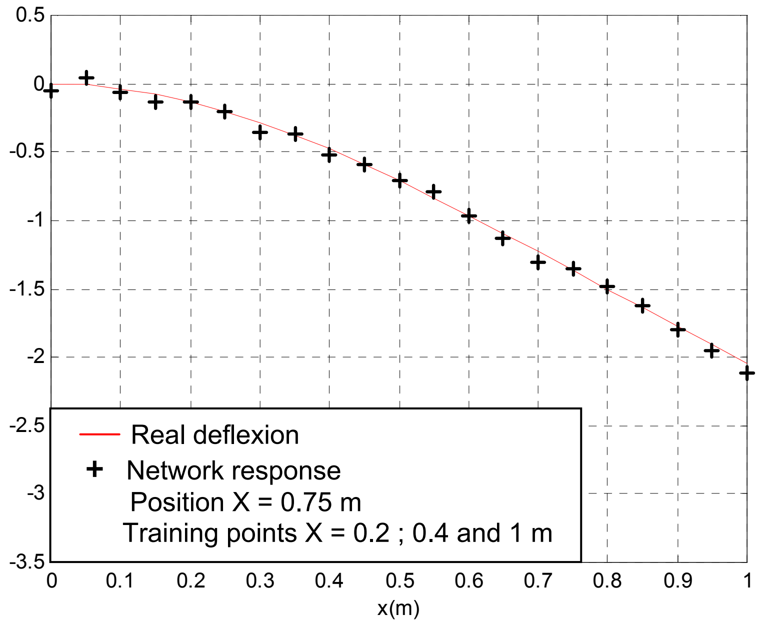

Figure 4- *Comparison between the network response and the real deflexion. 21 points meshgrid and 3 examples injected.*

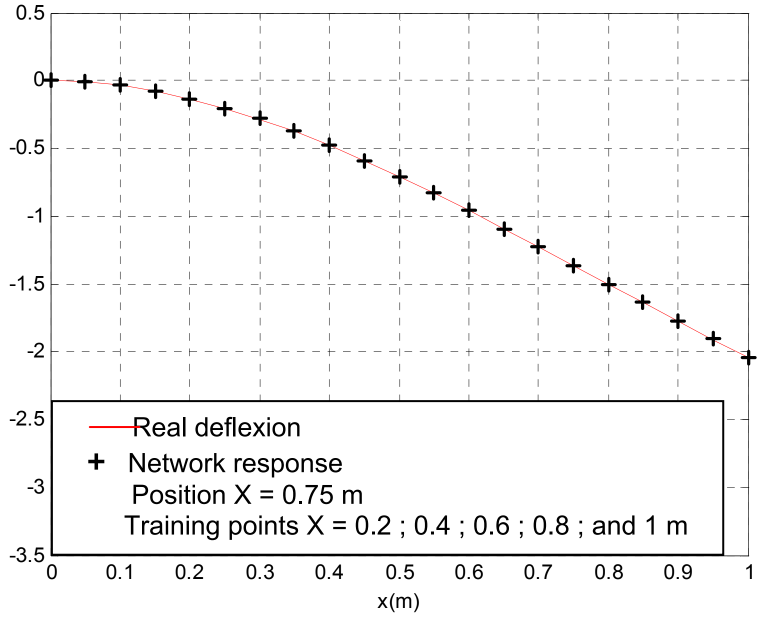

Figure 5- *Comparison between the network response and the real deflexion.*
21 points meshgrid and 5 examples injected.

In fact, this results confirmed through the ability of the neural network to find the excitation position from the beam deflection . Indeed the table 2 illustrates the slight difference between the real position and the one given by the network. A good agreement is obtained between the two results.

Table 2- *Comparison between the network response and the real deflexion.*
21 outputs and 5 examples for training.

Reals positions (m)	0.75	0.15
Positions given by the network (m)	0.745	0.158
Error rate %	0.56	5.73

It is to be also retained that the number of examples injected influences much more the result that the number of the network outputs corresponding to the number of points used during the beam meshgrid.
Since we pass to a complex deflection form, the case of a low rigidity beam, the results become erroneous even if the capacity of the network is increased (a number of examples injected and grid used). To illustrate this case we took the second.
Indeed, we note a higher error rate and which increases with the complexity of the deflection (Table 3).

Tableau 3- *Comparison between the network response and the real deflexion. 21 outputs and 17 examples for training.*

Reals positions (m)	0.97	0.10
Positions given by the network (m)	0.95	0.03
Error rate %	2	70

We also note that, if the position is outside the group of dots corresponding to the training, the error rate reaches 70 %.
We cannot increase indefinitely the network capacity, taking into account the calculators limits. The recommended solution is to change the network such as, for example, a network with hidden layers or a network with buckled layer. It will be the subject of another study.

4 CONCLUSION

In conclusion, the study undertaken here showed that the type of networks suggested, corresponding to an input layer and an output layer with an activation sigmoidal function, gives good results, as for the identification of the deformation, in the case of the first mode and it's more truth when the form of the deflection is simple.
The size of the network and the number of examples to be injected at the time of the training are not considerable to obtain this result.
On the other hand, the passage of the first mode to the second mode, complicates the problem. Indeed, the deformation form becomes more complex and it is more true when the beam rigidity becomes lower.
In prospect, and following this work we propose to change type of network : to use networks with hidden layers as well as the ringed networks.

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