Asociación Argentina
de Mecánica Computacional

Mecánica Computacional Vol XXVIII, págs. 181-188 (artículo completo)
Cristian García Bauza, Pablo Lotito, Lisandro Parente, Marcelo Vénere (Eds.)
Tandil, Argentina, 3-6 Noviembre 2009

FAULT DIAGNOSIS ON STEEL STRUCTURES USING ARTIFICIAL NEURAL NETWORKS

Adriana Zapico[a,b] and Leonardo Molisani[c]

[a]*Dpto. de Computación, Fac. de Cs. Exáctas, Físico, Químicas y Naturales, Universidad Nacional de Río Cuarto, Ruta 36 km 601, 5800 Río Cuarto, Argentina, adrianazapico@gmail.com*

[b]*Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Argentina*

[c]*Grupo de Acústica y Vibraciones, Fac. de Ingeniería, Universidad Nacional de Río Cuarto, Ruta 36 km 601, 5800 Río Cuarto, Argentina, lmolisani@ing.unrc.edu.ar*

Keywords: Neural Networks, Fault Diagnosis, Frequency Response Functions (FRFs).

Abstract. The goal of this effort is to diagnose fault on steel structures by using non destructive techniques. Ultrasonic techniques are usually applied in engineering for faults determination, thickness measuring, adhesive layers, and in metallurgy to establish the quality of welds in metallic pieces. But the ultrasonic techniques could be difficult or impossible to apply in structures with reduced space, i.e. car frameworks. Acoustic signals have been employed since ancient times for detecting faults. Striking an object produces a sound whose differences may be heard when the object is damaged, therefore the vibration signals can be applied to detect differences into a metallic structure. Moreover, the Frequency Response Function (FRF) is used in this work to detect damages in metallic structures. The FRFs are used as input in an artificial intelligent system such as neural nets to detect damage. In general, non destructive evaluation is applied to detect and localize structure faults by using a signal with wavelength smaller than the detecting fault. The method requires analyzing the object in numerous small sections just only to detect the fault. Damages in metallic structures cause small changes in resonance. This work considers global non destructive tests focused only on the estimation of the integrity of the system. Therefore, the whole structure is analyzed to detect damage with only one measure. Traditional fault structure detection practices usually require testing in numerous small sections. The technique used in this research decreases the fault detection costs drastically. The number of FRF spectral lines used to input the neural net is a small fraction of the total frequency range. The designing of a practical implementation requires the usage of a simple method for damage detection, i.e. neural networks. A supervised feed-forward network with Levenberg-Marquardt backpropagation algorithm is applied for testing goals. The net structure is a three-levels layer. The net has only one hidden layer and one output neuron that classifies the damage in the steel beams. The particular selection of the forty two spectral lines values results in forty two neurons as system inputs. After training on a small set of data, the neural network is able to identify the damaged beams with considerable accuracy. The network converges in average in less than twenty epochs. Focusing in the technological implementation, the artificial neural network obtains excellent results with few neurons.

1 INTRODUCTION

Ultrasonic techniques are usually applied in engineering for default determination, thickness measuring, adhesive layers, and in metallurgy to establish the quality of welds made between metallic pieces. But ultrasonic techniques could be very difficult or impossible to apply in structures with reduced space or complex shapes.

Since ancient times, acoustic signals are employed for detecting faults. In view of the fact that striking an object produces sound. Therefore sound differences may be heard by a human ear when the object is damaged.

The application of sound and the human ear for transmission and recognition depend on a natural system whose artificial duplication is only recently considered. One of the firsts monitoring systems was used for analyzing acoustic signals made by rotating bearings at constant speed.

Detecting lack of balancing depends upon the exceeding signal amplitude from a known level. In more developed systems, an analysis on the frequency domain is made to obtain the Frequency Response Functions (FRFs) of the structure. In example, the monitoring of the railroad wheels was a common practice of this kind of investigation. The main fault in railroad wheels is due to cracks in the wheel plate and border. The detection was performed by comparison of the Frequency Response Functions (FRFs) for wheels with the same operational service. A statistical comparison of the FRF permitted to classifies the damage produced in the wheels by the usage. The statistical studies used in train wheels' monitoring was mostly done during the 80's.

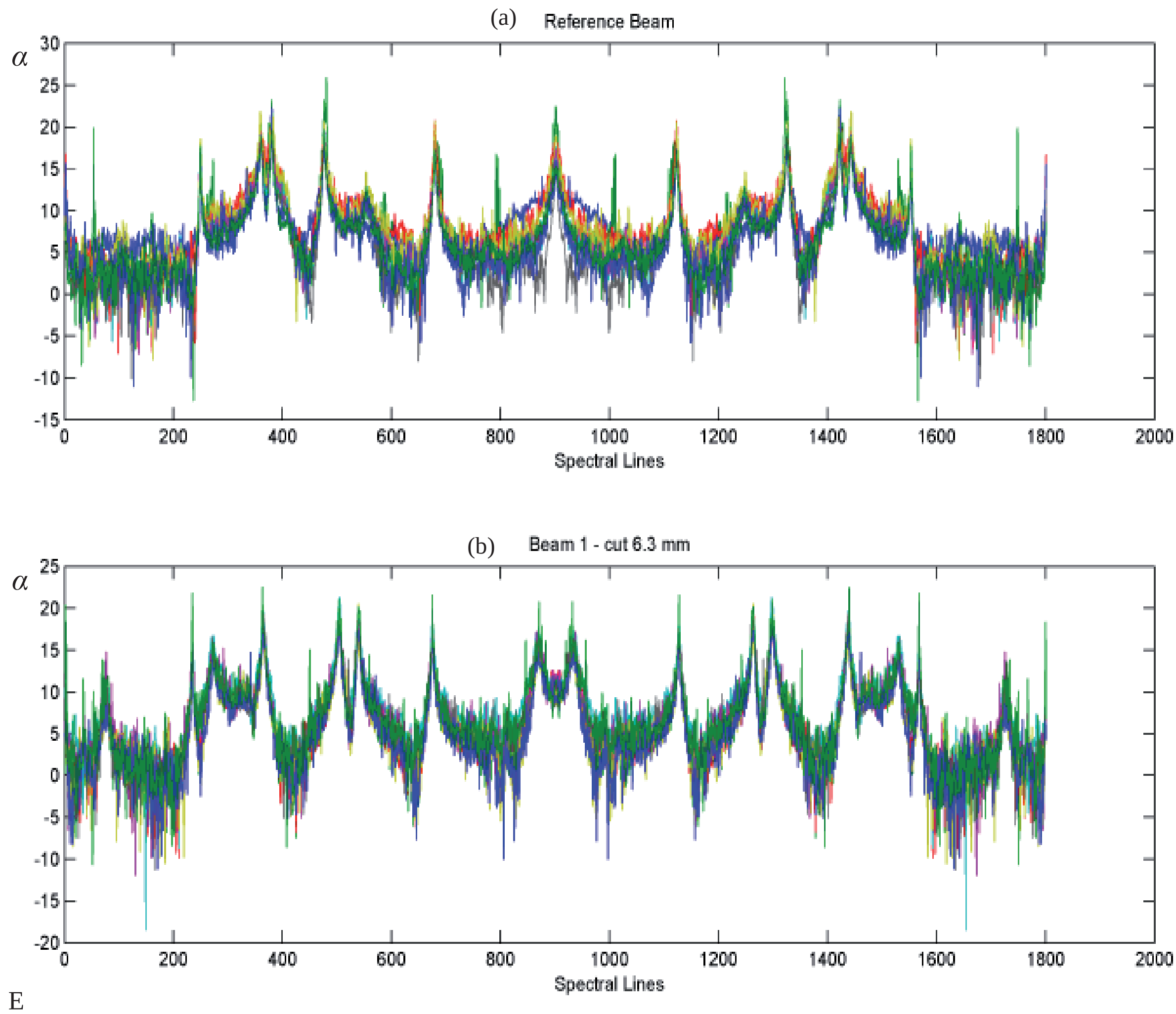
The concept of Frequency Response Function (FRF) is introduced in the next Section. In Section 3, the basic concept and application of neural networks for faults diagnosis on steel beams is developed to classify FRF's. Finally, a future work summary is presented in this effort.

2 FRF'S ACOUSTIC SIGNALS

The acoustic monitoring had been performed for many years since the man has the capability to distinguish from different sounds. Therefore, the sounds emitted by a metallic object have changes if the object suffers structural damages, i.e. bells. Moreover, damages in structures make changes in the object resonances. The changes in the resonances affect the object dynamical properties. In this endeavor, analysis in the frequency domain is performed to obtain the dynamical properties of the structures under analysis by measuring the FRF. The FRF obtained is the so called Accelerance $\alpha(\omega)$. The $\alpha(\omega)$ is defined as the ratio between the acceleration $A(\omega)$ and the external force $F(\omega)$ in the frequency domain.

$$\alpha(\omega) = \frac{A(\omega)}{F(\omega)} \tag{1}$$

Figure 1 shows two plots with FRFs for the reference and damaged metallic beams. The curves in the upper plot show the FRFs for a reference beam without damage where several curves are shown to probe measurement repeatability. The curves in the lower plot correspond to a beam with simulated damage in the operational conditions. The simulated damage is a cut with a known depth in different parts of the beam span.



E

Figure 1: FRF's acoustic signal for the (a) reference and (b) damaged beam respectively.

3 NEURAL NETWORKS

In this section, the basic concepts of neural networks are introduced. Later in this section, a particular application for fault diagnosis is described in order to show the potential technical applicability.

3.1 Basic Concepts

One of the goals of neural networks is to develop methodologies capable to deal with abstract and poorly defined problems. Neural networks have a broad application field, which includes: signal processing, control, medicine, pattern recognition, speech production, speech recognition, robotic, pattern classification, business, etc.

A neural network definition given by Haykin (2009) is "A neural network is a massively parallel distributed processor made up of simple processing units that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two aspects:

1. Knowledge is acquired by the network from this environment through a learning

process.
2. Interneuron connections strengths, known as synaptic weights, are used to store the acquired knowledge."

A neural network has three characteristic components:

- *architecture*: that is, the pattern of connections between the neurons,
- *learning algorithm*: usually called training algorithm, which is a method for establishing the connection weights,
- *activation functions*: are functions used to transform the activation level of a unit (neuron) into an output signal.

Each learning paradigm is linked to an abstract learning task (Haykin, 1999). The abstract learning tasks are, according with some authors, supervised learning, unsupervised learning and reinforcement learning. Perhaps, supervised learning is the most typically neural network setting. The procedure is based in a set of given example pairs and the aim is to find a function that matches the examples. That is, the desire is to infer which will be the output. The output is being provided with a set of training patterns including not only their inputs but also their targets. The capability of generalization is one of the benefits of neural networks. The neural nets have the capacity of generalizing the results to cases that have not been involved in training steps, i.e. to learn outputs for inputs that have not been previously considered.

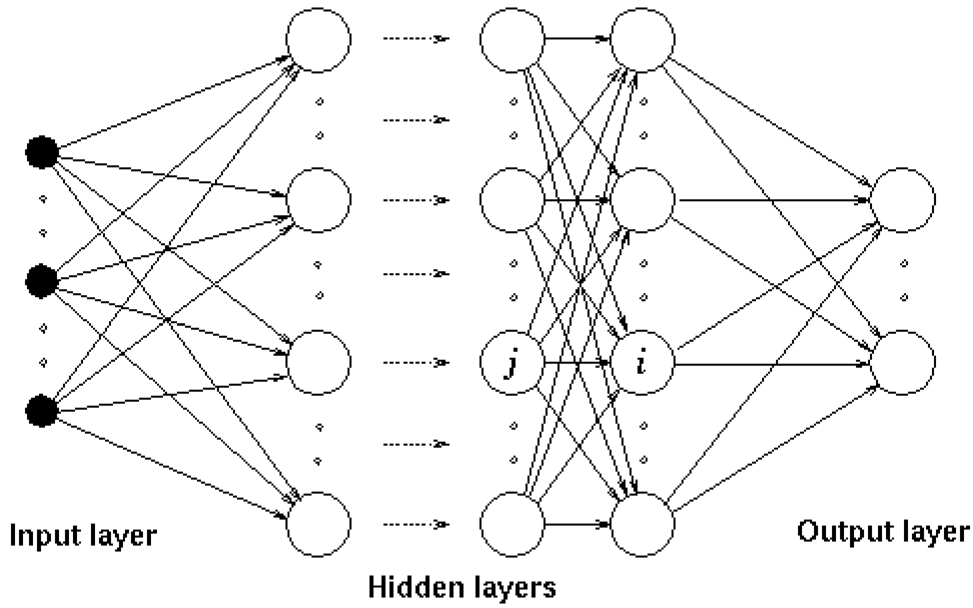


Figure 2: Neural Network's fully connected structure

The neural net model used in this research is a fully interconnected structure shown in Figure 2. The values incoming to a hidden node are multiplied by weights. A set of learning numbers are stored in the net system as seen in Figure 3.

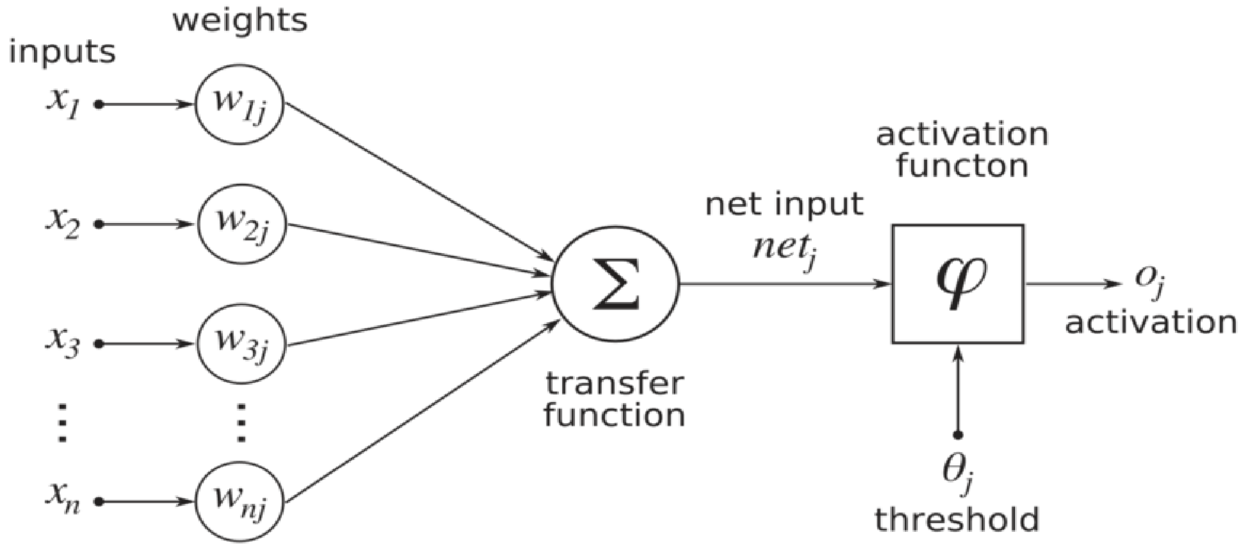


Figure 3: Neural Network's configuration: transfer and activation function.

The weighted inputs are then added to produce a single number, Σ (Figure 6). Later, this number is passed through a nonlinear mathematical function (transfer function), which is generally a sigmoid. This is a "σ" shaped curve that limits the node's output. That is, the input to the sigmoid is a value between -∞ and ∞, while its output is between 0 and 1. Other options for transfer functions are the step or hardlimit function shown in Figure 4, and the linear function.

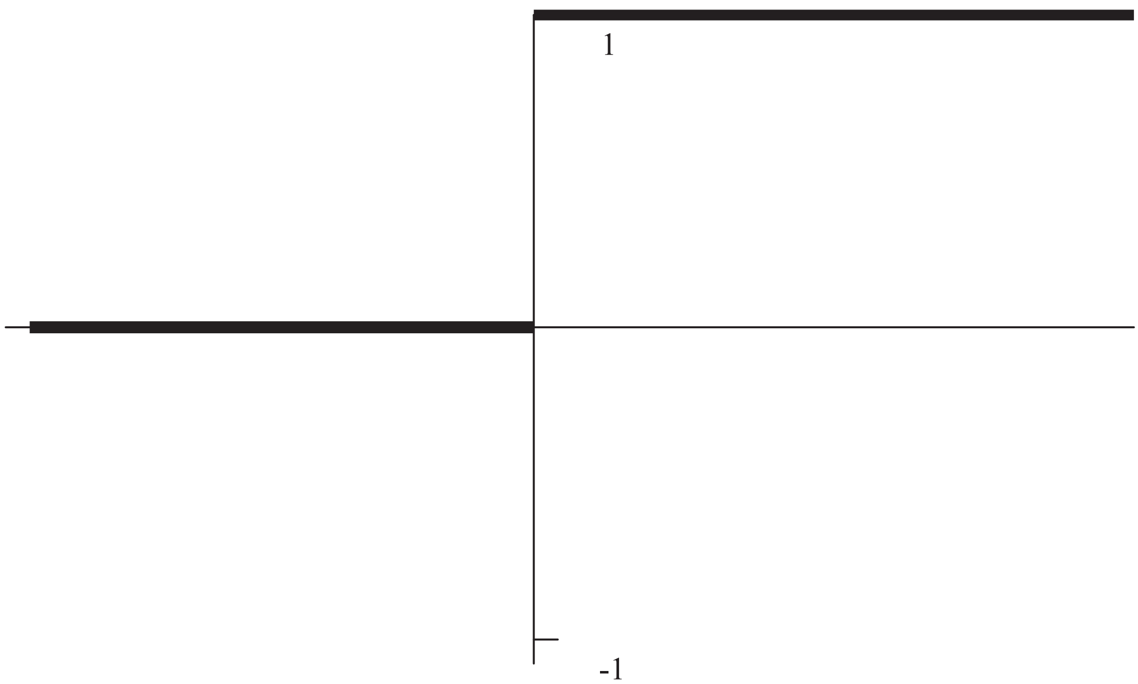


Figure 4: Unit step transfer activation function (hardlimit).

The sigmoid activation function and its first derivative are shown in Figure 5 and defined in equations (2) as

$$\sigma(x) = \frac{1}{1+e^{-x}}, \qquad (2)$$
$$\sigma'(x) = \sigma(x)\big(1-\sigma(x)\big).$$

Multilayered networks are capable of computing a wider range of Boolean functions than networks with a single layer of computing units, i.e. perceptrons.

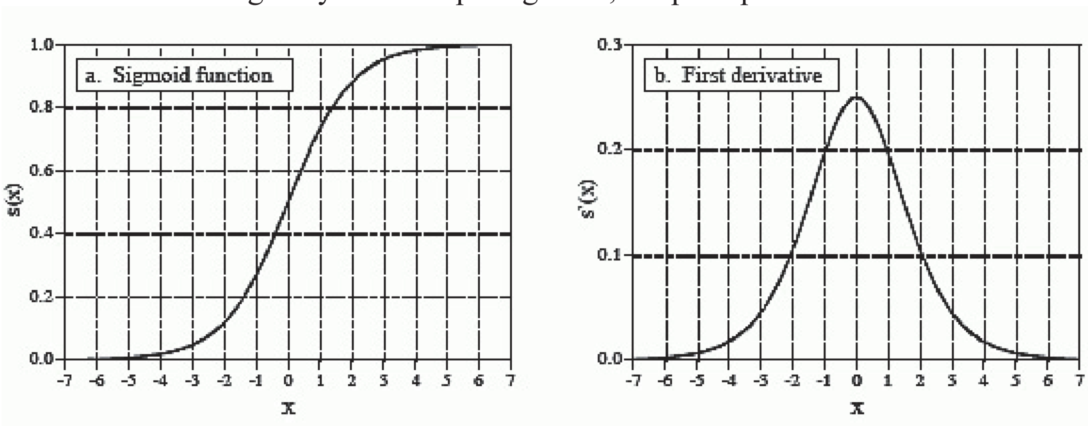


Figure 5: Neural Network's sigmoid activation and its first derivative.

However, the inclusion of hidden layers and consequently more neurons substantially increase the computational effort needed for finding the correct combination of weights. That is, more complicated structures may result in an explosion of weights and the effort required augment considerably. A special class of these networks is the feed-forward nets with backpropagation as learning algorithm.

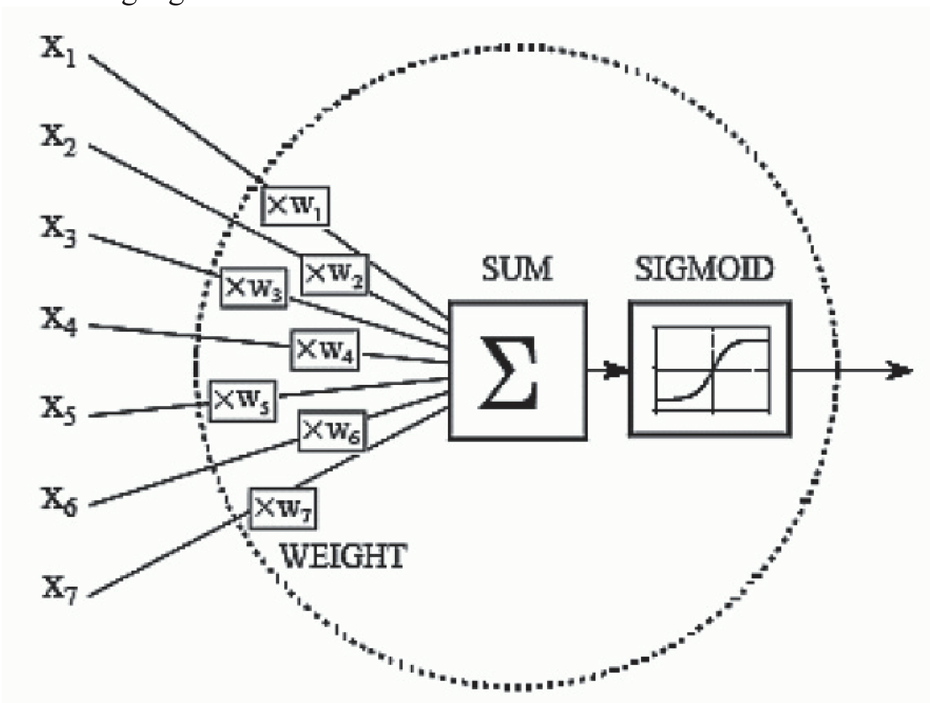


Figure 6: Neural Network's configuration viewing from a hidden neuron.

A feed-forward neural network is an artificial net in which connections between the units do not form a directed cycle (recurrent neural network).

The backpropagation algorithm is used to minimize the simulation error until the network converges to the expected performance function. Backpropagation looks for the error function minimum in the weight space by applying the gradient descent method (Rojas, 1996) . The combination of weights which minimizes the error function is considered to be a solution of the learning problem. A requisite for this method is the continuity and differentiability of the error function since they are involved in each iteration step. Backpropagation is used to look for the error function minimum by calculating the network error gradient with respect to the network's adjustable weights. In this procedure, outputs and targets are compared to calculate the value of a predefined error function. Then the error is updated and the weights are modified by a small amount to reduce the error function value. After the training process, the net usually converges to a state where the calculations error is small. When this occurs, the network converges because it has learnt the target.

Pattern Recognition has been involved in engineering activity since long time ago. At the beginning, pattern recognition has low applicability due to the hardware requirements for data acquisition and computing (Fukunaga, 1990 and Ripley, 1995). Then, hardware and software improvements bring an important impact in the Pattern Recognition field by using neural nets.

3.2 An Application

One advantage of neural networks versus other detection methods is that the neural net does not require a detailed physical model for the considered structure.

It is possible to recognize acoustic patterns for monitoring purposes. Therefore neural networks may be applied for pattern recognition (Akerberg, Jansen, & Finch, 1995) .

In some experiments developed at Houston University (Man, McClure, Wang, Finch, Robin, & Jansen, 1994), vibration signals were obtained for steel beams of rectangular cross section. Some of the beams had saw cuts for simulating faults. In this work saw cuts are also considered to simulate structural problems. Digital data were considered for training an artificial neural network to produce future signal values. There is known that Pattern Recognition is a usual application for neural networks (Bishop, 1995). There are several works in the open literature applying neural networks as classifier in fault detection (Chang, Chang, & Wang, 2000 , Chen & Wang, 2002 , Sun & Chang, 2002, and Zang & Imregun, 2001), but not in beans with free supported boundary conditions.

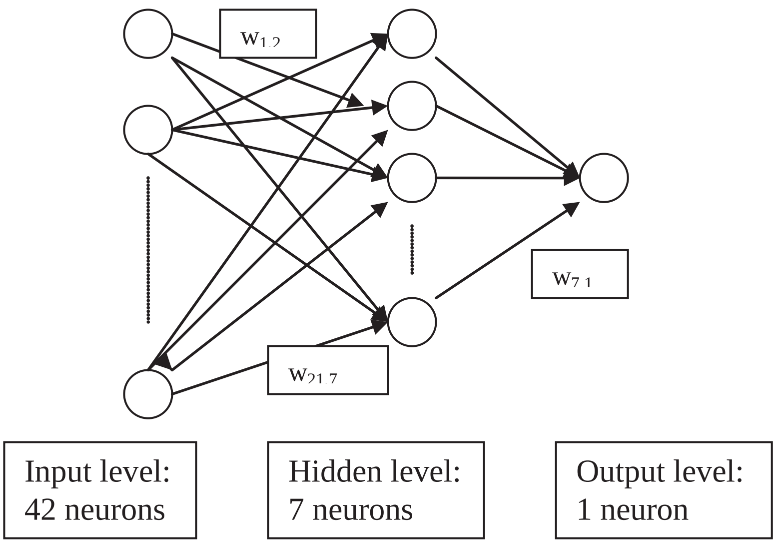


Figure 7: Our Neural Network's configuration.

Considering a simple neural network for fault detection in free supported steel beams, a supervised feed-forward network with Levenberg-Marquardt backpropagation algorithm is applied for testing goals. The system is a three-layer net which has forty two input neurons, one hidden level with seven neurons, and only a single output neuron. The output neuron classifies the beams into damaged or not damaged.

The net is trained to learn the weights. After applying the training on a limited number of training data, the neural network is able to identify the damaged beams with considerable accuracy. The net converges to the final system in less than twenty epochs in average.

Regarding implementation, it is worth to observe that the resultant neural net has relatively few neurons. Moreover, the procedure does not require to the object to be analyzed in small sections.

4 FUTURE WORK

In this article, the authors are interested in fault diagnosis. As a future work, the requirement for the neural network is to provide information about the location of the structural damage. Also, the authors are interested to investigate the applicability in metallic-composed material, and composed material-composed material. The general idea is to apply similar methodology for detecting faults on real time for different kind of structures and joints. Since neural networks are feasible to be programmed in electronic microcontrollers, a novel device is been designed in order to detect structural faults.

REFERENCES

Akerberg, P. M., Jansen, B. H., & Finch, R. D. (1995). Neural net-base monitoring of steel beam. *Journal of the Acoustical Society of America , 98* (3), 1505–1509.

Bishop, C. M. (1995). *Neural Networks for Pattern Recognition.* Oxford University Press.

Chang, C., Chang, T., & Wang, M. (2000). Structural damage detection using an iterative neural network. *Journal of Intelligent Material Systems and Structures , 11*, 32–42.

Chen, D., & Wang, W. (2002). Classification of wavelet map patterns using multi-layer neural networks for gear fault detection. *Mechanical systems and signal processing , 16* (4), :695–704,.

Ewins, D. J. (1986). *Modal Testing: Theory and Practice.* Research Studies Press Ltd.

Fang, X. L., & Tang, J. (2005). Structural damage detection using neural network with learning rate improvement. *Computers and Structures* (83), 2150–2161, .

Fukunaga, K. (1990.). *Introduction to Statistical Pattern Recognition.* Academic Press,.

Haykin, S. (1999). *Neural networks a comprehensive foundation.* Prentice Hall,.

Haykin, S. (2009). *Neural networks and learning machines* (3rd. edition, ed.). Prentice Hall.

Man, X. C., McClure, L. M., Wang, Z., Finch, R. D., Robin, P. Y., & Jansen, B. H. (1994). Slot depth resolution in vibration signature monitoring of beams using frequency shift. . *Journal of the Acoustical Society of America , 95* (4), 2029–2037, .

Ripley, B. D. (1995). *Pattern Recognition and Neural Networks.* Cambridge University Press.

Rojas, R. (1996). *Neural Networks - A Systematic Introduction.* Springer-Verlag.

Sun, Z., & Chang, C. (2002). Structural damage assessment based on wavelet packet transform. *Journal of Structural Engineering , 128* (10), 1354–1361.

Zang, C., & Imregun, M. (2001). Structural damage detection using artificial neural networks and measured frf data reduced by principal component projection. *Journal of Sound and Vibration , 24* (5), 813–827.