Zeitschrift: IABSE reports = Rapports AIPC = IVBH Berichte
Band: 68 (1993)

Artikel: Structural damage state assessment via neural networks
Autor: Brancaleoni, F. / Spina, D. / Valente, C.
DOI: https://doi.org/10.5169/seals-51870

Structural Damage State Assessment via Neural Networks

Détermination des dommages à l'aide de réseaux neuronaux

Bestimmung von Tragwerksschäden über neuronale Netzwerke

F. BRANCALEONI
Prof. of Struct Mech.
Univ. "G. D'Annunzio"
Pescara, Italy

Fabio Brancaleoni, born 1949, received his Civil Eng. degree at the Univ. of Rome, Italy. He is the National coordinator of the European Community NEWNET project, for the study of neural networks in Civil Eng.

D. SPINA
PhD Student
Univ. "La Sapienza"
Roma, Italy

Daniele Spina, born 1961, received his Civil Eng degree at the Univ. of Rome, Italy, where he is also attending a PhD course in Applied Mechanics. His main research interests lie in the field of Structural Identification.

C. VALENTE
Researcher
Univ. "G.D'Annunzio"
Pescara, Italy

Claudio Valente, born 1954, received his Civil Eng. degree at the Univ. of Rome, where he also obtained his PhD in Applied Mechanics. He carries out researches in plasticity, computational mechanics and Struct. Identification.

SUMMARY

This paper presents experiences in the implementation and use of neural networks aimed at a novel approach for detecting and characterising faults and other nonlinear mechanisms related to defects or damage in civil engineering structures. Fundamental aspects are addressed and discussed, such as learning stategies, network organisation-topology, error and convergence characteristics, normalisation procedures. While preliminary in nature, the results obtained show a considerable potential in the neural network approach, together with a number of open problems and with indications for future research lines.

RÉSUMÉ

L'article traite des expériences faites par la mise en application et l'utilisation des réseaux neuronaux, en vue d'une nouvelle approche pour la détection et la caractérisation de défauts et d'autres mécanismes non linéaires en liaison avec des dommages dans les ouvrages de génie civil. La discussion porte sur certains aspects fondamentaux du problème, comme les stratégies d'apprentissage, la topologie de l'organisation des réseaux, les erreurs et les caractéristiques de convergence ainsi que les procédures de normalisation. Les résultats obtenus jusqu'ici montrent les énormes possibilités offertes par cette méthode, mais également un certain nombre de problèmes restant en suspens et des indications relatives aux objectifs de la recherche future.

ZUSAMMENFASSUNG

Der Beitrag berichtet von Erfahrungen mit der Implementierung und Anwendung neuronaler Netzwerke bei der Entdeckung und Charakterisierung von Fehlstellen und anderer nicht-linearer Mechanismen infolge von Schäden im Ingenieurtragwerk. An grundliegenden Gesichtspunkten werden die Lernstrategien, die Topologie der Netzwerkorganisation, Fehler- und Konvergenzeigenschaften sowie Normierungsverfahren behandelt. Vorläufige Ergebnisse zeigen für diese Methode beträchtliche Möglichkeiten auf, aber auch ungelöste Probleme und die Richtung zukünftiger Forschung.

1. INTRODUCTION

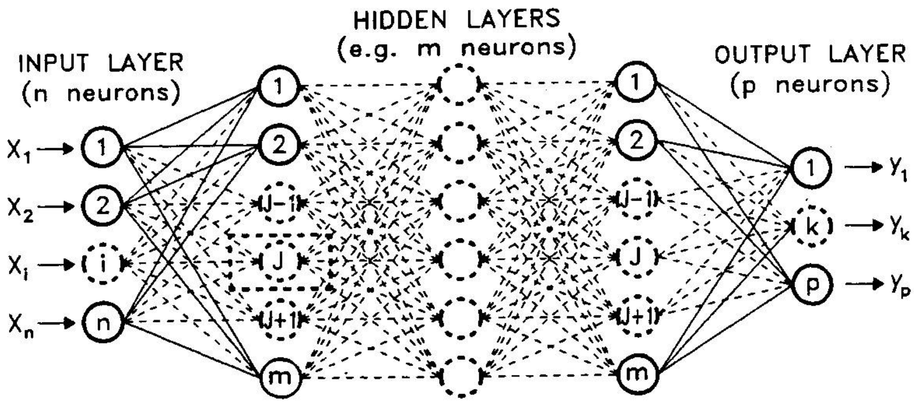
Repair and retrofitting of existing structures and infrastructures is in steady growth in the whole world, due to their increasing service life, as well as to the deterioration arising from accelerated loading and aggressive environments. Procedures which can improve reliability and prediction capability in these areas would be of major benefit to the technical community. The work presented is part of a research project directed toward the development and application of neural networks as a novel approach for detecting and characterising faults and other nonlinear mechanisms related to defects or damage in civil engineering structures. Fundamental aspects are addressed and discussed, such as learning strategies, network organisation-topology, error and convergence characteristics, normalisation procedures. The dynamic response of structures, comprising artificial signals from numerical models, experimental signals from laboratory tests and some examples on full scale structures, is adopted as network input. Mechanisms examined are the opening-closure of gaps (cracks) and the presence of nonviscous dissipation, including friction and hysteresis.

2. THE NEURAL NETWORK APPROACH

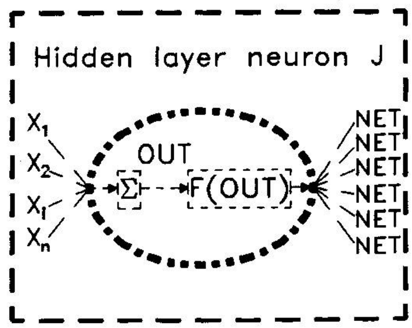
2.1 Generalities on Neural Networks

Without intending to provide a full discussion, well available in the many books and papers on the subject, see e.g. [1,2], a synthetic information shall be given for the unacquainted reader. Artificial neural networks are computational systems, composed of elements (the artificial neurons) that perform in a manner analogous to the most elementary functions of the biological neuron. Their birth in the present acceptation can be indeed traced to a fundamental work of Hebb, [3], showing how a neuron network could exhibit a learning behaviour. A neural network amounts to a highly interconnected system of artificial neurons arranged in layers, the first and last of which are respectively the input and output layers, while the intermediate ones are called hidden layers, see Fig. 1. The preliminary and fundamental phase of their use is that of *training*, in which a set of input patterns, representative of a specific phenomenon, is fed in and the processing algorithm in the hidden layers is tuned until each pattern matches to a required accuracy a given set of outputs. Once the network is trained, its use takes place feeding the input layer with new data, often called *test patterns*, selected within the same class of phenomena of the training phase, but different from the training ones: the output provides an estimate of the same kind of answers aimed at in training.

Such two-step procedure exploits many positive features. In training the net "learns" from experience, accumulates "knowledge" and it is "sensitive" to the environment. Furthermore, its response can be, to a degree, insensitive to input changes, resulting in "generalisation", i.e. in the capability of abstracting the essential features of a set of inputs. They are hence ideally suited to cope with systems affected by noise or distortion and with fuzzy problems in general. Note that a net generalises as a result of its structure and not by use of embedded artificial intelligence, a concept completely absent in its rationale. For system identification, the most attractive property is the potential to reproduce the behaviour of input-output systems, yielding non parametric black-box representations. This implies that no knowledge of the underlying physics is necessary, but no related information is obtained either. Such properties caused in the last decade a burst of activities, with theoretical developments and applications in heterogeneous fields, whenever parametric models were too demanding, if non impossible. Despite such accomplishments, it must be borne in mind that neural networks are simply a new curve-surface fitting algorithm, producing no more than a powerful and flexible multi-dimensional polynomial interpolation method. Their use should hence be strongly connected to the knowledge of the underlying algorithms, as well as to the understanding of potential and limits.



<u>Fig. 1</u> **Typical network structure**



<u>Fig. 2</u> **Basic MLP neuron**

2.2 Fundamentals of Multi-Layer Perceptron Back-Propagation (MLP) Networks

Multi-Layered Perceptron Back-Propagation (MLP) networks are adopted here [1,4,5,6,7]. They revealed in the last years the most reliable, becoming the present established state-of-the-art technique in the field. Earlier perceptrons were severely limited in what they could represent [13], until the development of back-propagation [5,6,7] led to practicable MLP's with any number of layers. The fundamental building block for an MLP is the *artificial neuron*, whose scheme is shown in fig. 2. The X_i are the inputs received from the previous layer neurons, to each of which it is assigned a weight. For each neuron a summation produces the term NET, subsequently modified trough an *activation function* F to yield the neuron output OUT. Commonly used are the sigmoidal function, adopted here, or the hyperbolic tangent, as they both show several useful features: i) they restrict the output between 0 and 1; ii) they have a simple continuous derivative; iii) they add automatic gain control, as for small input their derivative is high, while for large ones reduces progressively: this avoids saturation and attenuation. For MLP's, the phase of training becomes a process aimed at adjusting the neuron weights so that the application of a given input pattern, defined as a vector, produces the desired output, also in vector form. This is done via the already described procedure, called *forward pass*, and a subsequent *reverse pass*, in which the weight adjustment takes actually place.

Despite their success, MLP's have serious limitations in both application and implementation. A primary disadvantage is connected to the use of a steepest descent procedure, ensuring convergence to a minimum, but not to the absolute one. Second, there is no theoretical guide as to what the best stepsize should be. The convergence proof assumes infinitesimal weight adjustments, i.e. infinite training time: stepsizes can hence be assessed only through experience in each application field. This may lead to the need of a very large number of iterations to converge. On the other hand, a stepsize too large may cause solution divergence, paralysis or instability. This explains the interest in the development of innovative, more powerful and more reliable network concepts, to which a large research effort is being devoted worldwide [4,8,9,10,11,12].

2.3 Scope of Work

Most industrial applications of neural networks in engineering lay within Electronics and Control, and more recently also in Mechanical Engineering. At a research or pre-industrial stage, some excellent proposals are concerned with nonlinear systems identification [13,14,15,16], while fewer are devoted to structural fault detection [17,18]. In Civil Engineering, the authors are aware only of the rather questionable work [20], besides those within the European Community NEWNET project [21,22], to which the present belongs. To clarify the scope of this work, one must remeber that networks can *detect*, *predict*, *localise, classify* or *quantify* relevant phenomena. Cases of classification and quantification are presented here. A second decision area concerns the type of information to feed as input pattern, which should take the form most appropriate to allow the extraction of significant *features* of the phenomena in consideration. First, signals may derive from the raw or processed structural response. Processing may take place in the frequency domain, with first or higher order spectra [23], or in the time domain, e.g. through Hilbert transforms [24], or even in the time-frequency space [24]. In the frequency domain the typical input should be a sinusoidal excitation, leading to frequency response functions (FRF). As the final goal of this approach is the use on civil engineering structures, typically subjected to sinusoidal forces only through external devices which might limit operation and are often unwelcome, the practical use of FRF's is limited. Much more interesting are the free oscillations, with impulse response functions (IRF), or the excitation through random loads, including operational or environmental actions. This work is concerned with IRF only, i.e. with a free oscillation response network input. Furthermore, the free response can be represented via different variables, in the displacement or in the force domain. Here the displacement response is considered; however, this does not imply a preference indication, not yet mature. Within the above, a few more aspects must be discussed. First, signals including noise, generated via one d.o.f. numerical models, are used; this provides an assessment of the possibility of training networks on artificial signals, easily generated in large quantities, rather than on experimental ones. The limitations connected with the single d.o.f. training are well understood and the extension to multi d.o.f. systems shall be a natural prosecution of this work. Second, a very simple input, comprising only a single oscillation wave is used for training; also this aspect is considered of significance, as it tests the nets in conditions in which standard identification procedures are not easily applied and because in real applications one is often faced with scanty or short recordings.

3. MLP NETWORKS FOR PROPERTY CLASSIFICATION

3.1 Preliminary Remarks

Experiences in implementing networks as classifiers of mechanical systems properties are presented. For classification, the typical neuron output sought is binary: for each class it is provided one neuron, with a 1 or 0 output to stand for positive or negative answer. Two cases shall be discussed, concerning energy dissipation type selection and nonlinearity discrimination.

3.2 Characterising Energy Dissipation

Dissipation mechanisms considereded are: i) linear viscous damping; ii) dry friction; iii) hysteresis, with elastic-perfectly plastic constitutive law. Hence, the output layer comprises 3 neurons, trained to produce the 0-1 (No/Yes) binary output. Training was carried out on single waves, described from zero to zero through 21 time stations, resulting in a 21 neurons input layer, with different levels of white noise added. The dissipation rate selected was such that from 1 to 10 % of energy is lost in one cycle. Several topologies were considered, with 1 to 3 hidden layers and 4 to 21 neurons per layer: in general the performances were quite uniform, with a marginal improvement for larger and multi-layer schemes. No particular difficulties were observed in training: while a binary response was considered reliable when affected by an absolute error below 10^{-2}, the typical accuracy achieved was of the order of 10^{-4}. Only aspect worth mentioning is the necessity, to avoid excessive training time, of an analyst-monitored tuning of the back-propagation step. The real test of the reliability and generalising capabilities of a net is not a successful training, but its performance on other signals, not used in learning and hence "unknown". Once trained, the nets were used on a large set of test patterns, including i) signals belonging to the training classes (i.e. viscous damping, friction or hysteresis) and inside the training range (i.e. 1 to 10 % energy loss per cycle); ii) signals within the training class, but outside the training range (from 0 to 1 % or from 10 to 20 % energy loss per cycle); iii) signals of other nature, not belonging at all to the training mechanisms. The latter comprised white noises, oscillations to which a large noise was superimposed, multi-d.o.f. systems and other functions, among which to notice also elastic undamped oscillations. The results are summarised in Table 1, for some of the nets considered. A response was defined "true" when only the correct neuron was activated, with an error on the binary output below 0.02 (twice the accepted training error). On the contrary, it was defined as "uncertain" if more than one neuron was activated or if the error was over 0.02, and finally "false" if only one wrong neuron was activated, with an error below 0.02. First useful outcome, the network classification was always 100 % correct for patterns within the training classes and range (A rows in Table 1). When applied to signals within the training classes, but outside the training range (B rows), the results were still favourable, with a true response average of 70 %. For other signals (C rows), an unfavourable aspect showed: a majority of false answers. This stresses a trend, typical of simpler neural networks, to yield an answer anyhow, even for meaningless input. One must note that while an uncertain answer is acceptable, as it introduces a doubt element in the identification, nothing is worse than a clear, sharp, wrong response, specially dangerous when the class and range of the signals analysed is not easily determined in advance. To cope with such *false answers*, for the training classes the best measure is to extend, within reason, the training range, while for "other signals" one should use networks capable of their exclusion. As this is at present beyond the possibilities of existing algorithms, a chance lies in adding in training samples of signals to be refused, activating an "else" neuron. This was done appending 15 further such inputs, with the results shown in Table 2: the improvement is evident, with a massive decrease of false answers, despite the comparatively small training set. This underlines a potential in the approach, but industrial-professional use would require a larger and improved training, seeking a greater reliability. To note that in this case training small single-layer nets was unsuccessful and, even when achieved, two-layer ones performed better.

3.3 Damage Detection in a Coupled Mechanism

This example is concerned with the capability to discriminate a linear from a nonlinear response. The second is represented by a bi-linear stiffness constitutive law, typical of a gap or crack opening-closure phenomenon in a structural element. To make the identification more challenging, the nonlinearity level adopted was quite mild, with a stiffness variation from 0 to 10 %, and both the linear and nonlinear cases were coupled to a rather large viscous damping, with critical ratio from 0 to 0.1. The results obtained with a single-layer, 5 hidden nodes net were even more accurate than in the previous case. Not only the binary test patterns classification was 100 % correct within the training range, but also well outside, for damping ratios up to 0.2 and stiffness reduction up to 20 %. Beyond, the response deteriorated progressively but slowly, keeping a large percentage of true answers. This is specially interesting as, with the poor information provided, standard methods would not achieve the same, in particular for high damping, small nonlinearity cases, where the dissipation "cancels" most of the bi-linear oscillator response features.

4. MLP NETWORKS FOR PARAMETER QUANTIFICATION

4.1 Preliminary Remarks

In a first stage, it was attempted to implement quantifiers as an extension of classifiers, replacing the yes/no output with a numerical one. This line did not fail completely, but showed not very effective. After some effort, it was concluded that quantification could be accurate only if carried out on its own,

Network Topology		Network output(%)		
		True	Unc.	False
21-4-3	A	100	0	0
	B	73	18	9
	C	0	49	51
21-6-3	A	100	0	0
	B	64	12	12
	C	0	48	52
21-10-3	A	100	0	0
	B	72	17	11
	C	0	53	47
21-21-3	A	100	0	0
	B	75	16	9
	C	0	42	58
21-4-4-3	A	100	0	0
	B	67	12	11
	C	0	2	98
21-8-8-3	A	100	0	0
	B	74	16	10
	C	0	36	64
21-12-12-3	A	100	0	0
	B	76	16	8
	C	0	46	54

Table 1 Response for test patterns of energy dissipation classifiers without "other signals" option

Network Topology		Network output(%)		
		True	Unc.	False
21-10-4	A	100	0	0
	B	67	26	7
	C	49	37	14
21-4-4-4	A	100	0	0
	B	72	15	13
	C	75	10	15
21-12-12-4	A	100	0	0
	B	73	21	6
	C	75	19	6

A = Test patterns within training class and training range

B = Test patterns within training class but outside training range

C = Test patterns outside training class and range (unknown signals)

Table 2 Response for test patterns of energy dissipation classifiers with "other signals" option

aiming at one parameter at a time. Hence, the nets adopted have only one output neuron, yielding the scaled parameter value. As to topology, small single-layer nets proved effective; all the results presented were obtained with 21-5-1 schemes. An other general conclusion reached was that quantification might be effective only within the training range, while the distortion outside causes large errors, with lesser generalisation capabilities.

4.2 Rating Stiffness Nonlinearity

Reaching a high accuracy is here much more important than in quantification and proved correspondingly harder. This first example quantifies the stiffness variation from the response of the bi-linear oscillator treated in 3.3. The variation range is 0-10 %, with the net output indicating the stiffness ratio, from 1 to 0.9, and the training set comprising only 5 patterns.

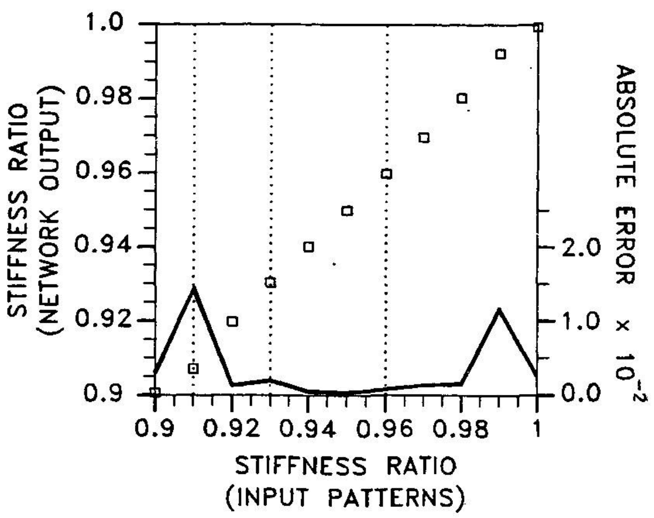


Fig. 3 Rating stiffness nonlinearity

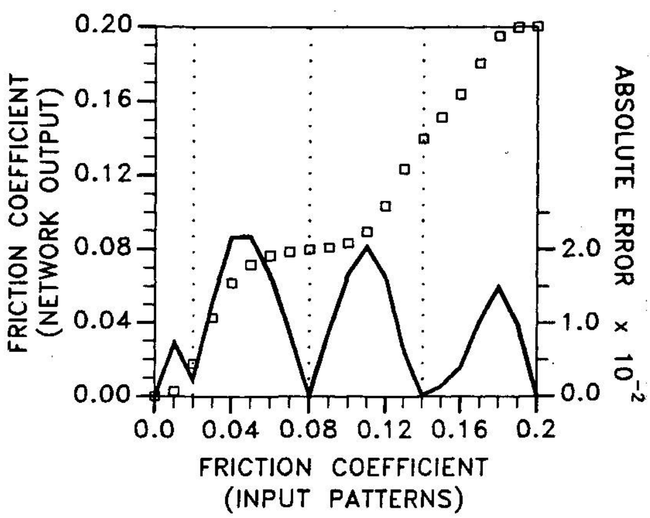


Fig. 4 Rating friction coefficient

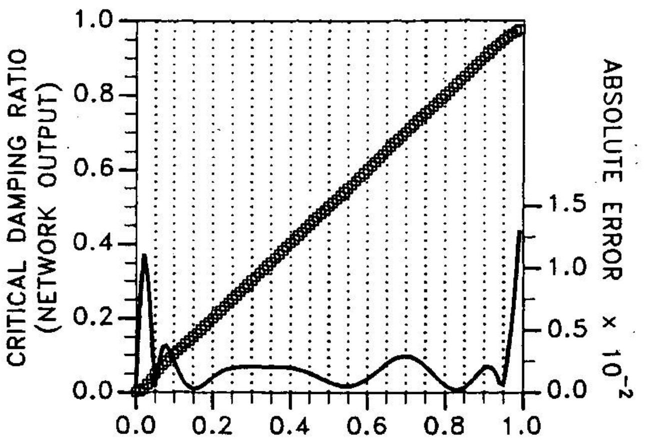


Fig. 5 Rating critical damping ratios in the 0-1 range

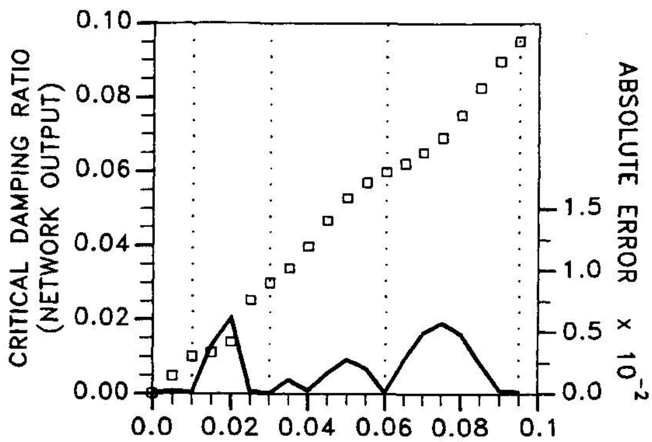


Fig. 6 Rating critical damping ratios in the 0-0.1 range

The results are shown in fig. 3: the boxes represent points in a correct response-net response plane for the test patterns, hence with a perfect output producing a straight line with $\pi/4$ slope. The error for each case is also superimposed in a solid line, while vertical dots indicate the training patterns locations. Reaching in training quite good accuracy, with absolute errors of the order of 1×10^{-3} proved not too difficult, but when the net was applied to test patterns the errors were one order of magnitude larger, with typical peaks at the training range edges. To improve the results, a first direction followed was the improvement of the training accuracy: consequences are shown with the next examples, aimed at energy dissipation mechanisms rating.

4.3 Rating Energy Dissipation Mechanisms

The first case shown concerns the quantification of the dry friction coefficient, treated with a net scheme analogous to the previous one. As anticipated, a better training accuracy was sought. This proved quite difficult, requiring higher weight momenta [4], sharper activation functions and careful supervising of back-propagation step, with greater instability liability. Nevertheless, accuracy was improved, with errors form 10^{-4} to 10^{-5}. Though, this proved a failure, yielding the results exemplified in fig. 4, with even lower accuracy for test patterns and characteristic error peaks between training points. Such behaviour is well known to be peculiar of neural networks, as very accurate reproduction of training points might imply a more uneven solution in terms of the polynomial approximation in the neuron output space. This underlines an aspect which is fundamental in network applications: the real and challenging target is not just to obtain an excellent training, but to generalise, keeping an elevate accuracy for unknown signals in the training class. From this point of view the guidance given by the theory, scarce also within the training procedure, is virtually absent and only experience might help. To improve the performances, an obvious measure is the increase of the training patterns number, as exemplified in fig. 5 with a network which quantifies viscous damping ratios in the 0-1 range, for which 20 patterns were used. The error is satisfactorily low for most of the range, but the peaks at the edges. Further improvements might be obtained specialising the net in narrower ranges, e.g. for 0 to 0.1 damping ratios, as in fig. 6, but error peaks are still present. Better result were achieved optimising the training points location and, more important, seeking training strategies yielding uniform error levels. This was successfully achieved with smooth activation functions and comparatively short steps, yielding very slow training. The quality attained is shown in fig. 7, for the quantification of yield ratios in elastic-perfectly plastic oscillators, where with only five training patterns the accuracy is uniformly of the order of 10^{-3}.

5. PERFORMANCES FOR EXPERIMENTAL SIGNALS

5.1 Laboratory Tests

To progress towards site applications, it has been started an experimental laboratory program, whose first specimen is a simply supported, 5 m long I steel beam, set with horizontal web and ballasted to obtain the desired frequency range, fig. 8. IRF responses have been recorded in some of the conditions examined previously, i.e.: i) linear oscillations; ii) friction, obtained by purposeful tightening of one support roller; iii) bi-linear stiffness, obtained trough an artificial crack at midspan. Several probes were placed on the specimen; the results presented refer to displacement transducers response.

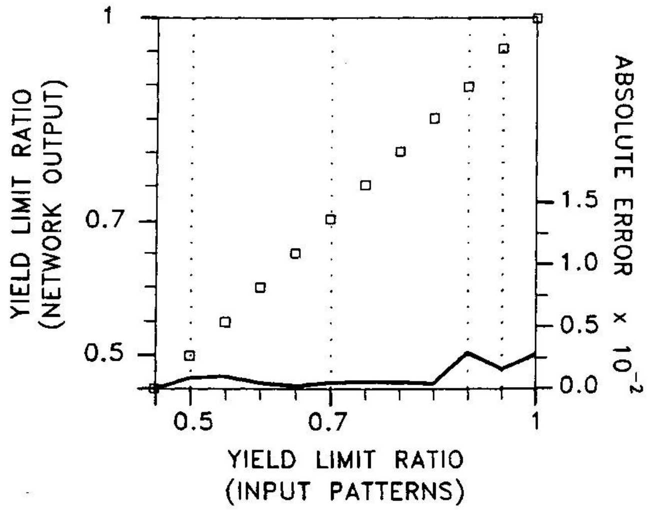


Fig. 7 Rating yield limit ratios

For the nonlinearity aspect, the net performances were satisfactory, considered its early development stage: the classification network described in 3.3 discriminated correctly the damaged-undamaged beam oscillations, while the quantification network of which in 4.2 rated the stiffness ratio of the bilinear constitutive law in 0.94. The theoretical design value, obtained through f.e. analyses, was 0.96, with an experimental value from static test, considered the most reliable, of 0.95. Further identifications from the dynamic response, via time domain Hilbert transforms [24], yielded values between 0.95 and 0.97.

Somewhat inferior were the results for the energy quantification field. The classifier indicated always correctly the presence of linear damping only, while its quantification was poorer, due to its very low value. The net rating was 0.0059, with exact values from envelope curves via Hilbert transforms of 0.0029. Note that the latter were obtained from a much richer information, i.e. the full recorded signal and not just a single wave. In fact, improvements, not reported as they are outside the scope of this paper, have already been obtained training the net on longer signals. When applied to friction identification, the classification was less reliable, though with a majority of true answers, and also inaccurate resulted the quantification. This is still being studied: a possible cause is considered the lack of symmetry of friction forces, introduced in one support only, with significant introduction of higher modes contribution.

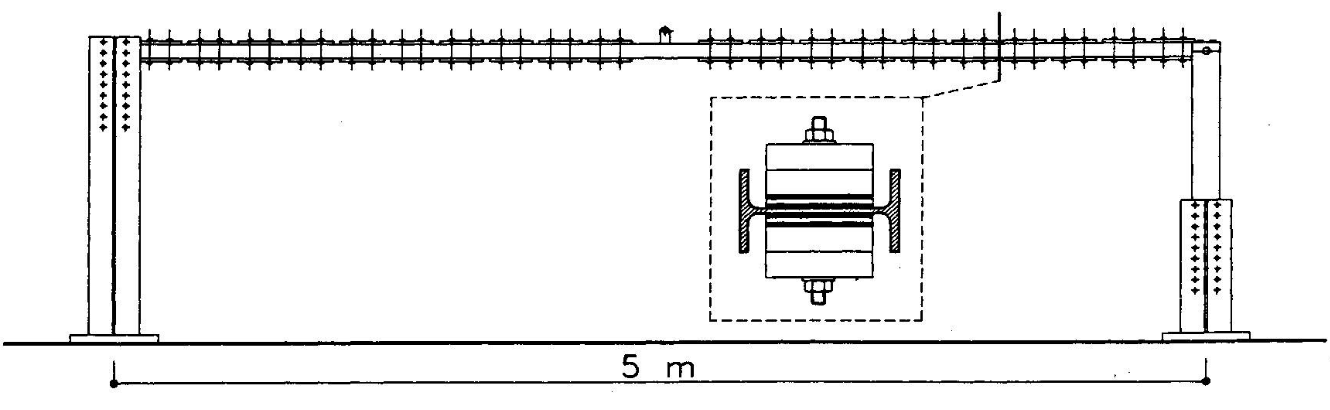


Fig. 8 Steel I beam experimental specimen

5.2 Full Scale Structures

For the sake of completeness, also some preliminary applications on real structures are presented, regarding a number of multi-span (31 m), simply supported, prestressed concrete viaducts, with the cross section shown in fig. 9, located on the A3 motorway in southern Italy. The dynamic tests, carried out during operation, were part of a retrofitting program.

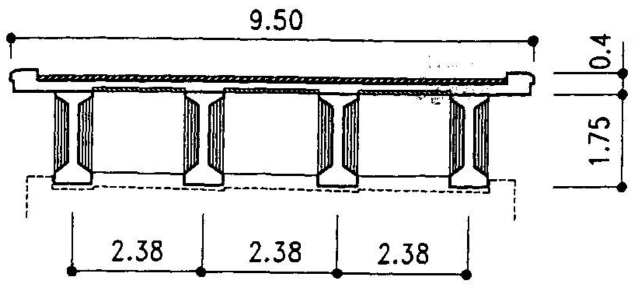


Fig. 9 Bridges cross-section

As the recording had been already analysed via standard identification methods, it was known that the response was characterised by the coupling of flexural and torsional modes and a modal filter had already been developed [24], to obtain single mode contributions for the treatment via Hilbert transforms, that were fed to the nets, aiming at linear damping quantification only. The critical ratios obtained from the networks for five recording samples were 0.015, 0.019, 0.016, 0.017, 0.048; standard processing procedures indicated for the same cases values of 0.018, 0.020, 0.013, 0.017, 0.047, with a very satisfactory correspondence, also considering the scattering of the original signals.

6. CONCLUSIONS

The experiences presented, though preliminary in nature and limited in scope, have shown a considerable potential in the neural network approach, which proved reliabile within the training range and capable of extracting information from limited signals. Classification and quantification should take place separately, outlining the development of concepts in which *neural networks arrays*, coupled for performance fusion to conventional procedures, classify a phenomenon first, to proceed subsequently to quantitative identification. Limited but promising results have also been obtained on experimental test cases. Such favourable aspects should not shadow the open problems encountered, in the first place the achievement of adequate *solution quality*, avoiding not only the known problem of convergence to local minima, but, far more substantial, providing reliable guidelines for strategies and topologies ensuring *generalisation and accuracy* on "unknown" signals. Specifically, future developments shall address training based on processed signals, treatment of multi d.o.f. systems and coupled mechanisms, together with a comprehensive laboratory and site tests program.

ACKNOWLEDGEMENTS

This work is part of the BRITE/EURAM NEWNET project, under grant with the Commission of the European Communities, whose financial support is gratefully acknowledged. The authors would also like to thank their partners: Professor J.R. Tomlinson, general coordinator, and Dr. K. Worden, Dept. of Engineering, University of Manchester, UK, Professor S. A. Billings and Dr. G.L. Zheng, Dept. of Automatic Control and Systems, University of Sheffield, UK.

REFERENCES

1. WASSERMAN P.D., Neural Computing, Theory and Practice. Van Nostrand Reinhold, New York, 1989.

2. LIPPMAN R.P., An Introduction to Computing with Neural Nets. IEEE Transactions on Acoustics, Speech and Signal Processing, 4-22, april, 1987.

3. HEBB D.O., The Organisation of Behaviour. John Wiley & Sons, New York,1949.
4. BILLINGS S.A., YAMALUDDIN R.D. & CHEN S., A Comparison of the Back-Propagation and Recursive Prediction Error Algorithms for training Neural Networks. Mechanical Systems & Signal Processing, 5, 233-255, 1991.
5. WERBOS P.J., Beyond Regression: New Tools for Prediction and Analysis in the Behavioural Sciences. Master Thesis, Harvard University, USA, 1974.
6. PARKER D.B., Learning Logic. Invention Report S81-64, File 1, Office of Technology Licensing, Stanford University, Stanford, California, USA, 1982.
7. RUMELHART D.E., HINTON G.E. & WILLIAMS R.J., Learning Internal Representations by Error Propagation. Parallel Distributed Processing, 1, 318-362, MA: MIT Press, Cambridge, USA, 1986.
8. BILLINGS S.A. & CHEN S., Extended Model Set, Global Data and Treshold Model Identification of Severely Nonlinear Systems. International Journal of Control, 50, 1897-1923, 1989.
9. PAO YOH-HAN, Adaptive Pattern Recognition and Neural Networks. Addison-Wesley, Reading, UK, 1989.
10. BROWN M. & HARRIS C.J., The B-Spline Neuro-Controller. Parallel Processing for Control, E. Rogers ed., Prentice-Hall, 1992.
11. BROOMHEAD D.S. & LOWE D., Multivariable Functional Interpolation and Adaptive Networks. Complex Systems, 2, 321-355, 1988.
12. CHEN S., BILLINGS S.A., COWAN C.F.N. & GRANT P.M., Practical Identification of NARMAX Models using Radial Basis Functions. International Journal of Control, 52, 1327-1350, 1990.
13. MINSKY M.L. & PAPERT S., Perceptrons. MA: MIT Press, Cambridge, USA, 1969.
14. CHU S.R., SHOURESKY R. & TENORIO M., Neural Networks for System Identification, IEEE Control and Systems Magazine, 10, 36-43, 1990.
15. CHEN S., BILLINGS S.A. & GRANT P.M., Nonlinear System Identification using Neural Networks. International Journal of Control, 51, 1191-1214, 1990.
16. NARENDRA K.S. & PARTHRASARAY K., Identification and Control of Dynamical Systems using Neural Networks. IEEE Neural Networks Trans., 1, 4-27, 1990.
17. MASRI S.F., CHASSIAKOS A.G. & CAUGHEY T.K., Structure-Unknown Nonlinear Dynamic Systems: Identification through Neural Networks. Smart Materials & Struct., 1, 45-56, 1992.
18. KUDVA J., MUNIR N., & TAN P.W., Damage Detection in Smart Structures using Neural Networks & FE Analysis. Smart Materials & Struct.,1,108-112, 1992.
19. GHABOUSSI J., GARRET J.H. & WU X., Knowledge-Based Modelling of Material Behavior with Neural Networks. J. Engng. Mech., 117, January 1991.
20. GARRET J.H. & GHABOUSSI J., Use of Neural Networks in Detection of Structural Damage. Computers & Structures, 42, 649-659, 1992.
21. BRITE/EURAM NEWNET Project on Neural Networks and new Signal Processing Procedures for Fault Detection in Civil Engineering Structures. 1rst joint Report to the Commission of the European Communities, Universities of Manchester (UK), Sheffield (UK) & "G. D'Annunzio" (Italy), October 1992.
22. WORDEN K. & TOMLINSON G.R., Modelling & Classification of Nonlinear Systems using Neural Networks. J. Mech. Systems & Signal Proc., to appear, 1993.
23. BILLINGS S.A. & TSANG K.M., Spectral Analysis for Nonlinear Systems. Part I & Part II, Mech. Systems & Signal Proc., 3 (4), 319-341, 1989.
24. BRANCALEONI f., SPINA D., VALENTE C., Damage Assessment from the Dynamic Response of Deteriorating Structures. Int. Workshop 'Safety Evaluation of Time-Variant and Nonlinear Structures Using Identification Approaches', Lambrecht, Germany, September 1992.