Cement & Concrete Composites 25 (2003) 703–709

Cement & Concrete Composites

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A neural diagnostic system for measuring strain in FRP composite materials

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Received 13 October 2001; accepted 12 September 2002

Abstract

In this paper a diagnostic system for measuring strain in FRP composite materials by using artificial neural networks is proposed. In particular the strain response of specimens of glass or carbon fibres arranged in epoxy resin matrix subjected to mechanical and thermal loads is analysed. The experimental results are compared with those obtained analytically and the advantages of using this neural diagnostic system, as compared to the use of the traditional system of temperature compensation, are given.

Keywords: Neural diagnostic; Measuring strain

1. Introduction

In the application of composite materials in structural engineering the accurate measuring of strains depends on the influence of thermal variation on the response of the strain gauge used. In fact, thermal variations can cause mistakes in the evaluation of the stress state existing in the structure and the influence of the thermal variations on the strain gauge can lead to mistakes both in the experiments and the planning of the component itself.

Generally, strain gauge temperature compensation is carried out by means of an external compensator applied to a specimen of the same material under test. In the case of composite materials the utilization of the previous external compensator can produce additional errors resulting from the different orientation of the strain gauge temperature compensation, which may give a residual thermal response.

Moreover, it should be noted that the usual strain gauges utilized are calibrated for homogeneous and isotropic materials, and that their utilization for composite materials can cause additional errors.

In all the cases in which the material has non-homogenous structure is difficult to utilize the reference tool in the conventional techniques for displacement measurement avoiding the influence of the temperature on the strain gauge. To overcome all these difficulties, and to compensate for both the thermal influence on the strain gauge and calibration problems, a diagnostic system based on artificial neural networks (ANNs) was developed.

ANNs have generated great interest in different disciplines, and there are many specialised applications throughout the fields of technology and engineering. Their success is directly dependent upon their ability to simplify and accomplish with speed many tasks not feasible using conventional techniques.

ANNs are employed to solve both problems of systems identification and signal processing: they show high immunity to disturbance or noise superimposed on the signal. The ANNs are not programmed, but they are trained to carry out assignments submitted to them. The training consists in iterative operations which modify the coefficients (weights), that characterise the neural network itself. The difference between a classical algorithm and a neural network, therefore, is that in the first case it is necessary to know the functional bonds by analysing a series of examples, constituted by pairs of input–output values (training set) whereas in the second it is not.

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doi:10.1016/S0958-9465(02)00103-8

This interesting behaviour on the part of the neural network is particularly useful in cases where it is not possible to know the functional relationships between the input and output data. Once trained the neural network is also able to operate with accurate precision on data not belonging to the whole training set.

This method allows the construction of a scheme for the neural pre-elaboration of the signal by a strain gauge with the purpose of reducing influence of variations in environmental temperature at a wide interval of values.

The advantageous use of the ANN require to perform accurately the three phases: (i) training phase, (ii) test phase and (iii) production phase.

The training phase is very important and determines the over all behaviour of the ANN is both the test and production phase. The most common rules to be followed are:

1. To set the input and output variables. In the case under consideration the input variables are deformation of the strain gauge and the environmental temperature. The output variable is the structure deformation.
2. The values of the variables of the training set are selected according to the problem under examination. In this case, once determined the range of variation of each variables, the training set is constituted by uniformly select the values. Often need to modify the training set, in particular increasing opportunely the data, according to increase the ANN properties in the production phase. Fortunately this is not a common situation to the application under examination.
3. The ANN architecture is, consequently, set according to the input and output variables. The number of the input and output variables set the number of neurones in the input and output layers, respectively. The number of neurones in the hidden layer is set in optimized way to (i) reduce the training error and (ii) to speed the training phase.

This paper, after dealing with the theoretical background of the ANNs, describes the neural diagnostic system proposed and shows the results of experiments which compare the response of the specimens of glass fibres unidirectionally arranged in epoxy resin matrix or of carbon cloth in epoxy resin matrix subjected to tensile tests using ANNs and temperature compensation strain gauges.

2. Theoretical background to ANNs

ANN architectures imitate the behaviour of the human brain and are based on the properties and features of the neurones and synapses of neurobiological systems. Neurones are the base units in which all processing activities are performed and are characterised by a summing property and a non-linear transfer characteristic, similar to the sigmoidal one. Synapses are the connections which transmit the information. These can be transmitted with modification by means of the synapse weights [1].

The key feature of the ANN structure consists of a parallel distributed network, comprising many artificial neurones interconnected by weighted connections. Each artificial neurone is characterised by an input vector, a single output value and a non-linear transfer characteristic. It processes information in a predetermined manner and furnishes the results either as the ANN's output or to the input of another neurone. The weighted connections store the information and the value of the weights is pre-defined or determined by a learning algorithm. The cross-connections between the neurones form: (i) a set of input layer neurones, (ii) a set of output layer neurones and (iii) a set of hidden layer neurones. The choice of the number of neurones in the input and output layers is closely connected to the level of accuracy desired. The number and dimensions of the hidden layers depend only on the ANN's performance achieved in terms of model fidelity and operating speed [2,3].

Amongst the numerous ANN architectures available in the literature [2], the feed-forward networks with one more or more hidden layers and the back-propagation learning algorithm, are the most common in measurement applications. Indeed, when compared with other architectures, they offer several successful applications in pattern classification, pattern matching and function approximation, as well as, in the learning of any non-linear mapping to any desired degree of accuracy. With the aim of providing detailed knowledge of particulars, the feed-forward networks with one hidden layer and the back-propagation learning algorithm are considered in this paper.

As is well known, the use of this ANN involves three separate phases which have to be followed, and which are depicted in Fig. 1:

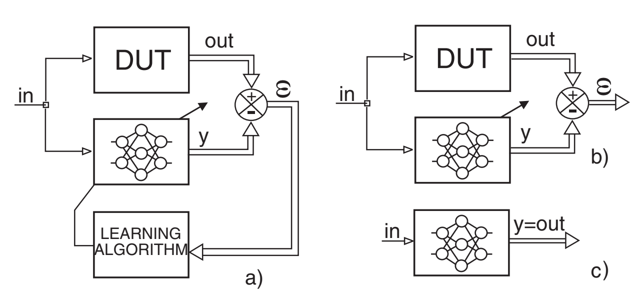


Fig. 1. Neural modeling phases of the device under test: (a) learning phase; (b) validation phase and (c) production phase.

1. the learning phase (Fig. 1a), in which the ANN is forced to furnish the desired outputs (out) in correspondence to a determined input (in): the learning set. In this phase the ANN learning level is verified by means of suitable performance indices (output error ε), and the objective function, defined coherently by the data of the learning set;
2. the validation phase (Fig. 1b), in which the ANN's generalisation capability is verified by means of data (the validation set) which are completely different from the data used in the previous phase;
3. the production phase (Fig. 1c), in which the ANN is capable of providing the required outputs (y) that correspond to any input.

In order to train the ANN to model physical phenomena it is necessary: (i) to specify the learning set constituted by an adequate number of output and target output vector pairs and (ii) to minimise the objective function, defined as the relative difference (normally in the Euclidean sense), between the actual ANN output and the target outputs. It is possible to minimise the objective function by using a learning algorithm. The strategy of the learning algorithm is devoted: (i) to determining the input/output transfer characteristic of each neurone by supervised learning section and (ii) to modifying the connection weights and the neurone bias by means of an adaptive process (error back-propagation) which minimises the output neurone errors. This phase ends when the ANN furnishes the outputs necessary for the learning set. Progress in the ANN learning phase is monitored through a decrease in the maximum relative error. Some effort must be devoted to determining the learning set in order to obtain high ANN accuracy.

In the validation phase, the ANN accuracy is tested using the validation set. These vector pairs are different from those of the learning phase, but have similar characteristics. If the ANN's performance does not reach the desired level of accuracy a new learning phase and a modified learning set are necessary. The modified learning set must take into account the additional new information obtained by the previous set. After the learning and validation phases, the production phase begins and the ANN is used to provide the corresponding outputs required for any input.

Trained in this manner, the ANN represents a valid model of the non-linear phenomena for which it has been trained. The main cost will be the time taken to set up the learning phase.

Some of the drawbacks connected with the training are difficulties in establishing opportune constituent data values for the training set; the possibility of reverting to a situation of local minimum that does not allow the network to reach the final training with the necessary precision; the elevated time required by the training phase. To overcome these drawbacks a method has recently been developed which allows the pre-elaboration of the measurement signals by opportune structures of calculation constituted from neural artificial networks.

3. Materials and experimental equipment

The experimental investigation was carried out on commercial FRP composite materials obtained by an automatic poltrusion process, with unidirectional glass fibres or carbon cloth arranged in an epoxy resin matrix.

$260 \times 40 \times 7$ mm specimens for composite material with glass fibres and $260 \times 36 \times 3.5$ mm for composite with carbon cloth, respecting ASTM D3039-74 standard, were obtained by cutting the 1 m flat bars to achieve a sufficiently wide isothermic zone.

The physical properties of the component materials are shown in Table 1, while the mechanical properties of the tested composite materials are given in Table 2.

The tensile tests were carried out using the experimental equipment illustrated in Fig. 2.

This is composed of an electromechanical test machine, a data acquiring device, a climatic cell and a personal computer.

Monotonic tensile tests were conducted up to 50% of the ultimate load, and stress–strain diagrams were obtained for temperatures of

- −20, 20, 80 °C for the composite materials with glass fibres,
- between 28 and 60 °C for the composite material with carbon cloth.

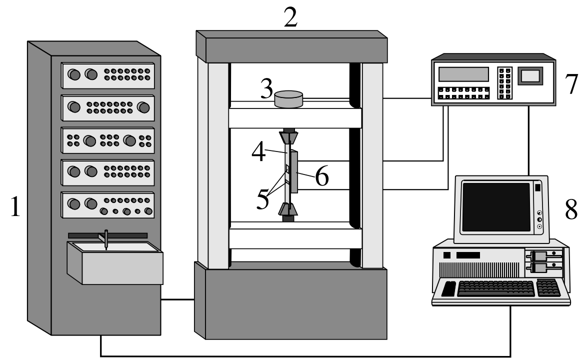
Electric strain gauges were placed at the centre of one side of the specimen to measure strain, while temperature was kept constant for the duration of the test by a

Table 1
Physical properties of the composite materials

Kind	Layer no.	Fibre (vol.%)	Matrix (epoxy resin) (vol. %)
Fibre glass	–	75	25
Carbon cloth	7	58	42

Table 2
Mechanical properties of the tested composite materials

Material	E (MPa)	ν	Ultimate strength (MPa)
Fibre glass	53.500	0.26	950
Carbon cloth	66.500	0.08	455



1: control device
2: universal testing machine
3: load cell
4: sample
5: strain gauges
6: climatic cell
7: data acquiring device
8: personal computer

Fig. 2. Testing set-up.

climatic cell. The strain gauge was effected without a temperature compensation gauge.

4. Thermoelastic behaviour

In this section, for the sake of brevity and clearness, the thermoelastic analysis was only conducted for the composite material with glass fibres unidirectionally arranged in an epoxy resin matrix.

The temperature effects in an orthotropic material, which is a fibrous composite, are generally different along the principal directions of orthotropy; all this can be taken into account by introducing different linear coefficients of thermal expansion α_i corresponding to the strain components [4–6].

By considering the case of a plane subjected to a stress condition acting in the xy-plane, the classical elastic constitutive equations referred to the x–y axes, can be written in the following form:

$$\{\varepsilon\} = [C]\{\sigma\} + \{\alpha\}\Delta T \tag{1}$$

where

$$\{\varepsilon\} = \begin{Bmatrix} \varepsilon_x \\ \varepsilon_y \\ \varepsilon_{xy} \end{Bmatrix}, \quad \{\alpha\} = \begin{Bmatrix} \alpha_x \\ \alpha_y \\ \alpha_{xy} \end{Bmatrix}$$

are the vectors of the elastic strains and of the thermal expansion coefficients respectively.

The thermal expansion coefficients referred to the x–y axes can be given as a function of the principal 1–2 axes by

$$\alpha_x = \alpha_1 \cos^2\theta + \alpha_2 \sin^2\theta \tag{2}$$

$$\alpha_y = \alpha_1 \sin^2\theta + \alpha_2 \cos^2\theta \tag{3}$$

$$\alpha_{xy} = 2(\alpha_1 - \alpha_2)\sin\theta\cos\theta \tag{4}$$

where θ is the orientation angle of the fibres with respect to the reference x-axis. Since the composite material examined has unidirectional fibres parallel among them with $\theta = 0°$, from Eqs. (2)–(4)

$$\alpha_x = \alpha_1, \quad \alpha_y = \alpha_2, \quad \alpha_{xy} = 0 \tag{5}$$

is obtained.

The thermal expansion coefficient along the two principal directions can be determined by the expressions:

$$\alpha_1 = [\alpha_f E_f + \alpha_m E_m(1-\eta_f)]/[E_f\eta_f + E_m(1-\eta_f)] \tag{6}$$

$$\alpha_2 = (1+\nu_m)\alpha_m(1-\eta_f) + (1+\nu_f)\alpha_f\eta_f - \alpha_1[\nu_f\eta_f + \nu_m(1-\eta_f)] \tag{7}$$

where E and ν are Young's modulus and Poisson's ratio of the fibres (f) and the matrix (m) and η_f is the fibre volume percentage.

Eqs. (6) and (7) indicate that the thermal expansion behaviour of the composite examined depends on the thermoelastic properties of the material components (E_f, E_m, ν_f, ν_m, α_f, α_m) and on the parameters of production technology.

The elastic parameters are generally certified by the company and have a negligible degree of uncertainty as far as the determination of the strain state is concerned. On the contrary, the thermoelastic parameters show a high degree of uncertainty.

The thermal expansion behaviour of the matrix is greatly influenced by several factors, the most important of which is the synthesis process and the successive fibre impregnation. It would seem therefore that strain measurements in a composite material subjected to mechanical and thermal loads can be carried out more accurately by experiments using strain gauges.

In a unidirectional composite material subjected to such loads the total strain given by the strain gauge is

$$\varepsilon_t = \varepsilon_m + \varepsilon_{\Delta t} + \varepsilon_r \tag{8}$$

where ε_t is the total strain of specimen tested, ε_m is the mechanical component, $\varepsilon_{\Delta t}$ is the thermal component and ε_r is the thermal component of the strain gauge used.

In order to determine the strain ($\varepsilon_m + \varepsilon_{\Delta t}$) only it is necessary to eliminate the thermal component ε_r of the strain gauge used from the total deformation ε_t.

5. Results and conclusions

In this section the first results of an experimental study, utilising a new method to compensate for the temperature influence on the resistance strain gauge output based on the use of ANN, are given.

The experimental investigation concerned: (a) commercial FRP composite materials with unidirectional glass fibres or carbon cloth in epoxy resin matrix; (b) commercial resistance strain gauges and (c) real temperature ranges of engineering practice.

The most significant results obtained are shown below.

The training set of the ANN has been organised as follows:

(a) the input data are both the deformations obtained from the output of the strain gauge and the material temperature;
(b) the output data are the loads obtained from the analytical model of the material.

5.1. Glass fibre composite

Fig. 3 shows both the experimental and analytical data utilized for the training set. In this figure the load versus deformation curves in the range from −20 to 80 °C for both the experimental and analytical evaluation are plotted.

Fig. 4 shows the load versus deformation plots in the range from −20 to 80 °C after the compensation by means of the ANN compared with the experimental and analytical ones.

The high level of compensation is a consequence of the fact that the ANN is able to compensate for

(a) the alignment error between the strain gauge and the material fibres;
(b) the calibration error, as a consequence of the fact that the strain gauge is calibrated using isotropic materials.

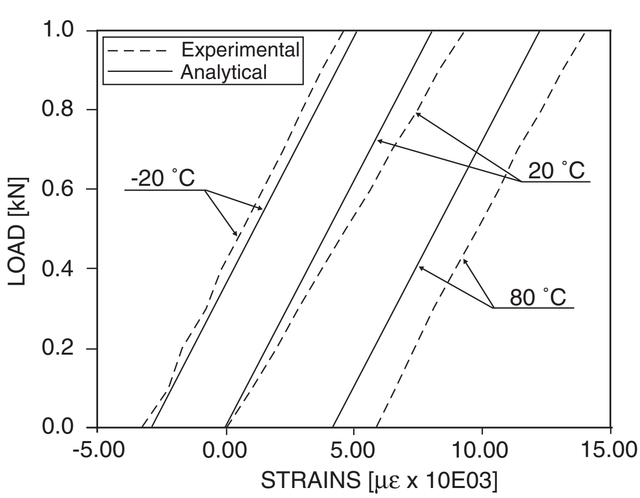


Fig. 3. Comparison between analytical and experimental σ–ε curves.

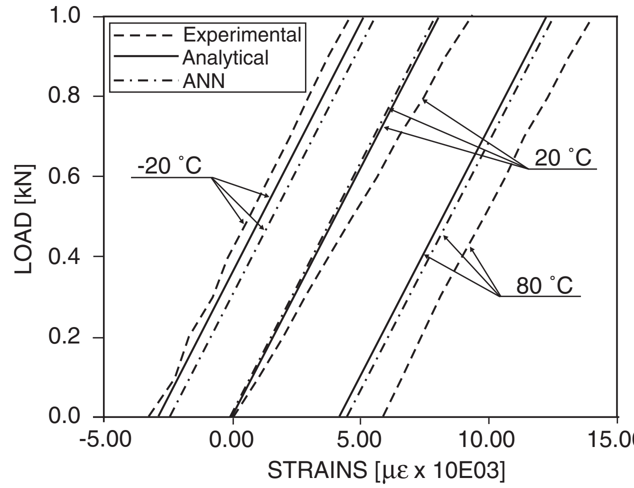


Fig. 4. Comparison among experimental, analytical and compensated by ANN σ–ε curves.

5.2. Carbon cloth composite

Fig. 5a gives the strain versus the load (thermal and mechanical) while Fig. 5b shows the strain versus the load after the compensation carried out using the ANN.

The values of the graphs of Fig. 5 are obtained by the values of the electric strain gauges cleaned by the thermical strain ones.

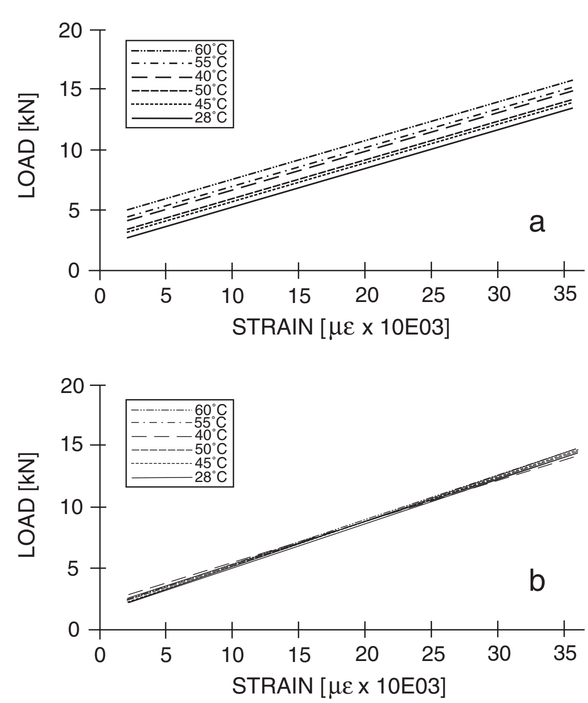


Fig. 5. Strain–load trend: (a) without a temperature compensation gauge and (b) with compensation by ANN.

The compensation effect consists in drawing the curves nearer to the one of 28 °C. This effect is evident even if an electric strain gauge is employed for the compensation.

The choice of a resistance strain gauge for composite materials depends on the surrounding conditions, test life, heterogeneity, thermal properties, maximum strains, stability of measurements, transverse sensibility and accuracy.

The thermal compensation of a resistance strain gauge applied to a composite material is complicated by the material anisotropy. Therefore it must try to eliminate the effects of temperature variations acting on the strain gauges during the mechanical strain measurements. To overcome these difficulties the most common procedures use self-compensated strain gauges or temperature compensation strain gauges. The first are commonly used for isotropic materials but not usually used for composite materials. In fact the combined effect of material orthotropy and transverse sensitivity produces a thermal residual response even when the choice of the thermal compensation coefficient of the strain gauge is correct.

The temperature compensation gauge method is that most often used for composite materials. It utilizes two resistance strain gauges: one active, applied to the material being tested and the other passive, applied to the same material not being tested but at the same thermal conditions. In order to obtain an optimum compensation the two resistance strain gauges (active and passive) must have the same orientation as that of the fibre. In fact an orientation error would mean different thermal expansion coefficients and thus a different thermal response of the two strain gauges applied.

Fig. 6 shows the thermal response of a strain gauge applied to a glass fibre composite material with a temperature compensation gauge in the range from 40 to 120 °C.

In particular Fig. 6a and b give the loads versus longitudinal deformations and the loads versus transverse deformations respectively. The change in position of the lines at high temperatures is clear.

ANN application overcomes all these difficulties and the lines of Fig. 6 coincide.

In the case under consideration, owing to the quasi-linearity of the physical phenomena in the range examined, the ANN architecture is the multilayer perceptron with two neurones in the input layer, eighth in the hidden layer and only one in the output layer. Each neurone is characterised by sigmoidal transfer function with slope coefficient equal to 0.92. The ANN was trained by means of the classical back-propagation algorithm based on the descendent gradient method. The quasi-linearity of the phenomena avoids the problems of local minima. The complete training phase required 300 epochs, each one constituted by 104 couples of input and output values.

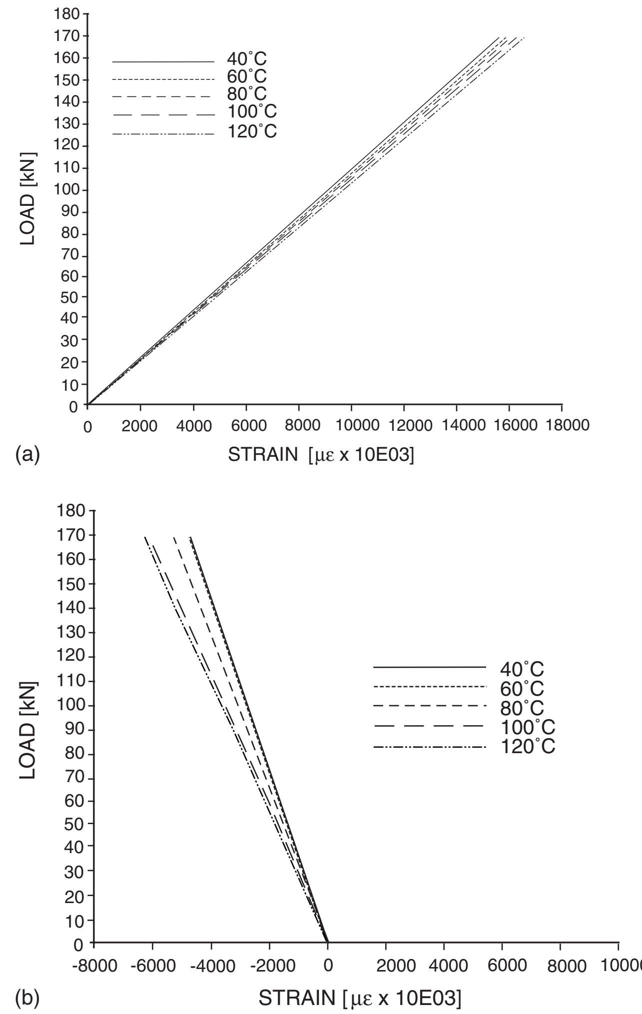


Fig. 6. (a) Load–longitudinal strain curves and (b) load–transverse strain curves.

In the range examined the trend is linear and consequently the curves can be obtained by the proportional factor. Essentially the ANN operates as follows:

1. automatically evaluates the proportional factor on the base of the sensed temperature;
2. provides the correct output values.

All these simple operation are performed automatically with high accuracy without need of (i) look-up table and (ii) interpolation procedure.

In brief the ANN use can be seen to properly compensate for the temperature influence on the response of electric strain gauges. An interesting aspect of the neural diagnostic system proposed is that compensation is independent of the material of the tested structure and depends only on the thermal properties of strain gauge strength.

Therefore, it is necessary to address the training of a new ANN for each type of strain gauge used. Another interesting aspect could be that of compensating for the influence of other environmental factors such as moisture.

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