Reduction of Elastomagnetic Sensor Errors by Using Neural Networks

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Abstract. *This article deals with possibilities of reduction of elastomagnetic sensor errors. Elastomagnetic sensors are used for measuring of massive pressure force (of range about 200 kN). At the same time with demands on sensor accuracy, a filter can be added to the measuring set. The function of this filter is to regulate the basic metrological characteristics of sensor in order to achieve the smallest deviation from an ideal transfer characteristic. The using of exactly defined algorithm of reducing sensor errors is not appropriate in this case. So, the unconventional solution is using of the neural networks.*

Keywords

Measurement, elastomagnetic sensor, neural network, non-linearity, hysteresis.

1. Introduction

In present, sensors have become an integral part of industry. They are the most important part of measuring sets because the total accuracy of a measurement is limited by a sensor. So the requirements for accuracy and reliability of sensors are getting higher. A sensor is a function component of an input block of a measuring set. A sensor is in direct connection with measured environment. A sensor as a primary source of information measures a physical, chemical or biological quantity and then according to a defined principle transforms it most frequently to electrical quantity.

Resistive tensometers are used for measuring distortion caused by tensile or pressure force very often. In present, elastomagnetic sensors have become very progressive for measuring the massive tensile or pressure force. The main advantages of elastomagnetic sensors are:

- high sensitivity (depending on sensor core material),
- sufficient output voltage and output power,
- very high reliability,
- mechanical toughness,
- ability of multiple force overloading,
- time-invariant properties (compared to resistive tensometers),
- simple construction,
- low cost.

The great disadvantage of these sensors is obtaining the correct expression of measured force values from input data with commonly used programmatic resources. Therefore the proposed solution is based on using feed-forward neural networks, which are able to solve the problems whose analysis is too complicated. Improvement of total accuracy of measuring system and reducing of elastomagnetic sensor errors are expected, too. The theoretical considerations are verified by experimental results.

2. Elastomagnetic Sensor

2.1 A Principle of Elastomagnetic Sensors

It is based on the existence of elastomagnetic (Villari) effect. It appears in a ferromagnetic material as follows: if an external force affects a ferromagnetic material, it is deformed. Consequently, relative distances of atoms in a crystal structure are changed. It causes a change of exchange forces, which activate spontaneous magnetization in domains of ferromagnetic material. This fact occurs as a magnetic polarization change or magnetic induction at the identical intensity of magnetic field acting on ferromagnetic material. If this material was isotropic before acting force, it becomes anisotropic. If it was anisotropic then the anisotropy of material is changed. The magnetic properties are represented by permeability and will be changed in accordance with an acting force [1].

Dependency of permeability change $\Delta\mu'$ on mechanical tension σ is described by the next relation obtained from thermodynamic equilibrium in ferromagnetic material:

$$\Delta\mu' = \frac{2\lambda_{ms}\mu^2}{B_{sef}^2} \cdot \sigma = k_M \cdot \sigma \qquad (1)$$

where λ_{ms} is a mean value of magnetostrictive coefficient in saturation, μ is a value of permeability when acting force is equal to zero, B_{sef} is an effective magnetic induction in saturation in harmonic magnetic field, k_M is a material coefficient. The relation is valid, if the direction of mechanical tension and the intensity of magnetic field are parallel [2].

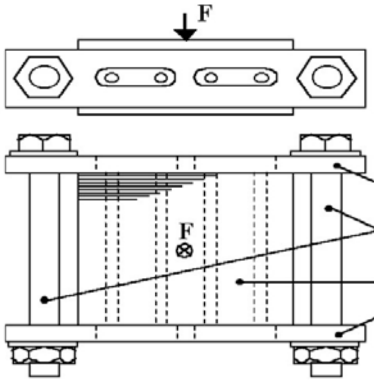


Fig. 1. The sketch of elastomagnetic sensor EMS-200kN, 1 – sheets, 2 – flanges, 3 – screws.

The next relation is valid for elastomagnetic sensor (Fig. 1), which is connected like a transformer (N_1 is a number of primary coils and N_2 is a number of secondary coils):

$$U_{2p} = \omega \cdot N_2 \cdot \Phi = 2\pi f \cdot N_2 \cdot \frac{N_1 \cdot I_1 \cdot S}{l_m} \cdot \mu \qquad (2)$$

where f is a frequency of an effective supply current I_1, S is a cross-sectional area of magnetic flux Φ (Fig. 2).

The output voltage depends on permeability change $\Delta\mu$ ($\Delta\mu = k_i \cdot \Delta\mu'$, where k_i is an interaction coefficient between a field of mechanical tension and a magnetic field):

$$\Delta U_{2p} = 2\pi f \cdot N_2 \cdot \frac{N_1 \cdot I_1 \cdot (r_2 - r_1)h}{l_m} \cdot \Delta\mu \qquad (3)$$

where r_1 is a semi-diameter of a winding hole, r_2 is a semi-diameter of an inscribed circle to the square part of a sheet element, and h is the thickness of a sheet element, then $S=(r_2-r_1)h$. So, l_m is a mean length of a magnetic line (see Fig. 2).

The output voltage of a sensor (composed of four elementary sensors) is approximately equal to:

$$\Delta U_2 = 4 \cdot \Delta U_{2p} =$$
$$= 4 \cdot 2\pi f N_2 \cdot \frac{N_1 I_1 (r_2 - r_1)h}{2\pi \dfrac{r_2 - r_1}{\log \dfrac{r_2}{r_1}}} \cdot \frac{2}{\pi} \cdot \frac{2\lambda_{ms}\mu^2}{B_{sef}^2} \cdot \frac{1}{2r_2 h} \cdot F =$$
$$= \frac{8 f N_2 N_1 I_1 \lambda_{ms} \mu^2}{B_{sef}^2 \pi r_2} \cdot \log \frac{r_2}{r_1} \cdot F \qquad (4)$$

So, if the effective supply current I_1 has a constant value and a frequency f, the effective output voltage is proportional to acting force.

The next simplifications lead to an inaccuracy of the final relation (4). The substitution of non-homogeneous magnetic field by homogeneous circle magnetic field causes an inaccuracy of this expression (non-homogeneous magnetic field is caused by deformity in edges of material of square type). The inaccuracy is caused by the substitution of non-homogeneous mechanical tension field by the homogeneous one, by ignoring of mechanical tension concentration around a winding hole, by ignoring of ferromagnetic plates of contacts, which transmit pressure to sensor, by ignoring defects of supply power (I_1 is not constant, it is changed by changing of sensor impedance). A marked measurable difference in result can be caused by the small differences in values B, μ (different places in ferromagnetic rolled-section).

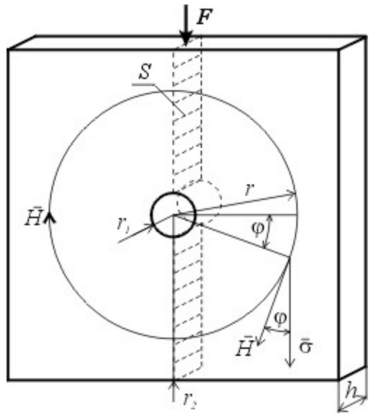


Fig. 2. The detail of a sheet element of an elastomagnetic sensor.

The practical manufacturing of elastomagnetic sensor EMS-200kN is shown in Fig. 3. The sensor core is made of 105 sheets. (the weight of sensor core is 560 g and the size is 56x56x23 mm). The sheets are glued on each other and screwed together. The number of primary and secondary turns is 5 and these parallel windings are placed in four holes.

Fig. 3. Elastomagnetic sensor EMS-200kN.

2.2 Measuring Apparatus

The measuring apparatus was set in order to achieve the metrology characteristics. It consists of a power supply (G), an amplifier (▷), a digital voltmeter (V), a variable loading resistor (R) and an elastomagnetic sensor (S) – in Fig. 4. The measured force (F) was produced by a hydraulic press (400 kN). In accordance with IEC 61 298-2 standard [7], the transfer characteristic was achieved by using the apparatus. The optimal working parameters for sensor EMS-200kN were – an effective supply current 0,7 A, a frequency 400 Hz and a temperature 23°C [3]. Sensor output effective span (the difference between the output voltage of the unloaded sensor and the output voltage of the loaded sensor by acting nominal force 200 kN) was approximately 60 % of the effective voltage of the unloaded sensor.

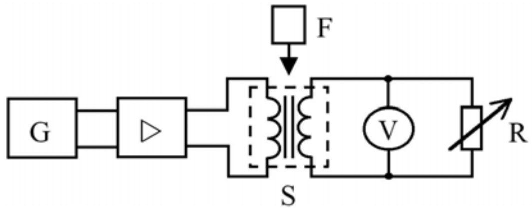


Fig. 4. The measuring apparatus.

The measured dependences of the output voltage on the acting force *U*$_{2\uparrow}$=*f(F)* (if the force was increasing from 0 kN to 200 kN – characteristic upward) and *U*$_{2\downarrow}$=*f(F)* (if the force was decreasing from 200 kN to 0 kN – characteristic downward) are shown in Fig. 5.

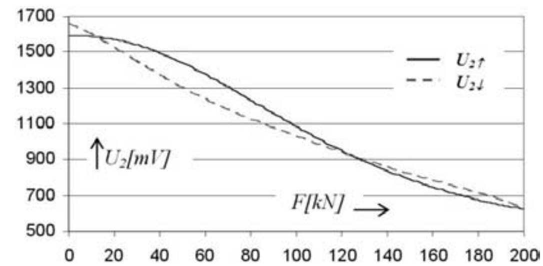


Fig. 5. The measured dependence of the output voltage *U*$_{2\uparrow}$=*f(F)* and *U*$_{2\downarrow}$=*f(F)*.

As we can see, the transfer characteristic is non-linear and its curvature depends on the hysteresis error. There are two problems:

- finding of the ideal transfer characteristic according to the best conversion of the output sensor voltage to the measured force,
- reduction of sensor errors.

For that purpose, the linear line was computed from the gained sets of measurements (characteristics upward and downward) by the least square method. It was the ideal transfer characteristic for this case.

2.3 Errors of EMS-200kN

IEC 60 770 standard [8] defines the error of transfer characteristic as a difference between a measured quantity and a corresponding ideal output value. Generally, percentage error is expressed according to a span of an ideal output and it is defined:

$$e = \left(\frac{y_{measured} - y_{ideal}}{y_{\max} - y_{\min}} \right) \cdot 100\% \cdot \qquad (5)$$

The positive error means that the measured value of a sensor output is bigger than the ideal output value (Fig. 6).

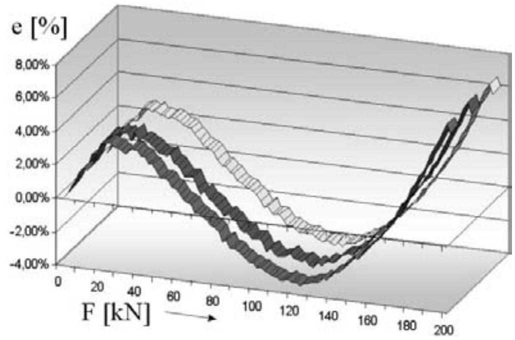


Fig. 6. Transfer characteristic errors of individual measurements.

Non-linearity (6) is defined as the maximum difference between the average characteristic y_{mean} (from measured characteristics) and the specific characteristic (the linear line). The linear line $y_{lin}=K_0+K_1.x$ is calculated by the least square method. This case is called independent non-linearity.

$$\delta_{lin} = \left(\frac{y_{mean} - y_{lin}}{y_{\max} - y_{\min}} \right)_{\max} \cdot 100\% \cdot \qquad (6)$$

Hysteresis error (Fig. 7) causes that sensor output values *y* are different for identical input values *x* (according to increasing or decreasing input quantity). Basically, the relation (7) can define the hysteresis error:

$$\delta_{hys} = \left(\frac{y_{\uparrow} - y_{\downarrow}}{y_{\max} - y_{\min}} \right)_{\max} \cdot 100\% \cdot \qquad (7)$$

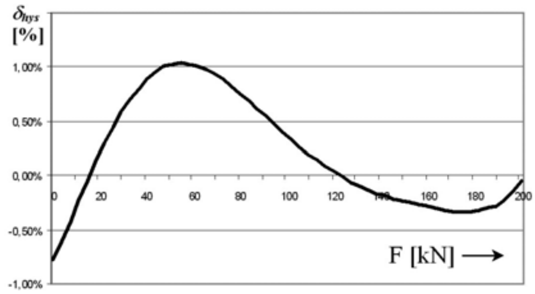


Fig. 7. The characteristic of hysteresis error.

IEC 60 770 standard defines also other errors like inaccuracy, measured error and non-repeatability, etc.

3. An Introduction to Neural Networks

Neural network (NN) is a form of multiprocessor computer system with simple processing elements, a high degree of interconnection and adaptive interaction between elements. In present, artificial NNs are used esp. as adaptive signal processors (hardware implementation) for real time robotics applications or as models of data analysis methods.

Neural networks (NN) analogous to statistical models work with large amount of data, NN solve problems of approximation functions, prediction problems, linear and non-linear regression and data classification. The advantages of neural networks are learning from examples, input-output data mapping, adaptability to changing conditions of environment, and error resistance.

In 1987, Hecht-Nielsen [4] showed that three-layer feed-forward neural networks with sufficient number of neurons in hidden layer are able to approximate every continuous mapping at required accuracy. This universal approximation theorem is fully completed in [5]. It gives a mathematical verification about approximation of arbitrary continuous function.

The problem of neural network with one hidden layer consists of global interaction of neurons. Improvement of approximation in some point causes approximation degradation in other point. In accordance with approximation, the neural network with two hidden layer can be better, because the local attributes are extracted in the first hidden layer – some neurons of the first hidden layer divide input area to the sub areas and other neurons of this layer learn the local attributes of these sub areas, and the global attributes are extracted in the second hidden layer – the neurons of this layer combine the outputs of the first layer neurons and learn global attributes of sub areas, the second layer neurons are passive outside of this sub areas [6].

The ability of modeling multi-dimensional non-linear relationships can be considered as the most important advantage of NN. Neural models excel in simplicity and fastness. On the basis of available data, NN can learn and generalize no matter the component formula does not exist.

4. Experiments

For the purpose of error reduction of elastomagnetic sensors, two different proposals can be designed:

- The neural network is trained to regulate properly the sensor transfer characteristic (input and output of NN are data of the same type) and the conversion of the output sensor voltage to the measured force is done mathematically
- The neural network is directly trained to conversion of the output sensor voltage to the measured force, so input (output sensor voltage) and output (measured force) of NN are data of different type, in Fig. 8.

The neural network proposal consists of a proper topology selection, a specification of a number of layers (mainly hidden) and a number of neurons, a selection of a learning algorithm and a setting of proper learning parameters. The neural network works in two phases. In the learning phase synaptic weights are changed by learning algorithm. The weight change rule is developed from the perceptron learning rule. Weights are changed by an amount proportional to the error at which unit times the output of the unit feeding into the weight. In the phase of life, the synaptic weights are not changed; NN is prepared to provide outputs for unknown input patterns.

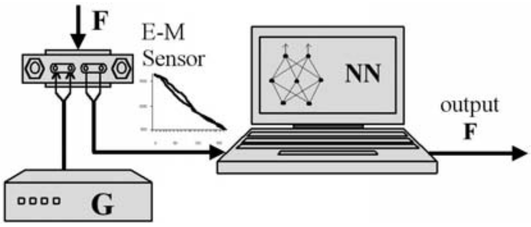
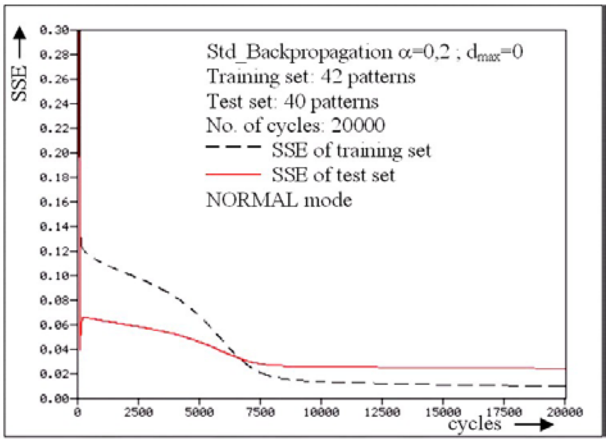
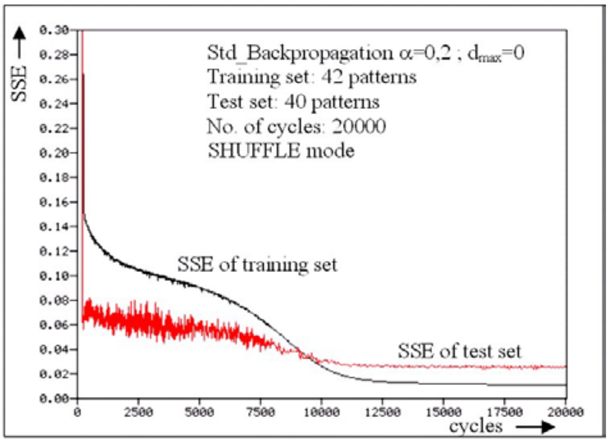


Fig. 8. The proposed solution of error reduction of EMS-200kN.

The success of the life phase is conditioned by selection of a training data set and a validation of a data set during the learning phase. Minimal (but optimal) neural network topology is also very important. The advantages of minimal topology are less difficult hardware implementation, better computing rate and lower price.



a)

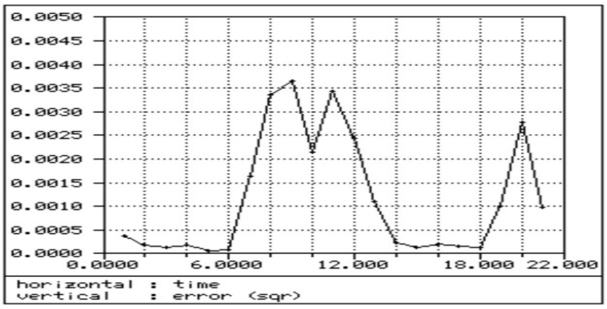


b)

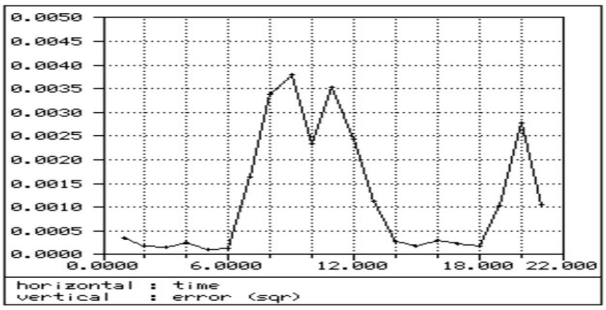
Fig. 9. Learning processes - a) gradually presented training patterns, b) accidentally presented training patterns.

The measured sensor values were divided into training and test sets. The neural network described above was created in simulation program SNNSv4.2 (Stuttgart Neural Network Simulator) [9]. The learning algorithm Std_Backpropagation was used with parameters α=0,2 (learning parameter specifies the step width of the gradient descent) and d_{max}=0 (the maximum difference between a teaching value and a unit output which is tolerated). The weights were adjusted by basic backpropagation algorithm in the steepest descent direction. Topological_Order was used as an update function. Randomize_Weights initialization function set up all weights and the bias with distributed random values. The values were chosen from the interval <-1; 1>. The number of neurons in hidden layers was changed. Act_Logistic was used as an activation function and Out_Identity was used as an output function of the units. The final minimal topology consisted of two hidden layers with five neurons in each of them.

The NN was trained by ordered set consisting of measured sensor data (Normal mode). In the second case, the measured sensor data were presented to the NN accidentally (Shuffle mode). Two different learning processes (Normal and Shuffle mode) are shown in Fig. 9, but after a finite number of training cycles, the sum square error (SSE) of both processes was approximately the same. The increasing of training cycles decreased the SSE error of training set, so the NN respond to known data was better. However, the NN respond to untrained data was worse – over-trained NN, in this case neural network memorized the patterns rather than generalized well. The Fig. 9 also shows the convergence of learning processes error (for training and validation set) towards certain values. The SSE error of training set was 0.01033 and SSE of validation set was 0.02441 for Normal mode. The SSE error of training set was 0.01045 and SSE of validation set was 0.02508 for Shuffle mode.



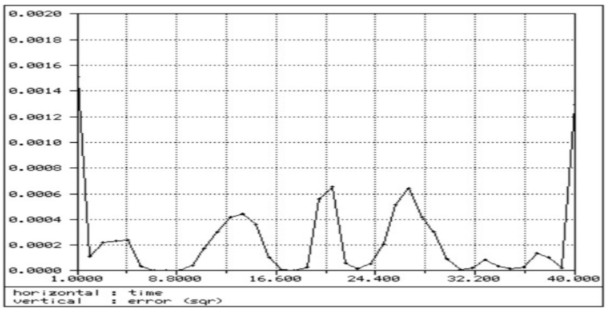
a)



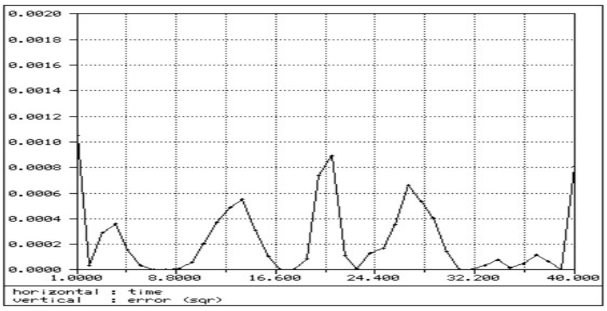
b)

Fig. 10. Error of validation data after learning of NN - a) gradually presented training patterns, b) accidentally presented training patterns.

The error $sqr=(t_i - o_i)^2$ of validation set (t_i – are targets of NN and o_i – are outputs of NN in validation process) is shown in Fig. 10. The patterns were gradually (Fig. 10a) or accidentally (Fig. 10b) presented in learning process. However *sqr* error of validation data was almost the same in both cases. To summarize, the feed-forward neural networks present almost the same results for time invariant input data. These results are independent from presented training patterns (gradually vs. accidentally).



a)



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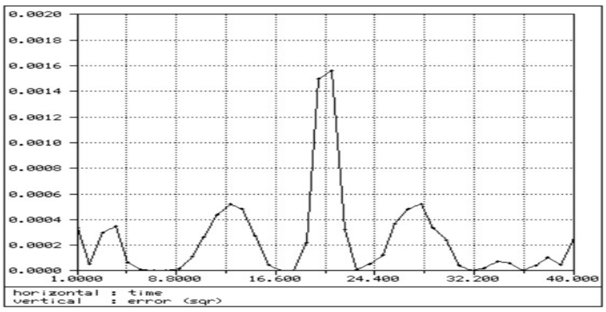

c)

Fig. 11. The *sqr* error process for three different testing sets.

A neural network reaction was similar for test data in the phase of life. The testing was done with three testing sets. Although the *sqr* error processes of individual test sets were different (Fig. 11), the SSE error of presented test sets was approximately the same (SSE error of the first test data was 0.01077, the second test data 0.01057, the third test data 0.01045). It means that a decreasing of error in some point causes an increasing of error in another point. However, from global point of view, there are not any significant changes. A comparison of errors according to IEC 770 standard is shown in Tab. 1. These errors correspond with measurements of pressure force without neural network model and measurements with NN model.

	Without NN model	With NN model
Inaccuracy	<-5,20 %; 6,97 %>	<-3,95 %; 3,89 %>
Measured error	6,67 %	3,16 %
Non-linearity	**6,67 %**	**3,07 %**
Hysteresis	**1,30 %**	**1,21 %**
Non-repeatability	1,60 %	2,05 %

Tab. 1. The comparison of errors according to IEC 60 770.

The reduction of non-linearity error by neural network model is more than half. It is due to learning process, when targets of training set were data corresponding to measured force and it was a linear change. The neural network improved the hysteresis error from 1,30 % to 1,21 %. In this case the neural network model showed a good ability to extract properties of input data and transfer them to output.

5. Conclusion

It is very difficult to obtain the correct expression of elastomagnetic sensor output in measured force by means of commonly used programmatic resources. Neural networks can do some things, which would otherwise be very difficult. In particular, they can form a model of their training data, which stand for output sensor data, or data from a complex manufacturing process. NN can form a model of an unknown algorithm, or algorithm with many variables (it is easier to let the network learn from examples). The problem of neural network is not only regression analysis of transfer characteristic regarding to training set and recomputation of values into a measured force, but also extrapolation of values out of training set (problem of generalization).

The proposed solution is based on successful using of feed-forward neural networks. Advantages of neural networks led to the error reduction of elastomagnetic sensor. By using of proposed feed-forward neural network, the non-linearity error was reduced from 6,67 % to 3,07 % and hysteresis error from 1,30 % to 1,21 %.

To summarize, feed-forward neural networks are able to compensate error of the elastomagnetic pressure force sensor EMS-200kN. The great addition of this proposal is the computation of output sensor voltage into measured force compared to computation by formula (where accuracy of result can not be guaranteed). Not a small advantage of neural networks is the great speed of hardware implementation (NN with minimal topology), it is especially important when real time applications are required.

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