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COMMUNICATIONS

# SELECTED TYPES OF NEURAL NETWORKS FOR MAGNETOELASTIC SENSOR ERROR SUPPRESSION

**Jozef Vojtko** *

Magnetoelastic sensors belong to non-linear systems with hysteresis. These sensors used in measurement are prone to errors due to their material properties. The sensor errors can be suppressed by means of conventional or unconventional techniques - neural networks. The paper brings out the results of magnetoelastic sensors errors suppression by using selected types of neural networks.

K e y w o r d s: measurement, magnetoelastic sensor, neural network, non-linearity, hyteresis

## 1 INTRODUCTION

The main advantage of magnetoelastic sensors in comparison with the classic wire ones or semiconductor ones is their marked sensitivity and higher resistance to environmental moisture. These properties predestinate them for use in civil engineering and geo-technological applications [2]. Magnetoelastic sensors of pressure force are currently based on the change of core permeability caused by mechanical stress, while altering its magnetization. The sensor works as a transformer with a variable coefficient of transformation. Under the action of an external force the output voltage changes. Some shortcomings of magnetoelastic sensors are higher power consumption, noticeable sensor errors, *eg*hysteresis and nonlinearity [6].

At present, the requirements for accuracy and reliability of sensor measuring systems are getting higher. The total accuracy of standard measuring system can be significantly improved by adding a data conditioning block. The aim of the paper is to present selected types of neural networks as an effective tool for errors suppression.

## 2 MAGNETOELASTIC SENSOR EMS–120KN

The pressure force sensor EMS-120 kN is an input block of a measuring system, Fig. 1. One of criteria of sensor applicability are its errors. The standard IEC 60 770 [3] defines inaccuracy $\delta_{ina}$, measured error $\delta_{me}$, repeatability $\delta_{rep}$, hysteresis $\delta_{hys}$, linearity error $\delta_{lin}$ and process of measurement evaluation. Sensor errors presented in Fig. 1 are computed in compliance with the standard.

The output sensor characteristic is depicted in Fig. 2. It consists of $U_{2\uparrow}$ (if force $F$ increases from 0 kN to 120 kN) and $U_{2\downarrow}$ (if force $F$ decreases from 120 kN to 0 kN). In order to enable conversion of the output sensor voltage into the measured force, a straight line ($U_{2lin} = -6.0726\,F + 1658.21$) is calculated by the least square method.

Then the transfer characteristic is obtained

$$F = \frac{U_2 - 1658.21}{6.0726} \quad \text{(kN, mV)} \tag{1}$$

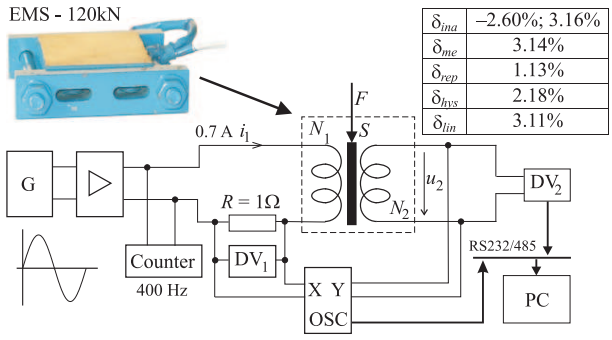


**Fig. 1.** Measuring apparatus connection with magnetoelastic pressure force sensor EMS-120 kN; generator (G), amplifier (w), pressure sensor (S), resistance $R = 1\Omega$, digital voltmeters (DV1 and DV2), oscilloscope (OSC), computer (PC), acting force (F)

The dependence of minimal differences ($ZO_{min}$) and dependence of maximal differences ($ZO_{max}$) from the input quantity are depicted in Fig. 3. The difference between the output average characteristic and the straight line (calculated by the least square method) is labeled as $ZPL$. These characteristics are reported as a percentage of the ideal output span.

Inaccuracy can be determined as the maximum of characteristic $ZO_{max}$ and minimum of $ZO_{min}$ . Similarly, the linearity error can be determined as the maximum of characteristic $ZPL$. This nonstandard representation by metrological characteristics ($ZO_{min}$, $ZO_{max}$ and $ZPL$) is closely associated with uncertainty of measurement. The characteristics are more suitable for errors representation and comparison of neural networks types.

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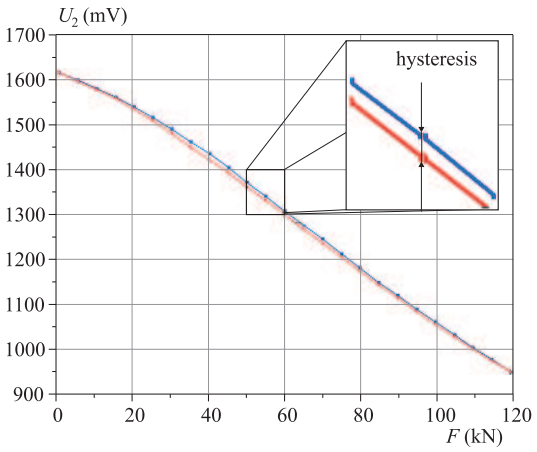


**Fig. 2.** Output sensor characteristic

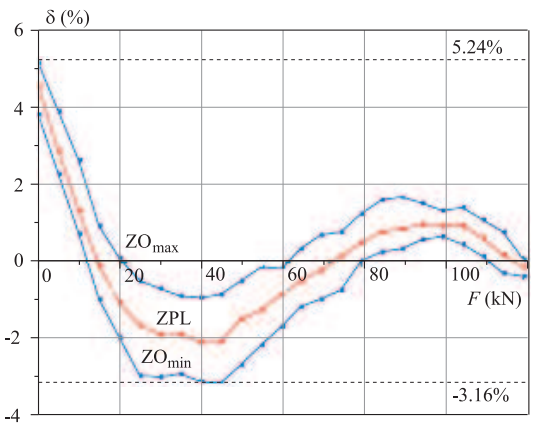


**Fig. 3.** Sensor error characteristics $\delta = f(F)$

## 3 SELECTED TYPES OF NEURAL NETWORKS

An original solution usable for error suppression is described in the work [5], which concentrates on hysteresis modelling. A multi-layer perceptron and radial basis functions are used for error reduction of experimentally modeled sensors in [1]. However, hysteresis is not taken into consideration. In these works only feedforward neural networks are presented. We suppose that the performance of recurrent neural networks can improve, especially when hysteresis is suppressed.

We deal with the following types of neural networks:

- Feedforward neural networks (FFNN),
- - RBF neural networks (RBF),
- - Time delay neural network (TDNN),
- - Elman neural networks (ELM).

The research is focused on finding the network, which suppresses errors most efficiently. There is no general rule yet, how to design a good neural network model, but there are a lot of possibilities from experimental methods.

The design of the neural network (NN) is made in MATLAB7, Neural Network Toolbox 4.0, PC AMD Athlon 1200, RAM 512 MB and operating system Windows XP. To obtain the best possible neural network model we experimented with the parameters like the number of training epochs, type of training algorithm (gradient descent backpropagation GD, GDM, GDA, GDX, quasi-Newton BFG, OSS, Levenberg-Marquardt backpropagation LM, resilient backpropagation RP, scaled conjugate gradient SCG) and the number of neurons in the hidden layer. Our experiments showed that LM algorithm had the fastest convergence for function approximation problems and for networks containing up to hundred weights. This advantage is especially noticeable if a very accurate training is required. The LM uses an adaptive learning rate.

Performance is measured according to the specified network performance function MSE, which returns the mean squared error.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)^2$$

where $N$ is number the of training data, $y_i$ is the output of neural network, $t_i$ is the target. The MSE versus training epochs is shown in Fig. 4.

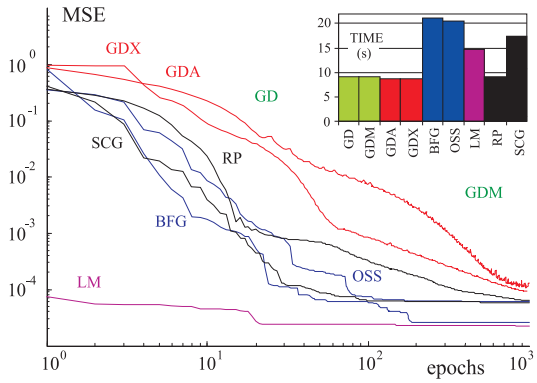


**Fig. 4.** MSE processes of training algorithms

The number of neurons in the hidden layer of individual neuron networks types is stated by analysis in a wide range. Some conclusions related to the problem are noticed:

- - FFNNs with more than one hidden layer are not more successful in error suppression,
- - neural network works as a look-up table if the hidden layer consists of many neurons, the network is unable to generalize input data,
- - TDNN with multiple time delay in input loses approximation capability, similar to ELM with more context neurons.
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All the types of neural networks reach the best results at certain specific parameters. For example, RBF reaches the best results at the spread constant $\sigma = 0.6$. Parameter $D = 2$ is the optimal input delay for TDNN. 1000 training epochs for all the types were sufficient for convergence of all the neural networks types. The number of neurons in the hidden layer for considered types is stated in Tab. 1. NN design is described in more details in [7].

## 4 EXPERIMENTS

After this analysis, three test sets were used for errors determination of measuring systems with NN. All experiments were made in accordance with standard IEC 61 298, [4]. The errors of the measuring system are computed by [3]. The results are reported in Tab. 1.

**Table 1.** Experimental results

| | FFN | RBF | TDNN | ELM | MOD |
|---|---|---|---|---|---|
| No.* | 6 | 7 | 6 | 4 | 5** |
| $\delta_{ina}$ | –1.25 | –1.34 | –1.12 | –1.34 | –0.97 |
| $\delta_{me}$ | +1.27 | +1.37 | +1.03 | +0.97 | +0.74 |
| $\delta_{rep}$ | +1.01 | +1.07 | +0.68 | +0.78 | +0.41 |
| $\delta_{hys}$ | +1.63 | +1.65 | +1.70 | +1.74 | +1.68 |
| $\delta_{lin}$ | +2.11 | +2.05 | +1.28 | +1.40 | +0.56 |
| $\delta_{lin}$ | +0.24 | +0.25 | +0.33 | +0.36 | +0.22 |

Comparison of the measuring systems with the neural network leads to the following conclusions:

- - topology on NN (number of neurons in hidden layer) has the biggest influence on sensor errors suppression,
- - all measuring systems with any NN can suppress sensor errors ($\delta_{ina}$, $\delta_{me}$, $\delta_{lin}$),
- - any NN system can not suppress random error represented by $\delta_{rep}$,
- - only NN systems with feedback (ELM) or with time delay of input patterns (TDNN) can suppress hysteresis $\delta_{hys}$, feedforward NN (FFNN and RBF) are not able to reduce the hysteresis,
- - simplicity and design speed are advantages of FFNN and RBF,
- - higher implementation complexity is a disadvantage of TDNN and ELM, ELM networks due to feedback are prone to instability. From this point of view, design of these systems is more complicated.

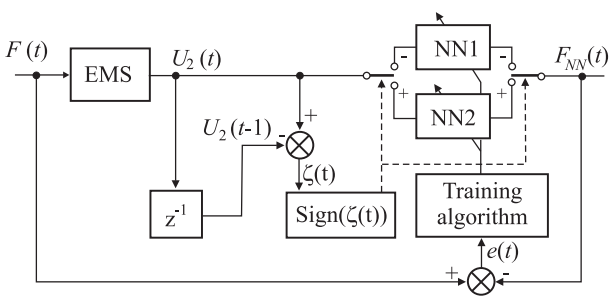


**Fig. 5.** Modular neural network measuring system for errors suppression of magnetoelastic sensor (EMS)

For further errors suppression, let us try to utilize the natural material property of magnetoelastic sensor - hysteresis. We presented a new solution which consists of two feedforward NN modules (NN1 and NN2) combined into a single system - modular neural network system (MOD), see (Fig. 5). If we used recurrent NN as modules NN1 and NN2, MOD system did not provide such good results. Our proposal uses advantages of feedforward and recurrent NNs.

Parameter $\zeta$ determines the module of the system that will be used.

$$\varsigma(t) = U_2(t) - U_2(t-1)$$

NN1 is activated if $\zeta < 0$ and NN2 if $\zeta > 0$. The output of the model remains unchanged if $\zeta = 0$. It is described in the next relation

$$F_{NN}(t) = \begin{cases} sim(\mathrm{NN1}, U_2(t)) & - \text{ if } \varsigma(t) < 0 \\ sim(\mathrm{NN2}, U_2(t)) & - \text{ if } \varsigma(t) > 0 \\ F_{NN}(t-1) & - \text{ if } \varsigma(t) = 0 \end{cases}$$

Similar to previous cases, the number of neurons in hidden layers was stated, 5 neurons in both modules NN1 and NN2. In the same way, three test sets were used for errors determination of the MOD measuring system. The results of error suppression are reported in Tab. 1, column MOD.

Suppression of selected errors by means of neural networks (FFNN, RBF, TDNN, ELM, MOD) and comparison with standard error determination algorithm (without neural network, labeled as EMS) is shown in Fig. 6.

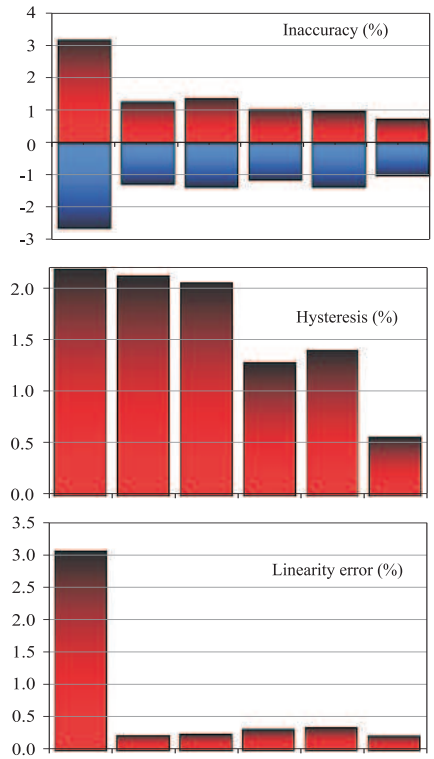


**Fig. 6.** Errors suppression by means of selected types of neural networks

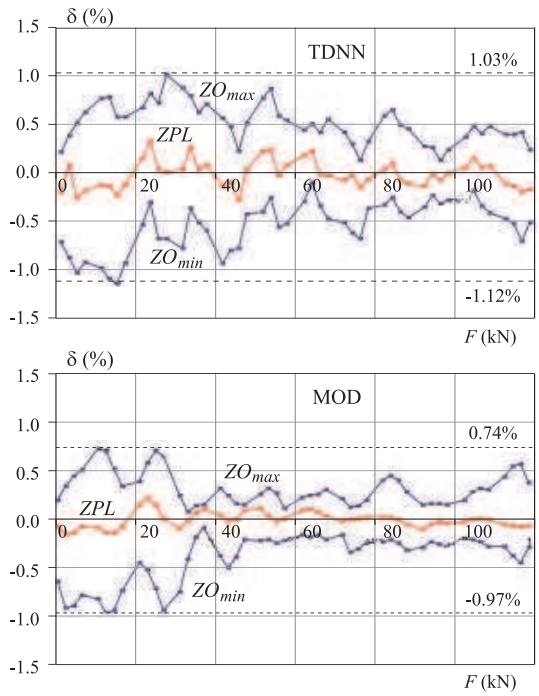


**Fig. 7.** Metrological characteristics of measuring systems with TDNN and MOD

Metrological characteristics ($ZO_{min}$, $ZO_{max}$, $ZPL$) of measuring systems with TDNN and MOD are shown in Fig. 7. Utilization of these systems for error suppression is noticeable in comparison with Fig. 3 (system without NN).

## 5 CONCLUSIONS

The paper brings comparison of selected neural networks types for magnetoelastic sensor errors suppression. In addition, a new approach to error suppression by using modular neural networks is presented.

Implementation of modular neural networks into a measuring set solves the problem with conversion of output sensor voltage into measured force and suppresses errors; inaccuracy - from (-2.60%; 3.16%) to (-0.97%; 0.74%), linearity error - from 4.63% to 0.22%, hysteresis - from 2.18% to 0.56%.

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