

# PRESSURE FORCE SENSOR BASED ON ELASTOMAGNETIC PHENOMENA

DOC. ING. IRENA KOVÁČOVÁ, CSc.<sup>1</sup>  
PROF. ING. DOBROSLAV KOVÁČ, CSc.<sup>2</sup>

**Abstract:** The paper deals with a elastomagnetic sensor (EMS) of pressure force and neural network (NN) design in order to achieve linear output of such sensor.

**Keywords:** Elastomagnetic sensor, Villary's effect.

## 1 Introduction

Elastomagnetic sensors are becoming more widespread owing to their extensive use in industrial and civil automation. However, designing low-cost and accurate sensors still requires great theoretical and experimental efforts to materials engineers. But this task can be solved by advanced electronic techniques for automatic calibration, linearization and error compensation.

## 2 Basic properties of elastomagnetic sensor

The elastomagnetic sensor of a pressure force is utilizing the Villary's phenomena principle, which consists in the fact that if a ferromagnetic body is subjected to mechanical stress, its form is changed and consequently its permeability is changed too. Since the permeability determines the magnetic field in a ferromagnetic body, so also is changed the magnetic field and we could measure its changes by changes of the induced electric voltage. On the base of the above mentioned one can see that the pressductor can be described as a transformer in which the mutual inductance between the primary and secondary windings is changed proportionally to the acting stress or to the

<sup>1</sup> KEPM FEI TU Košice, Letná 9, 042 00 Košice, Slovak Republic, e-mail: Irena.Kovacova@tuke.sk

<sup>2</sup> KTEEM FEI TU Košice, Park Komenského 3, 042 00 Košice, Slovak Republic, e-mail: Dobroslav.Kovac@tuke.sk

pressure, but only in the case that magnetizing current  $I_m$  is constant. The elastomagnetic sensor equivalent electrical scheme is shown in Fig.1.

We can see that the described circuit is fully corresponding to the transformer in which the dependence between magnetic intensity and magnetic induction is given by nonlinear hysteresis curve.

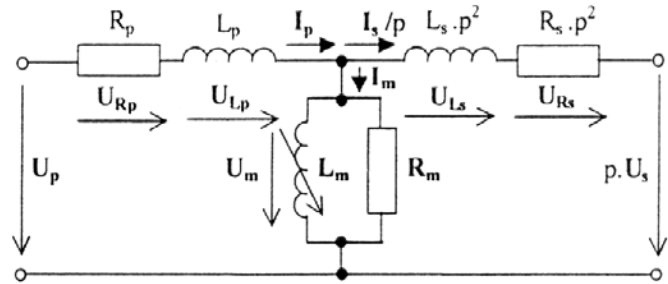


Fig.1 Elastomagnetic sensor equivalent electrical scheme

We can obtain the maximum useful signal if we will reduce output current  $I_s$  to the minimum and also if we will eliminate the influence of primary current  $I_p$  effective value instability. In this case the magnetizing voltage  $U_m$  is corresponding to the maximum output voltage  $U_s$  for given operating point which is depending on the primary current  $I_p$  value and the causing force. Such a way can be reduced the power of the feeding source.

### 3 An design of the feeding and evaluating circuits

The feeding circuit must be fulfilling basic condition which consists in the current feeding request, because only in this case the change of the output secondary voltage  $U_s$  will be represent the change of pressure force causing on the elastomagnetic sensor. An example of such feeding source realization is shown in Fig.2. Such a way is simply possible to secure realization of the harmonic constant current source by step down line voltage transformer with small output power. For second request fulfilling which is concerning to the secondary winding current  $I_s$  minimum value we must secure as high as possible input impedance of evaluating circuit. A simple and suitable output evaluating subcircuit can be realized by OA as it is shown in Fig.3.

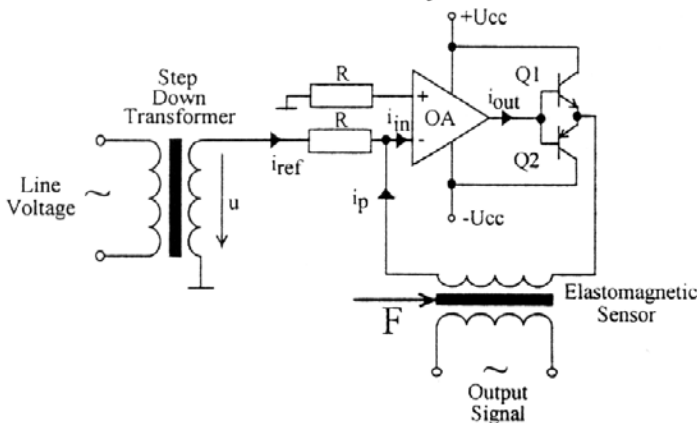


Fig.2 An example of the optimal feeding source

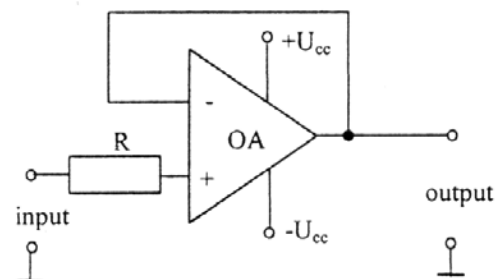


Fig.3 An example of output subcircuit connection with high impedance

## 4 Neural network design

The neural network (NN) is expected to eliminate transformer nonlinearity. However, NN output should be linear and expressed by equation of straight line. In order to achieve this aim, several NN models were designed. The difference between linear output and the real sensor output is shown in the Fig.4. The characteristics  $\Delta U_i$  is gained from output sensor voltage  $U_{2\uparrow} = f(F)$  (if force is increasing) and characteristics  $\Delta U_d$  is gained from  $U_{2\downarrow} = f(F)$  (if force is decreasing). The NN task is to reduce the deviation between  $U_{2\uparrow}$ ,  $U_{2\downarrow}$  and linear regression of sensor output. Finally, the characteristics  $\Delta U_i$ ; and  $\Delta U_d$  should approach zero line. The most common artificial neural network, called multilayer perceptron, was used for this purpose. Conception of NN is

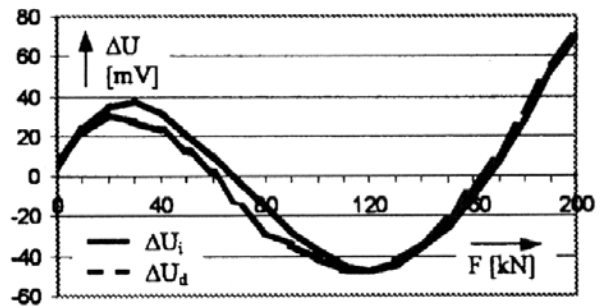


Fig.4 Differences between the linear and the real sensor outputs

shown in Fig.5. The sensor output is at the same time the NN input. However, in this proposal the two NN input neurons are used. The first one is directly connected to sensor via ADC converter and the second one is also connected, but with time delay. This connection should provide a smaller error of NN output characteristics when the force changes.

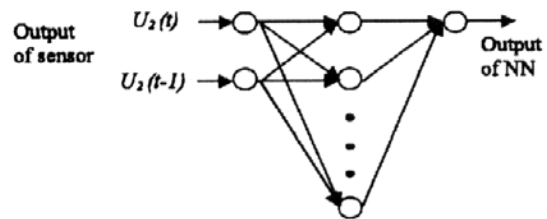


Fig.5 The conception of NN

## 5 Training process

The topology of NN consists of 10 neurons in hidden layer, which seems to be the most convenient according to computing speed and accuracy. There were 10 000 training cycles used. Like a learning algorithm the backpropagation was used and it offers an effective approach to the computation of the gradients. The learning parameter  $\eta$ , which specifies the step width of the gradient descent, was changed in the wide range (see Fig.6 and Fig.7). Here is the SSE (sum of square errors) dependence on training cycles. As we can see, the training process with higher learning parameter achieves smaller SSE at the constant number of training cycles. The training process was carried out in two parts. In the first part, the training patterns were presented to the NN one by one and in the second part, the training patterns were presented to the NN accidentally. The results of these processes can be seen in the Fig.6 and Fig.7.

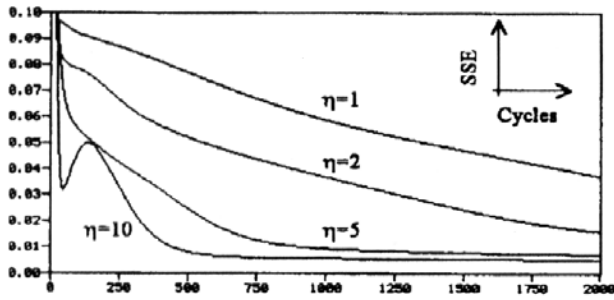


Fig.6 The training process - part one

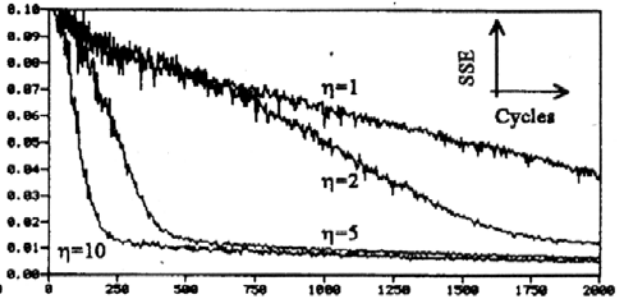


Fig.7 The training process - part two

## 6 Conclusion

The neural network simulator SNNS v4.1 was used for simulation of designed NN. The NN should have decreased the sensor error and its output should have been a linear function. Fig.8 shows the difference between tested data  $\Delta U_{\text{test}}$  and linear regression. The linearity error of sensor output was  $\delta_s = 4,34\%$  (for tested data  $\delta_s = 2,69\%$ ). The linearity error of NN output of designed model was  $\delta_{\text{NN}} = 1,25\%$  in comparison with a classical model were the linearity error was  $\delta_{\text{NN}} = 1,53\%$ . The finally, the designed model of error correction of elastomagnetic sensor by using NN achieves quantitatively lower linearity error in comparison with sensor output. Although the elastomagnetic sensors have some expressive advantages usually they don't achieve so metrological quality as resistance transducers. They are predetermined for hard field conditions and aggressive corroding media. Their output signal is even 1000 times greater as signal of resistance transducers and this fact enables to simplify feeding and data evaluation as it is described in this paper. Also they are less sensitive against extremist electromagnetic interferences. A general construction of these sensors can be realized with smaller costs and dimensions.

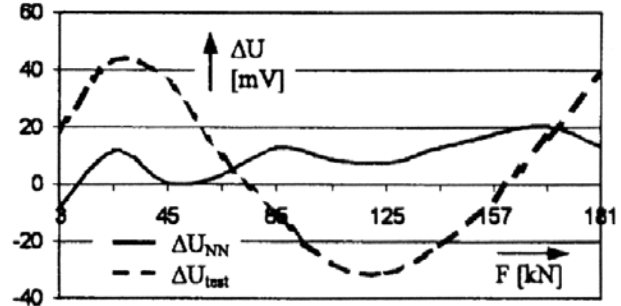


Fig.8 Differences between tested data, NN output and linear regression

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