IDENTIFICATION OF COUPLING MECHANICAL EFFORTS USING NEURAL NETWORKS

PACS REFERENCE: 43.40.

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ABSTRACT
A method based on neural networks for the identification of coupling mechanical efforts is presented. The unknowns of the problem are the injected mechanical forces assuming that their specific locations are known. The method and the choice of the architecture of the neural networks are described. Using several strategies, the influence of the number of inputs, number of neurons in the hidden layer and number of training data set is investigated. Two experimental validations are presented. Vibration signals measured by strain gages are used as input data.

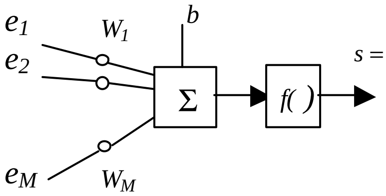
I. INTRODUCTION AND PRINCIPLE OF THE METHOD

Various methods are available to identify the coupling mechanical efforts between a vibrational source and a receiving structure. They combine all measures and calculations and differ by their difficulty of use, by their sensibility or their robustness with measurement errors, by their accuracy and by their degree of simplification. A method based on the neural networks is proposed for avoiding certain problems of calculation by remaining relatively easy to use and without requiring many sensors. The goal is to identify unknown efforts of coupling but the positions of which are known. In the principle, the receiving structure is excited one after the other at each of the positions of coupling (initial efforts). The vibratory response in amplitude and phase of the receiving structure is obtained at various points. A series of combinations of amplitude and phase of the initial efforts at the points of coupling is defined. The vibratory answers corresponding to each of the efforts are added linearly to obtain a global response. The inputs of the network are the modulus of the global vibratory responses. The outputs are the corresponding efforts, at the points of coupling, in amplitude and phase. This series of combinations is going to allow to establish the set of training of the network. When the vibrational source to be characterized is coupled at the receiving structure, the vibratory answers under operating condition are inputs of the neural network. The neural network tries to associate these new inputs to the closest learnt configuration. The calculated outputs are the recognized coupling efforts.

II. NEURAL NETWORKS AND DEFINITION OF PARAMETERS

The programming of networks is boring. To avoid this long computer work, the practical application is made by using the MATLAB software and its specific library NEURAL

NETWORKS [1]. An elementary neuron is described fig. 1. it possesses *M* inputs (e_1, ..., e_M) and one output *s*. The weights *Wi* and the bias *b* are unknowns.



$$s = f\left(\sum_{i=1}^{M} W_i e_i + b\right)$$

Fig. 1 Elementary neuron.

f is the transfer function. The network is generalized to process the case of *M* inputs and *N* outputs. He can include several hidden layers containing Q_1, Q_2, ... neurons. Every transfer function may be different. Arbitrarily, it is the same in the same layer. The network will be specified by: M-Q_1 Q_2...-N. The functioning of the network contains three phases, the phase of training, the phase of test and the phase of recognition. For the training of the network, we have *Ja* couples of vector of inputs and outputs. *Ja* is the number of sets of training. These sets are presented to the network in the form of an input matrix **Ea[***M, Ja***]** and a target output matrix **Sa[***N, Ja***]**. As we shall see afterward, the training of the network allows to allocate values to the weights and to the bias. These values depend on their preliminary initialization, unpredictable. In the phase of test, we arrange a restricted number *Jt* of sets of inputs and outputs who allows to accept or to refuse the weights and the bias proposed by the network. These sets are presented under forms of input matrix **Et[***M, Jt***]** and a target output matrix **St[***N, Jt***]**. In the phase of recognition, the new inputs of the network are contained in a vector **Er*(M)***. The recognized outputs are contained in the vector **Sr*(N)***.

III. APPLICATION OF THE BACKPROPAGATION NON LINEAR NEURAL NETWORK

We are more particularly interested in the "backpropagation" neural network. This last one is used inside 85 % of the works using neural networks [2]. It allows to resolve a problem of identification in case the outputs are not linearly separable [3-4]. In our case the chosen parameters are the following ones :

- The number of inputs (vibratory responses) is a priori in excess and a strategy of choice is implemented to decrease this number of inputs (see § IV.1).
- The outputs are the efforts to identify. The transfer function f of neurons in output is linear.
- A single hidden layer [2] is sufficient to process a given problem. Q_c, the number of neurons of the hidden layer is given by :

$$Q_c = \sqrt{MN} \qquad \textbf{\textit{(1)}}$$

With *M* is the number of inputs of the network and *N* is the number of neurons in output. The transfer function *f* is a tan-sigmoïd $f(x)=A(e^{kx}-1)/(e^{kx}+1)$, *with a constant A*).

- The number of sets of training: for a neural network M-Q_c-N with *M* inputs, Q_c intermediate neurons and *N* outputs, the total number of unknowns I whom the network has to affect during the phase of learning is:

$$I = Q_c\ (1+M) + N(Q_c+1) \qquad \textbf{\textit{(2)}}$$

Rigorously, it would be necessary to have at least the same number of sets of training. We fast realize that this criterion is difficult to respect. For example, a network with 10 inputs and 4 outputs with a hidden layer containing 7 neurons leads to 109 unknowns and requires at least 109 sets of training. In the practice the number of sets of training is more limited.

- Two parameters allow to adjust the convergence of the "backpropagation" network in phase of training. The learning rate l_r and the momentum m_c .

IV. STRATEGY FOR THE CHOICE OF THE PARAMETERS OF THE NEURAL NETWORKS

A first numerical study [5] showed that a processing of the data must be done to have chances of success for the experimental validation of the method. The principles of processing are exposed in this paragraph. The configuration of neural networks will thus depend on the frequency.

Choice of the number of the inputs of the network based on a dynamics of measure

We are interested in the optimal choice of the number of sensors and in their positions. We have a set of sensors a priori in excess. There are several possible strategies [5]. Most of the works in this domain concern the acoustic or vibratory active control. One of the possible ways would be the use of genetic algorithms. A simpler strategy is proposed. It is based on the dynamics of measure, this allows to reject sensors who give a level of vibration close to the background noise.

Choice of the inputs of the neural network based on the values of the set of recognition and the limit values of the sets of training

A neural network can interpolate a new situation (set of recognition) knowing a big number of learnt situations (sets of training). The vibratory data of the sets of training in input of the neural network are not inevitably the same order of magnitude as those of the set of recognition. Indeed the efforts allowing to generate the sets of training are artificial (vibrating shaker or impact hammer) and the efforts to recognize are generated by the vibrational source. So that the neural network can interpolate, the set of recognition has to be situated within the limits of the sets of learning and this for all the sensors. A sensor must be rejected when the value of the set of recognition is situated outside the limits of the values of the sets of training.

Choice of the number of sets of training

We are interested in the optimal choice of the number of sets of training. The convergence of the network is slowed down when the neural network has to learn sets of very close inputs to which we associate very different target outputs. It is the case when different forces generate close vibrations in the points where are situated the sensors. We have a number of sets of training a priori in excess. One of the sets of training is rejected if it is too close to the other one (use of the Principal Components analysis).

V. PRESENTATION OF THE EXPERIMENTAL SET-UP

The receiving structure was an aluminium plate of dimensions 0.5 m x 0.4 m x 0.0016 m. It was inserted between two very stiff steel frame. This first one was fixed to the other one by 24 screws who crossed the plate (fig. 2). The vibratory data which were the inputs data of the neural networks were obtained by using strain gages (350 W / ref. CEA-13-125 UW-350) stuck at 16 points distributed on the periphery of the plate (positions *J1* to *J16*, fig. 3). These sensors are light and do not modify the receiving structure. They allow to measure the vibrations of the plate until 800 Hz. These sensors are little expensive and can be thus let permanently on a test bench.

Fig. 2 : Experimental set-up.

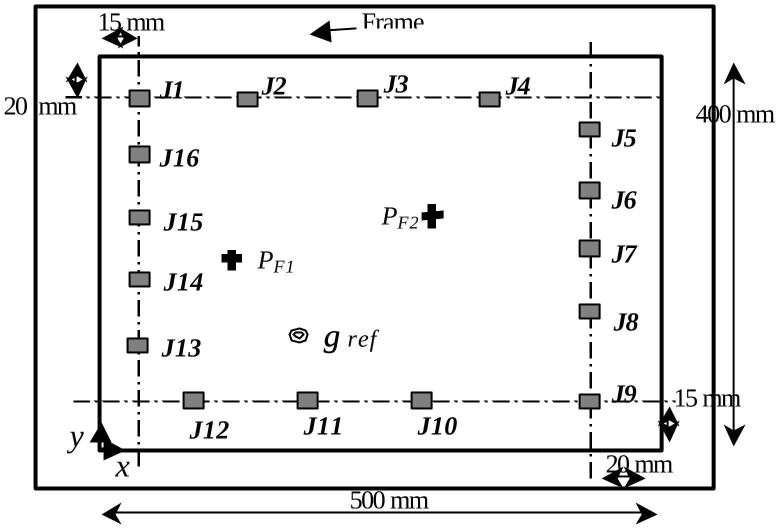


Fig. 3 : frame, plate and location of sensors (*J1* to *J16*) , excitation points (P_{F1}, P_{F2}) and reference sensor g_{ref}

According to the configurations, the plate was excited at one or two positions. Both positions of the forces P_{F1} and P_{F2} are shown on the figure 3. As the case may be, *F1* and *F2* was generated by a shaker B&K 4809 or by an impact hammer (PCB 208A03 ICP). The phase reference signal was supplied by an accelerometer (PCB U353B18 ICP) stayed in the same position for all the configurations of measure (γ_{ref}, fig. 3). The data acquisitions were made with the hardware HP VXI and with the LMS software.

IV. IDENTIFICATION OF ONE PUNCTUAL NORMAL FORCE

In this first case, one had to identify the punctual normal force *F1* injected by a shaker in the aluminium plate described previously. The signal of excitation was a white noise in the frequency band [0-1200 Hz]. The maximum number of inputs was 16 vibratory data measured by strain gages. The output was the force *F1*. In that case, the distribution of the neurons of the neural network was 16, 4, 1 at the maximum. The network architecture, phase of training, phase of test and phase of recognition and the possible strategies of data reduction were to be reconsidered for each frequency.

<u>Phase of training:</u>
An impact hammer was used to constitute the sets of training. The initial spectrum of the force *F1* injected by the impact hammer is drawn on fig. 4. The vibration spectra were measured by the 16 strain gages by injecting the effort at position P_{F1}. The force spectrum and the 16 vibration spectra were averaged on 5 repeated shocks. This force spectrum and the vibration spectra formed the initial set of training (16 inputs and one target output). The weighting of the amplitude of the force spectrum allows to calculate 18 sets of training. The coefficients of weighting of the 18 efforts are the following ones: 1000 * [1.5 1.4 1.3 1.2 1.1 1 0.9 0.8 0.7 0.6 0.5 0.4 0.3 0.2 0.1 0.05 0.025 0.0125]. The 18 force spectra are represented on the fig. 4.

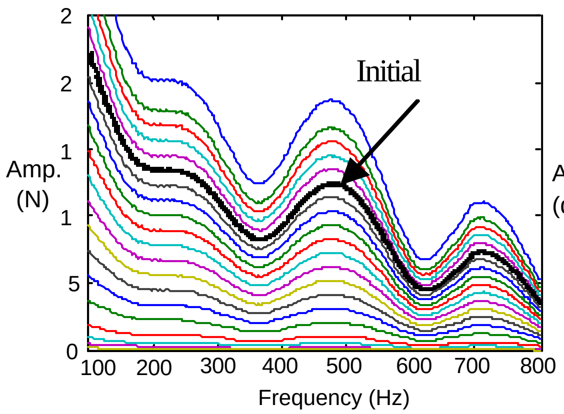


Fig. 4 : sets of training : the initial force spectrum and the 18 calculated force spectra

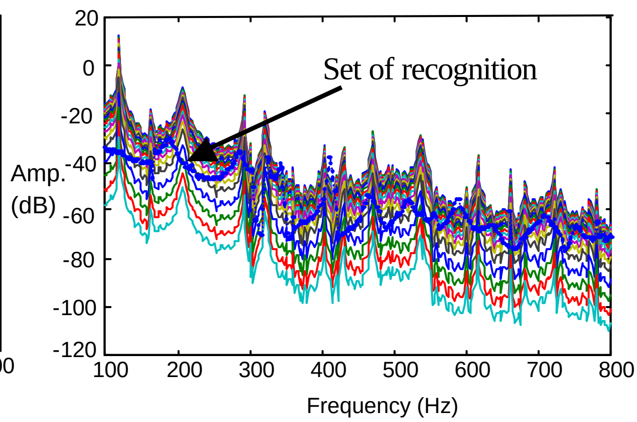


Fig. 5: set of recognition and 18 sets of training for the receiver location *J6*

As an example, the 18 vibration spectra are represented on the fig. 5 for a receiver located at *J6*. The parameters for the phase of training were the following ones: the maximal number of iterations = 16000, the maximal average quadratic error 0.0001, the learning rate l_r = 0.01, the momentum m_c = 0.9. The frequency bandwidth of calculation is [100-800 Hz] by step of 2 Hz.

<u>Phase of test :</u>
A single set of test was used for the phase of test. It corresponded to the 1st set of the sets of training. The maximal distance between the force calculated by the neural network and the target force is fixed at +/-1%.

<u>Phase of recognition :</u>
A shaker was then fixed at position P_{F1}. It simulated a vibrational source. Under operating condition, the 16 strain gages allowed to generate the set of recognition. The force sensor inserted between the shaker and the plate allowed to measure the injected force. This

measured force could so be compared with the output of the neural networks. As an example, the set of recognition is superimposed to the 18 sets of training for the receiver at position *J6* (fig. 5). The level of the measured force is superimposed to the level of the force recognized by the neural networks on the fig. 6. The measured force *F1* is in very good agreement with that calculated until 600 Hz. Above that frequency, the calculation overestimates the measure about 5 dB.

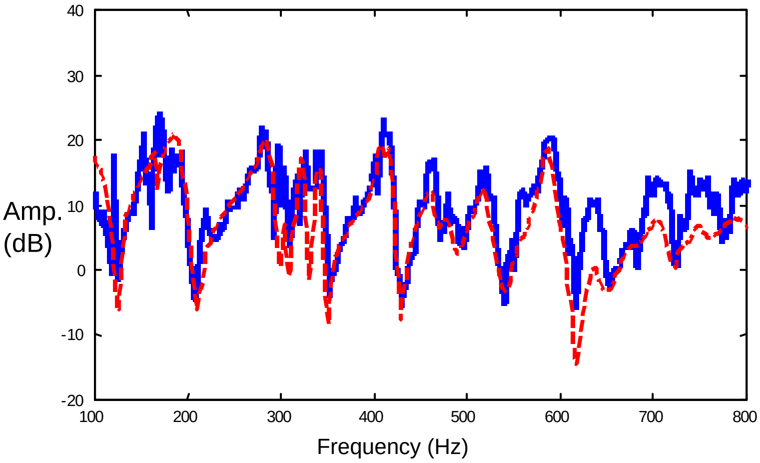


Fig. 6 : level of effort, recognized (¾) and measured by the force sensor (---).

$(20*\log 10(|F|))$

V. IDENTIFICATION OF TWO PUNCTUAL NORMAL FORCES

In this second case, one had to identify two punctual normal forces *F1* and *F2* injected in a plate by two shakers (in phase) supplied by the same signal. The plate was the same as described previously. The signal of excitation was a white noise in the frequency bandwidth [0-1200 Hz]. An impact hammer had allowed to excite the plate successively to the position P_{F1} and then to the position P_{F2} to constitute the sets of training. The maximum number of inputs was 16 vibratory data measured by the strain gages. The two outputs were the modulus of the forces *F1* and *F2*. In that case, the distribution of the neurons of the neural networks was 16, 6, 2 at the maximum. The architecture of the neural networks, phase of training, phase of test and phase of recognition and the possible strategies of data reduction were to be reconsidered for each frequency.

Phase of training:

The efforts allowing to create the sets of training were generated by an impact hammer. The spectra of the sets of training were obtained by chaining the following stages:
A force *F1*, only, was injected at position P_{F1} by an impact hammer. The initial spectrum of *F1(f)* was measured by a force sensor (5 repeated shocks). 16 vibration spectra (amplitude and phase) were measured by the strain gages (for the 5 repeated shocks).
A force *F2*, only, was injected at position P_{F2} by an impact hammer. The initial spectrum of *F2(f)* was measured by a force sensor (5 repeated shocks). 16 vibration spectra (amplitude and phase) were measured by the strain gages (for the 5 repeated shocks)
The initial spectrum of force *F1 (f)* was weighted to obtain 8 spectra of decreasing amplitude *F1(f)*1000* [1.6 1.3 1 0.7 0.5 0.3 0.1 0.05]*. The initial spectrum of the force *F2(f)* was weighted to obtain 8 spectra of decreasing amplitude *F2(f)*1000* [1.6 1.3 1 0.7 0.5 0.3 0.1 0.05]*. For each positions *J1* to *J16*, we calculated 64 (8x8) spectra of complex vibrations by linearly adding the responses generated by the various calculated forces.
The parameters for the phase of training were the following ones : the maximal number of iterations = 40000, the maximal average quadratic error 0.01, the learning rate, l_r = 0.01, the momentum m_c = 0.95. The frequency bandwidth of calculation is [100-400 Hz] by step of 2 Hz.

Phase of test:

An only one set of test was used for the phase of test. It corresponded to the 1st set of the sets of training. The maximal distance between the force calculated by the neural network and the known force was fixed at +/-1%.

Phase of recognition :

The two vibrating shakers were then fixed to the point P_{F1} and to the point P_{F2} (see fig.2). They simulated a vibrational source. For each vibrating shaker, a force sensor allowed to measure the injected force. A "stinger" was inserted between the vibrating shaker and the force sensor. These two measured forces could be compared to the two forces recognized by the neural networks. Under operating condition, the 16 strain gages allowed to obtain the input data of the network for the phase of recognition. Attempts were made to identify the phase between the two forces, but unsuccessfully. The level of the force spectrum *F1* (respectively *F2*) recognized is superimposed to the measured one by the force sensor on the fig. 7 (respectively fig. 8). We can notice a maximal error of 10 dB between the measured spectra and the recognized spectra.

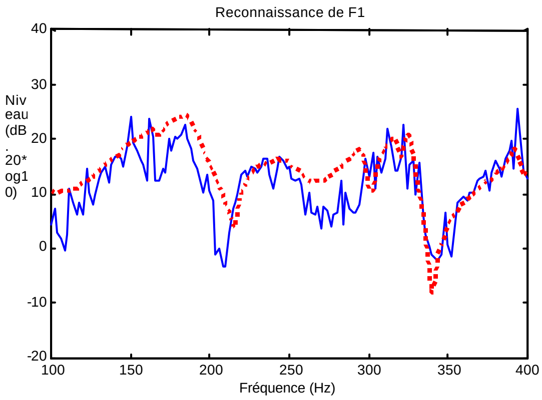


Fig. 7 : force *F1* calculated (—) and measured (---)

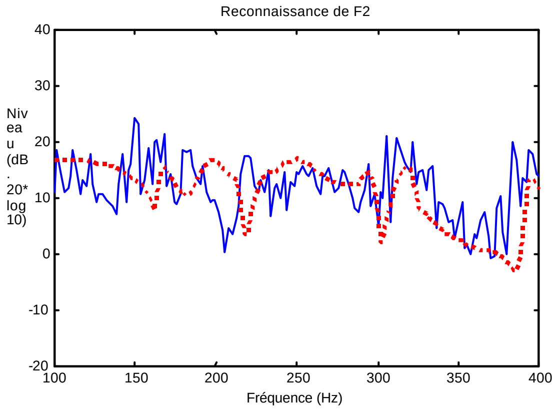


Fig. 8 : force *F2* calculated (—) and measured (---)

VI CONCLUSIONS

A method using neural networks was experimentally operated to identify mechanical efforts of coupling. The receiving structure was a plate. The sensors of vibration were strain gages stuck on the plate. The processing of the inputs data and the sets of training of the neural networks is a compulsory stage. Several strategies were implemented. At first, the plate was excited by one punctual normal force. The sets of training were obtained by using an impact hammer. The force to be identified was injected by a vibrating shaker. The measured force and the recognized force are in good agreement on the frequency bandwidth [100-800 Hz] with a maximal error of 5 dB. In the second time, the plate was excited at two points. The sets of training were obtained by using an impact hammer injecting a force one after the other at each of the two points. The two forces to be recognized were simultaneously injected by two vibrating shakers. The differences in dB between the modulus of the measured forces and those identified can reach 10 dB and more for several frequencies. The tendencies of curves measured vs calculated are however well respected in the frequency bandwidth of analysis [100-400 Hz]. The phase between the two forces was impossible to obtain.

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