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POLYNOMIAL IDENTIFICATION OF STRAIN GAUGE THERMAL OUTPUT FOR THE DETERMINATION OF DEFORMATIONS WITH NEURAL NETWORKS

ABSTRACT

Strain gauges are used in different areas, especially in the design and development of new technical constructions and model testing. Also, strain gauges are incorporated in the functional part of many instruments and devices. They are mostly used as sensors in transducers designed to measure such mechanical quantities as forces, moments, pressures, accelerations, etc. They have an important role in shipbuilding and marine transport in general. In this paper we have suggested and shown an approach to the identification of strain gauge thermal output curve on the example of a product available at the market. Neural network simulated in MatLab has been applied. The neural network has been adapted to simulate a real system with 10^{-9} order of magnitude error. As it is well known, strain gauges measure deformations of 10^{-6} order of magnitude. It is obvious that the network error cannot influence the measurement results because of its being smaller by three orders of magnitude.

KEY WORDS

strain gauges, deformation, neural network, identification, thermal output

1. INTRODUCTION

Increasing requirements which have to be met by modern technical constructions with regard to economical quality and safety assign very sophisticated tasks to engineers. Testing of any new construction to check its behaviour in real working conditions regardless of wide usage of computers in designing constructions, CAD (Computer Aided Design) appears as an imperative [1, 2, 3]. Modern measurement technique makes such testing possible. A special role is played by experiments which can be applied not only to models but also to original constructions [4]. A process of the kind suitable either for laboratory or industrial applications in strain gauge measurement. Such a process determines construction deformations in order to define stress at critical points of its surface. Nowadays, electrical-resistance strain gauges have dominant position as they superseded all other systems for the measurement of static and dynamic deformations of machines and technical constructions. Besides, these basic application strain gauges are frequently used as sensors in all kinds of devices and instruments, which has enabled measuring of different mechanical magnitudes such as forces, moments, pressures, accelerations, using electricity. Strain gauges are most frequently used in maritime affairs and shipbuilding where they are specifically applied in deformation and stress testing of ship construction in case of collision as well as in checking ship safety with or without delicate cargoes in critical navigation conditions.

1.1. Strain gauges

The function of electrical-resistance strain gauge is based on the change of electrical resistance in conductors depending on the variation of length. All strain gauges have a basis made either of paper, synthetic resin or a similar material onto which the active part has been stuck. The active part can be made of thin wire of 0.025 mm in diameter or of metal foil attached to the basis and shaped by a photolithographic process [1, 5].

Normal (axial) strain (ε) has been defined as a relative change of the length of an object. The order of magnitude of such deformations measured in practice is very small (10^{-6}) so that they are usually called microstrains ($\mu\varepsilon$).

There are different types of strain gauges. Some of them require extensive knowledge of materials used in electrical engineering such as piezoelectric strain gauges, which make the resistance change in a non-lin-

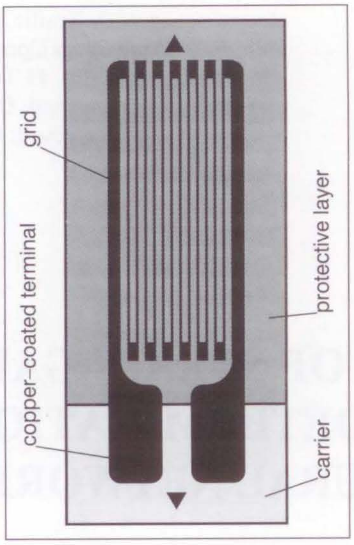

Figure 1 - An example of strain gauge

ear manner. Metal strain gauges are still most commonly used in practice.

A metal strain gauge consists of very fine wire or metal foil on a grid which accentuates its sensitivity to deformations in which process the influence of the Poisson (transversal) deformation is reduced to a minimum. The grid is connected to a thin carrier attached to the object which is being tested so that its deformation is directly transferred to the strain gauge responding with a linear change of its electrical resistance.

Installation and performance characteristics of a strain gauge are influenced by: an alloy sensitive to deformation (A-, P-, D-, L- alloy), self Temperature--Compensation number (S-T-C), materials used for the basis (polyamides, epoxy-phenolis, etc), resistance of the grid, length of the strain gauge as well as a selection of the corresponding additional features. Condition determining the strain gauge to be used are: accuracy, test duration, stability, resistance to periodical loads, temperature, simplicity of installation, lengthening and environment conditions [1, 5, 6, 7, 8].

The most important strain gauge parameter is its sensitivity to deformation. It is quantitatively expressed as a factor of measure and is defined as the ratio of electrical resistance and length change [1]:

$$k=\frac{\Delta R/R}{\Delta L/L}=\frac{\Delta R/R}{\varepsilon} \tag{1}$$

where R stands for electrical resistance, ΔR change of resistance, L length, ΔL change of length which causes the above mentioned resistance change and ε normal strain.

Example: If a specimen with a 500 $\mu\varepsilon$ is tested, and if a strain gauge with k = 2 is used, the change of electrical resistance is only $2 \cdot (500 \cdot 10^{-6}) = 0.1\%$. For a gauge with 120 Ω resistance there is only a 0.12 Ω change to be measured. In order to measure such small resistances and compensate for temperature sensitivity, strain gauges are always used in some sort of bridge configuration such as the Wheatstone bridge. Figure 2 shows some standard commercial configurations.

For the measurement of a deformation caused by bending load we can use either a quarter of a bridge circuit, a half of the Poisson bridge circuit, a half of a bridge circuit or a complete bridge circuit. In order to measure a deformation caused by axial load two strain gauges are used in the opposite branches or a complete Poisson bridge circuit. Deformations caused by torsional load are measured using a complete bridge circuit.

1.2. About neural networks

Human brain goes through an uninterrupted process of comprehending and modelling complex systems. Imitating such process it allows people to develop the process of learning which can be used in modelling different systems such as maritime, air, generic or management system. In order to apply brain functionality and such algorithms with the currently available equipment and software support it is impor-

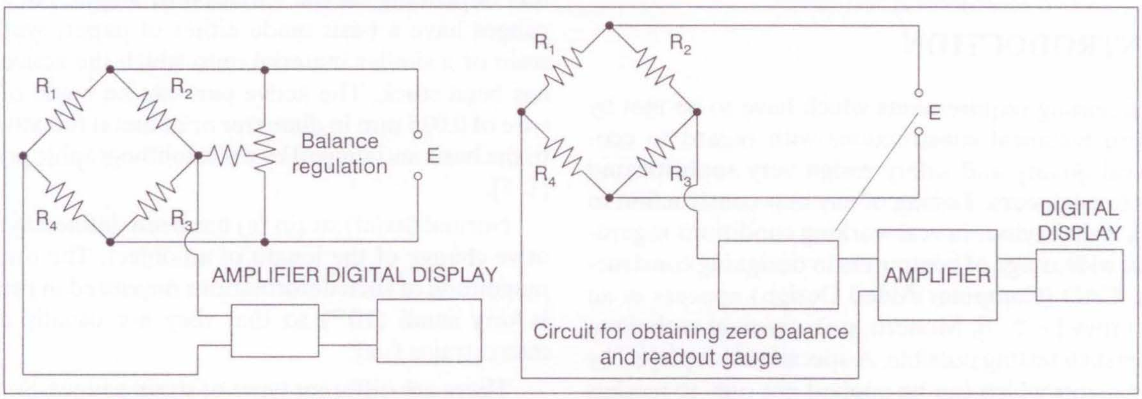

Figure 2 - Commercial deformation indicators: a) output voltage is amplified and displayed on an indicator (digital voltmeter), b) output voltage of the bridge is annulled by equal voltage of opposite polarity introduced into the circuit

tant to know that nowadays a single neurone in the human brain functions much more slowly than computer processors. The secret of human brain lies in parallel work which at present cannot be easily imitated. Parallel computers are being developed whereas present-day computers incorporate only a few processors working parallel, which is insignificant when considering the number of neurones in the human brain. Brain cells are mutually connected by multiple interconnections whose complexity is enormous. This high-level interconnection allows work on more than one task simultaneously. In order to store an item of information into the computer memory, the item's address must be precisely known: if the item gets lost, it cannot be retrieved. Within the brain, data are widely distributed and their contents are in most cases retrievable even if they are only partly known. Computer processors are highly accurate and do not tolerate errors while neurones with their low accuracy can be damaged without consequently affecting the brain overall function. Artificial neural networks (ANN) are an attempt at imitating interconnections and parallel data processing in the brain with the velocity and accuracy of a computer processor [9–12].

ANN have the possibility of learning by altering their internal parameters according to certain rules allowing generalisation, grouping, recognising or organising a set of data determined by the users. The ANN structure consists of a great number of simple, processing units which communicate by sending signals mutually. Each ANN model consists of three components: input layer, output layer and hidden layer. The input layer receives data entering the network, output layer sends the data out of the network while the hidden layer retains its input and output signals within the network.

Each neurone can be shown in Figure 3 with its transmitting function and a bias as well as its adding capability [10].

2. NEURAL NETWORK IDENTIFICATION PROBLEM

A model is usually identified when regulating or simulating an object or a process. The controller design can be a direct or an indirect one. The former is itself a neural network while the latter is not itself a neural network but is based on the model of processing by an ANN.

The procedure to follow in order to identify the system consists of four basic stages: experiment, selection of a model structure, model evaluation and its validation as shown in Figure 3. Experimental data have been obtained by measuring. On condition that the data have been correctly patterned, the next stage is selecting the model structure. Understandably, this is

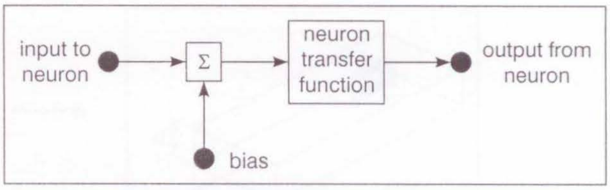

Figure 3 - A neurone model

much more difficult in the case of a non-linear than in the case of a linear model. It is necessary to determine the network repressors as well as the ANN structure. Whether the network parameters and structure have been correctly chosen can be determined by comparing experimental and simulated data. If they nearly correspond, the modal has been accepted, but if the error is greater than the allowed, another model is required [10 – 14].

3. STRAIN GAUGES THERMAL SENSITIVITY

Ideally, a strain gauge attached to a tested object corresponds to the deformation applied to the object. The material of which the strain gauge is made as well as the material of the object tested react to temperature variations. Thus, for example, with the nominal resistance of 1000 Ω, an aluminium strain gauge with k = 2 has an equivalent error of deformation of 11.5 με/°C.

When the installed strain gauge has been connected to the deformation indicator and the instrument has been balanced, additional changes in temperature of the installed strain gauge will usually bring about resistance change which is independent of mechanical deformation caused by stress in the tested object. Its exclusive cause is the change in temperature.

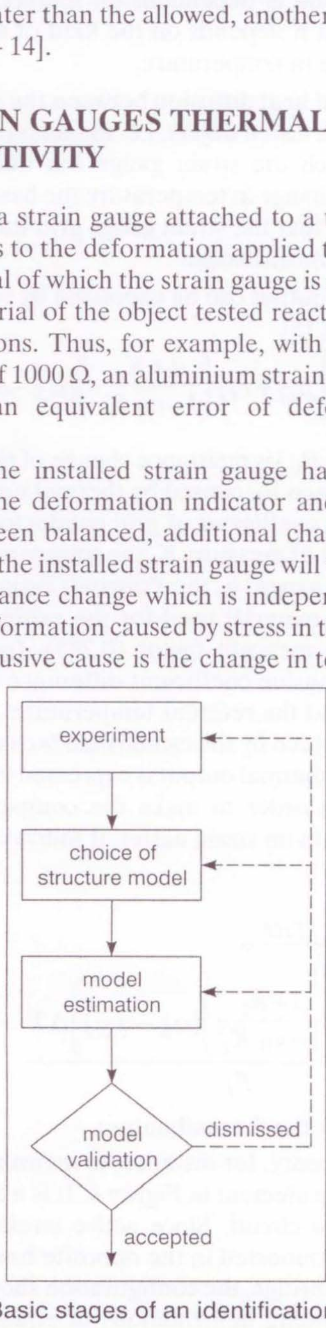

Figure 4 - Basic stages of an identification procedure

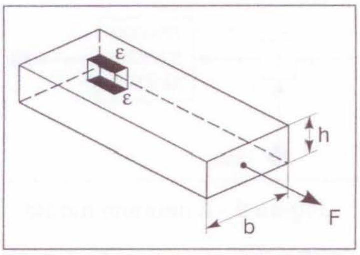

Figure 5 - Axial load of the elastic element in the form of a prismatic bar

There are two causes of resistance change, which result in the thermal output:

- electrical resistance of the conductor of which the grid is made is dependant on temperature which means that it depends on the kind of material and the change in temperature,
- differential heat diffusion between the grid conductor and the tested object, i.e. the material of the basis to which the strain gauge has been attached. With the change in temperature the basis extends or shrinks so that the strain gauge grid itself is subject to extension/shrinkage.

Thermal output can be expressed by relative resistance change [5].

$$\left(\frac{\Delta R}{R_0}\right)_{T/O}=\left[\beta_G+F_G\left(\frac{1+K_t}{1-\nu_0 K_t}\right)(\alpha_S-\alpha_G)\right]\Delta T \quad (2)$$

where $(\Delta R / R_0)$ is resistance change of the initial referent resistance R_0 caused by thermal output, β_G the temperature coefficient of grid conductor resistance, F_G the factor of measure, K_t the transversal sensitivity of the strain gauge, ν_0 the Poisson's ratio of the standard testing material used for the calibration of the strain gauge measure factor (0.285), $(\alpha_S - \alpha_G)$ the thermal expansion coefficient difference between the measured and the referent temperature. If the equation (2) is divided by the established factor of measure (F_I) and the thermal output is expressed in units of deformation in order to make the comparison of the measured data on strain easier, it follows that [1, 5]:

$$\varepsilon_{T/O}=\frac{\left(\frac{\Delta R}{R_0}\right)_{T/O}}{F_I}=$$

$$=\frac{\left[\beta_G+F_G\left(\frac{1+K_t}{1-\nu_0 K_t}\right)(\alpha_S-\alpha_G)\right]\Delta T}{F_I} \quad (3)$$

where $\varepsilon_{T/O}$ is the thermal output.

It is necessary, for instance, to measure the deformation of the element in Figure 4. It is a case of a half of the bridge circuit. Since active strain gauges are electrically connected in the opposite branches of the Wheatstone bridge, the configuration shown in Figure 4 annuls bending deformations of equal values and

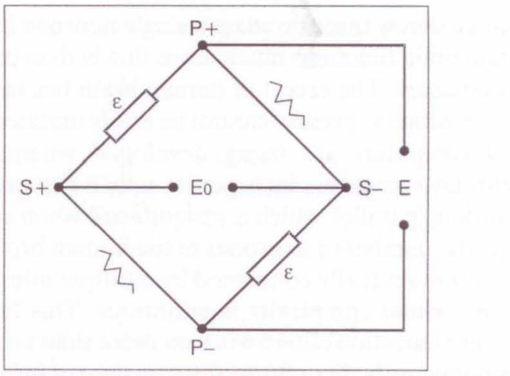

Figure 6: Electrical configuration for the measuring of axial load of the elastic element (⁓ designates the resistor in the non-active branch – the non-active strain gauge, while ▭ designates the resistor in the active branch – the active strain gauge)

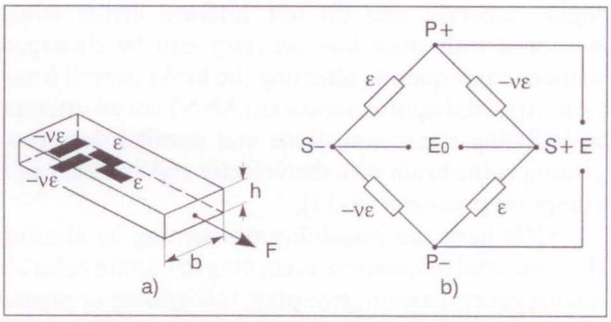

Figure 7 - a) Axial elastic element – complete Poisson bridge circuit, b) electrical configuration

opposite signs. The bridge output amplitude caused by axial load is relatively high, but non-linear. The non-linearity amounts to 0.1% per 1000 microstrains caused by axial load in the elastic element. Then the normal strain can be calculated as:

$$\varepsilon=\frac{F}{E\cdot b\cdot h} \quad (4)$$

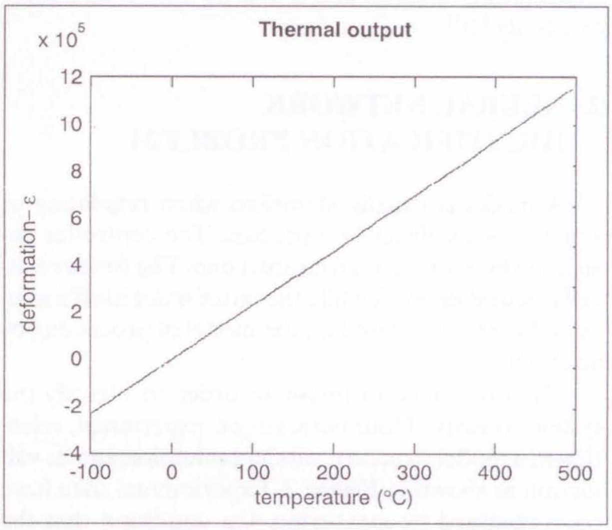

Figure 8 - Neural network input – thermal output of an actual product

and the voltage ratio (Figure 5) is expressed as:

$$\frac{E_0}{E}=\frac{F\varepsilon}{2+F\varepsilon} \tag{5}$$

However, with this configuration any kind of strain gauges thermal output is added and the temperature compensation is rather bad. Consequently, in the case of axial load the most commonly used configuration is that of a complete bridge (Figure 7 a, b).

For axial loads the most common configuration of a complete bridge is the one with the axial strain gauge and transversal strain gauge both on its upper and lower surfaces. The output is not only greater by the factor (1 + ν) in relation to the previous alternative with two strain gauges but it is also less non-linear (approximately [(1 - ν)/10] % per 1000 microstrains). This alternative has good temperature compensation. In this case the normal strain is calculated from (4) while the voltage ratio is expressed as [5]:

$$\frac{E_0}{E}=\frac{F\varepsilon(1+\nu)}{2+F\varepsilon(1-\nu)} \tag{6}$$

4. NEURAL NETWORK SIMULATION IN MATLAB AND THE RESULTS

As help in the computer correction of the thermal output the strain gauge manufactures ordinarily provide polynomials representing the thermal output curve for a particular manufactured series. The polynomial is expressed as:

$$\varepsilon_{T/0}=A_0+A_1T+A_2T^2+A_3T^3+A_4T^4 \tag{7}$$

MatLab with the toolboxes has been used in the simulation process. Two cases of coefficients for the A-alloy have been considered, while the temperature has been taken in degrees Celsius and then in degrees Fahrenheit. Instead of experimental data the following MatLab code has been taken for the number of the code which generates a curve corresponding to the manufacturer series A4BAF2B made by Micro-Measurements so that the code generates a curve corresponding to the manufacturer's specifications of a certain product [5, 10, 13].

For the design of the neural network NEWLIND function has been used. Its program code contains a part of net code = network (1, 1, 1, 1, 0, 1, 1) which in the MatLab syntax means that there is one network input, one network output, and one layer of neurones. All neurones are mutually connected and there is one pre-signal (see Figure 3.). The number of neurones is equal to the number of independent data which are processed.

% eps is not defined. The network must simulate it on the basis of the measurement

% results which are 100% simulated here

t = -100:0.5:500; % temperature range

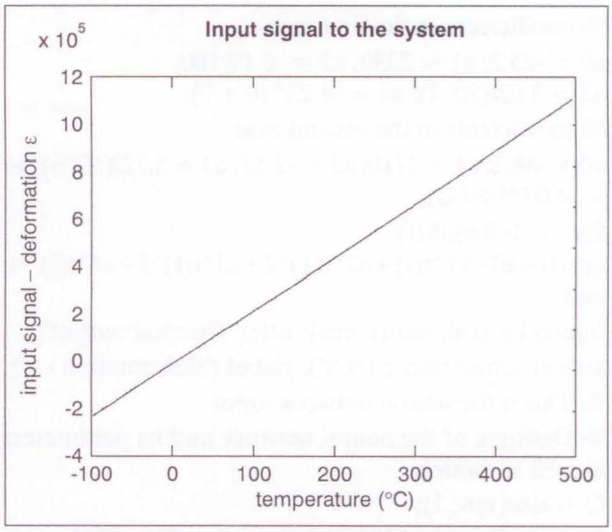

Figure 9 - Input signal to the system

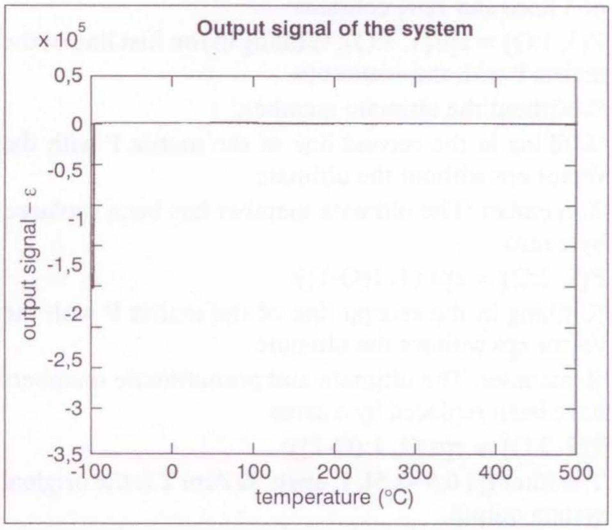

Figure 10 - Output signal of the system

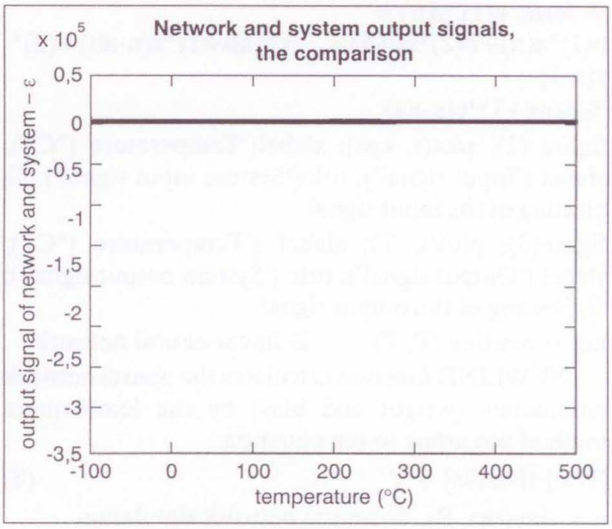

Figure 11 - Comparison of the network and system signals

```
% coefficients in the first case
a0 = -25.2; a1 = 2330; a2 = -6.19/100;
a3 = 3.62/(10^4); a4 = -4.23*10^(-7);
% coefficients in the second case
a0 = -88.2; a1 = 2710; a2 = -2.53; a3 = 6.72/(10^6); a4
= -4.03*10^(-8);
for i = 1: length(t);
eps(i)=a0+a1*t(i)+a2*t(1)^2+a3*t(i)^3+a4*t(i) ^4;
end;
figure(1); grid; plot(t, eps); title('Thermal output');
xlabel('temperature (°C)'); ylabel ('deformation - ε');
% This is the neural network input
% Defining of the neural network and its parameters
as well as models
Q = size(eps, 2);
% as size(eps) = 1201, it follows that Q = 1201
P = zeros (3, Q) % Initialization of a matrix composed
of 3 lines and 1201 columns
P(1, 1:Q) = eps(1, 1:Q); %filling in the first line of the
matrix P with the vector eps
% without the ultimate member.
% filling in the second line of the matrix P with the
vector eps without the ultimate
% member. The ultimate member has been replaced
by a zero
P(2, 2:Q) = eps (1, 1(Q-1));
% filling in the second line of the matrix P with the
vector eps without the ultimate
% member. The ultimate and prenultimate members
have been replaced by a zeros
P(3, 3:Q) = eps (1, 1:(Q-2));
T = filter ([1 0.5 –1.5], 1, eps); % Aim T is the original
system output.
% FILTER – This function implements the difference
equation ordinarily shown in
% form: a(1)*y(n) =
b(1)*x(n)+b(2)*x(n-1)+...+b(nb+1)*x(n-nb)-a(2)*
y(n-1)-...-
% a(na+1)*y(n-na)
figure (2); plot(t, eps); xlabel('Temperature (°C)');
ylabel ('Input signal'); title('System input signal'); %
plotting of the input signal
figure(3); plot(t, T); xlabel ('Temperature (°C)');
ylabel ('Output signal'); title ('System output signal');
% plotting of the output signal
net = newlind (P, T)        % linear neural network
```

NEWLIND function calculates the neural network parameters (weight and bias) by the least-square method according to the equation:

$$[W\, b]\cdot[P\ units] = T \tag{8}$$

```
a = sim (net, P); % neural network simulation
figure (4); hold on; plot(t, a, '-r'); plot(t, T, '.b');
xlabel('Temperature (°C)'); ylabel('Output signal of
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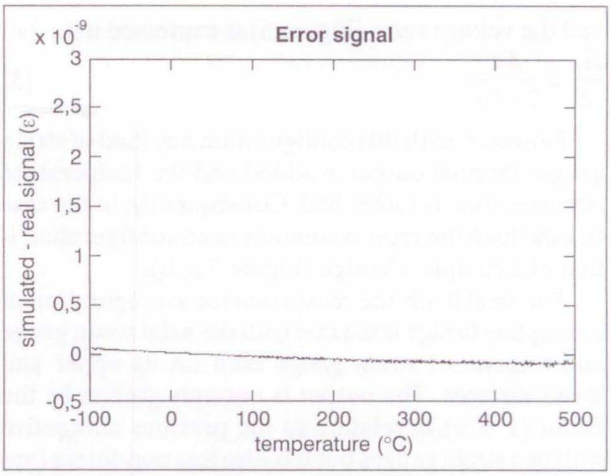

Figure 12 - Simulation results: simulated neural network error in relation to the actual product curve

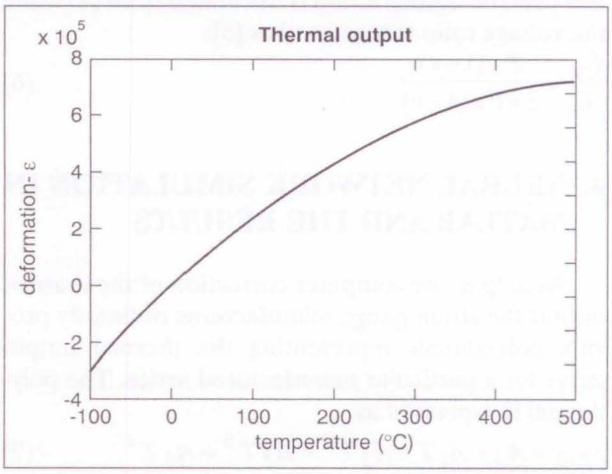

Figure 13 - Neural network input in the second case considered

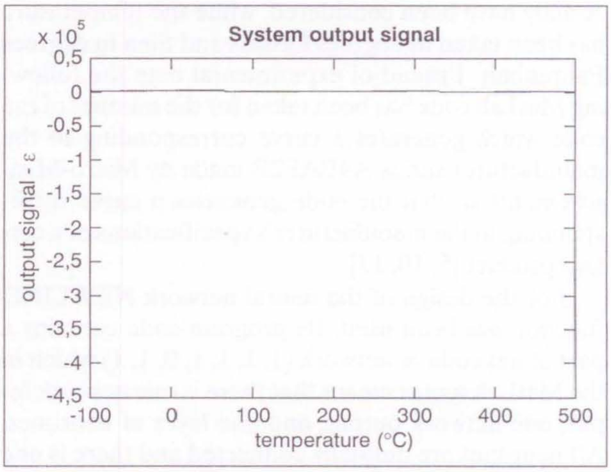

Figure 14 - System output signal

```
the network and system'); title ('Output signal of the
network and system, comparison');
e = T – a; figure (5); plot(t, e, [min(t) max(t)], [0 0],
'.r'); xlabel ('Temperature (°C)'); ylabel ('Error'); title
('Error signal');
```

In case other parameters are selected (see the beginning of the program code) in the equation (7), the results are shown in figures 13, 14, 15 and 16.

5. CONCLUSION

The voltage applied to the strain gauge bridge causes in each branch a loss of power which must be completely dissipated in the form of heat. Only an insignificant part of the input power is available at the circuit output. This causes the sensor grid of each strain gauge to function at a higher temperature than the basis to which it has been attached. The heat generated inside the strain gauge is to be brought to the surface onto which the gauge has been installed. The flow of heat through the pattern causes a rise in the temperature of the basis. The rise in temperature is the function of its heat capacity and the strain gauge power level. Consequently, strain gauge electrical resistance varies not only with deformation but also with temperature. Furthermore, the relationship itself between deformation and resistance alteration depends on temperature.

Once the installed strain gauge has been connected to the deformation indicator and the instrument has been balanced, later temperature changes of the installed strain gauge will in most cases bring about resistance changes. This resistance change caused by temperature is independent of mechanical deformation in the tested object to which a strain gauge has been connected. Its exclusive cause is temperature change and it is for this reason that it is called the strain gauge thermal output.

The paper demonstrates the polynomial simulation of a strain gauge thermal output. Neural network has been used with this aim for the first time. Thermal output is non-linear by nature whereas a linear neural network has been used in this case. This means that the problem has been linearised. Linearisation has been carried out with satisfactory precision if the error criterion is taken into consideration as the difference between production and simulation thermal output. This simulation has been carried out for one product and it does not mean that the same conclusions can be drawn for any other strain gauge. In each particular example, what has to be established is what the neural network is like and what parameters of the neural network correspond best. In a similar way, it is possible to construct an even more accurate linear or non-linear neural network for a given case. However, the more accurate a network, the more complicated it is, and in this case it has been demonstrated that it is unnecessary to construct more complicated models.

In the result, differences can be seen between the curves in degrees Celsius and in degrees Fahrenheit; however, they do not derive from the nature of the phenomenon, but from its mathematical formulation as polynomial coefficients are different.

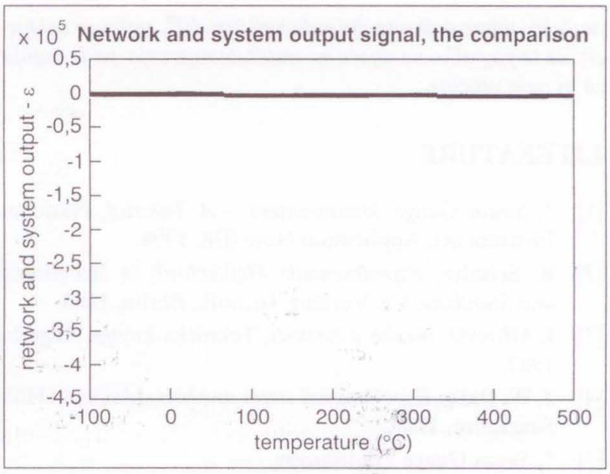

Figure 15 - Comparison of the network output and the given curve

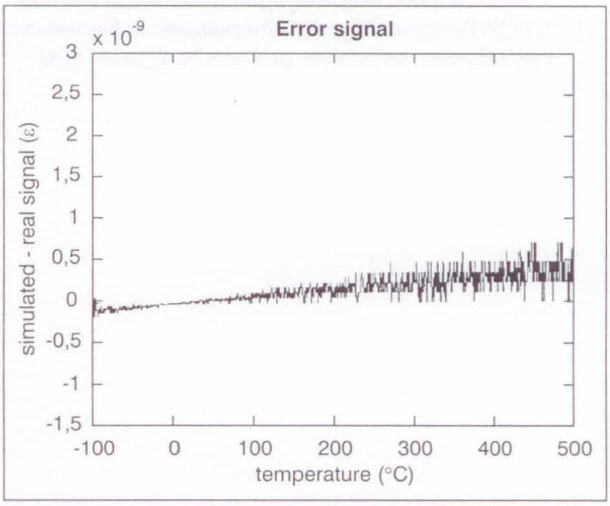

Figure 16 - Simulation result: simulated neural network error in relation to the actual product curve

IDENTIFIKACIJA POLINOMA TERMALNOG ODZIVA MJERNE TRAKE S NEURALNIM MREŽAMA KOD ODREĐIVANJA DEFORMACIJA

SAŽETAK

Mjerne trake imaju veliku primjenu u različitim područjima, naročito pri projektiranju i razvoju novih konstrukcija, te njihovom modelskom ispitivanju. Također, mjerne trake ulaze u sastav dijelova mnogih uređaja i instrumenata, gdje se najviše koriste kao osjetila u pretvornicima za električno mjerenje različitih mehaničkih veličina: sila, momenata, tlakova, ubrzanja, itd. Značajna je njihova primjena u brodogradnji i pomorskom transportu. U ovom članku predložen je i prikazan jedan pristup identifikaciji krivulje termičke karakteristike mjernih traka na primjeru konkretnog proizvoda dostupnog na tržištu. Primijenjena je neuronska mreža, koja je simulirana u MatLabu. Neuronska mreža se adaptirala tako da simulira pravi sustav s pogreškom reda veličine 10^{-9}. Kako mjerne trake

najčešće mjere deformacije reda veličine 10^{-6}, može se zaključiti da ta pogreška ne utječe na rezultate mjerenja, jer je manja za tri reda veličine.

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