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Analytical and Neural Correctors of Temperature Sensors Dynamic Errors

1. Introduction

Dynamic temperature measurements play an important role in many industrial processes. Temperature sensors working in harsh environmental conditions usually have poor dynamic properties and their application is limited to measurements of slow temperature changes. Correction of the sensor dynamics is essential for improving the accuracy of dynamic temperature measurements, as well as optimizing temperature control.

Methods of temperature sensor dynamic errors correction based on analytical sensor model and on (ANN – *Artificial Neural Networks*) are proposed and discussed in this paper.

2. Dynamic models of temperature sensors

For small temperature ranges and constant sensor working conditions a simplified linear and lumped parameter model of a temperature sensor given by the operator transfer function (1) is used in practice [6].

$$G_T(s) = \frac{\Theta_T(s)}{\Theta_O(s)} = \frac{1}{\prod_{i=1}^{n}(1+sN_i)} \tag{1}$$

where:

- $\Theta_O(s)$ – Laplace transform of the changes in the temperature of the medium surrounding the sensor,
- $\Theta_T(s)$ – Laplace transform of the changes in the temperature of the sensing element evoked by the change of temperature Θ_O,
- N_i – thermal time constants.

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Parameters of model (1) – thermal time constants are identified in an experimental way on the basis of the sensor's input and output signals. The order of the model n depends on the sensor's size and construction, heat exchange conditions, and also on the accuracy required in a given application. For low inertial RTD with a thin sheath the model of the second order usually yields high approximation accuracy [2, 8].

In wide temperature ranges, thermophysical properties of the sensor's constructing material and of the surrounding medium are functions of temperature.

3. Classical correction

3.1. Correction method

In general, the role of the corrector is to improve system performance. Correction can be implemented as a serial, parallel, serial-parallel or a closed loop method. The main idea of the serial correction method, which is considered in the paper, is shown in Figure 1 [9].

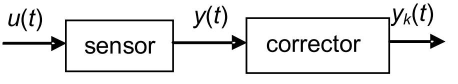

Fig. 1. Schematic diagram of the serial correction method

For a linear sensor-corrector system the overall transfer function $G_{TK}(s)$ is given by:

$$G_{TK}(s) = G_T(s) G_K(s) \tag{2}$$

where:

$G_T(s)$ – transfer functions of the sensor,
$G_K(s)$ – transfer functions of the corrector.

Considering the sensor model given in (1) for $n = 1$, the model of the corrector is given by equation (3) [9]:

$$G_k(s) = K_k(1 + sN_k)/(1 + sN_k / k_k) \tag{3}$$

where:

N_k – corrector's thermal time constant,
k_k – correction coefficient.

For properly designed corrector, for $N_k = N_1$ the resulting time constant of the sensor-corrector system is k_k-times smaller than the sensor's time constant N_1. On the other hand, the sensor output signal is contaminated by the noise (Fig. 2). Increasing k_k results in a wider band at high frequencies and stronger amplification of noise. Therefore the value of k_k should be a compromise between reducing the dynamic error and not amplifying the noise.

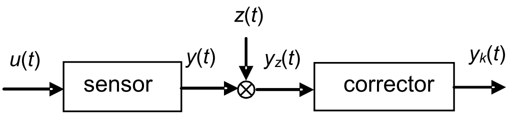

Fig. 2. Schematic diagram of the serial correction system in which the noise is taken into account

The popular criterion of correction coefficient determination is minimisation of mean sum square error (MSSE). For the system in Figure 1, when the sensor's input signal and the noise generated at the corrector's input are not correlated, a total MSSE of the system can be evaluated from the equation [11]:

$$\overline{\varepsilon^2} = \int_0^\infty S_{uu}(\omega)\left|1 - G_{TK}(j\omega)\right|^2 d\omega + \int_0^\infty S_{zz}(\omega)\left|G_K(j\omega)\right|^2 d\omega = \overline{\rho^2} + P_z \tag{4}$$

where:

$S_{uu}(\omega)$ – density of the input signal the power,

$S_{zz}(\omega)$ – density of the noise power,

$\overline{\varepsilon^2}$ – mean sum square error of correction.

The first dynamic component of the error $\overline{\rho^2}$ decreases with the increase of correction coefficient k_k and equals zero for an ideal corrector, while the second component P_z, depending on the noise, increases with the increase of k_k. The error function described by the equation (4) has always one minimum [11]. In practice the value of k_k is verified in experimental way.

In order to improve correction systems dynamics analogue or digital signal filters are used. As it is shown in Figure 3 they can be placed before the corrector (filter I) or after the corrector (filter II).

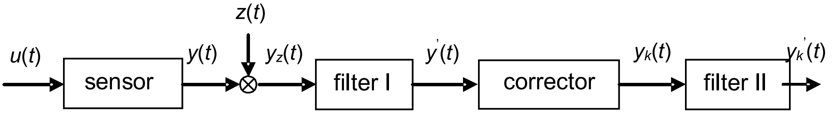

Fig. 3. Schematic diagram of the serial correction system with noise filtering

For a higher order sensor's model ($n > 1$) the same corrector structure (3) is often used in practice. If only the sensor's dominant time constant N_1 is much longer than its other time constants, the shorter time constants can be neglected [6]. In this case the best correction result is obtained for $N_k = N_1$. Higher order corrector models are not implemented in practice, because they strongly amplify noise.

3.2. Correction algorithms

The corrected temperature value can be obtained in several ways. Two computer algorithms for classical correction were implemented by the author.

In the first algorithm proposed by the author, the impulse response of the corrector $g_k(t)$ corresponding to the transfer function (3) is computed from:

$$g_K(t) = K_K \left[\frac{k_k}{N_K}(1-k_k)\exp(-k_k t / N_K)\cdot 1(t) + k_k \cdot \delta(t) \right] \tag{5}$$

for the given vector of time samples $\boldsymbol{t}$ and constant sampling time interval Δt. Discrete impulse response is stored in computer memory. Then, in the second step, the corrected value of the temperature is calculated on-line from the convolution equation:

$$y_K(k) = \sum_{i=0}^{m-1} g_K(i) y(k-i) \tag{6}$$

where:

$g_K(i)$ – corrector's impulse response,
$y(k)$ – sensor's output signal,
m – number of non-zero samples of $g_K(i)$.

Because the sampling frequency has an influence on the final correction result, its value was chosen experimentally.

In the second algorithm, the ARX (*AutoRegressive with eXogenous variables*) model of the corrector was developed. For the transfer function given by (3) the corrector's differential equation is:

$$y_k(t) + \frac{N_k}{k_k}\frac{dy_k(t)}{dt} = K_k \left[y(t) + N_k \frac{dy(t)}{dt} \right] \tag{7}$$

and the corresponding difference equation:

$$y_k(k) + \frac{N_k}{k_k \Delta t}\left[y_k(k) - y_k(k-1) \right] = K_k \left\{ y(k) + \frac{N_k}{\Delta t}\left[y(k) - y(k-1) \right] \right\} \tag{8}$$

where Δt is sampling interval.

Than the corrector's ARX model is:

$$y_k(k) = -a_1 y_k(k-1) + b_1 y(k) + b_2 y(k-1) \tag{9a}$$

where:

$$a_1 = \frac{-N_k}{k_k \Delta t + N_k}, \quad b_1 = k_k K_k \frac{\Delta t + N_k}{k_k \Delta t + N_k}, \quad b_2 = -k_k K_k \frac{N_k}{k_k \Delta t + N_k} \tag{9b}$$

In the first step of algorithm, the coefficients a_1, b_1, b_2 are computed from the equations (9b). Then, the corrected value of the temperature is calculated on-line from equation (9a). In this algorithm only three coefficients are stored in the memory and its computational effort is less comparing to the first algorithm, which uses equations (5) and (6).

4. ANN based correction

In the ANN-based correction method, proposed by the author, the artificial neural network plays the role of a corrector and implements an inverse model of the sensor [4, 5]. The neural corrector is built on the basis of the sensor's input and output signals. A general discrete-time model of the corrector can be described by a nonlinear difference equation (10), which is a generalization of linear equation (6):

$$y_k(k+1) = f[y(k), y(k-1), ..., y(k-n+1)] \tag{10}$$

The method for training the corrector's model is shown in Figure 4.

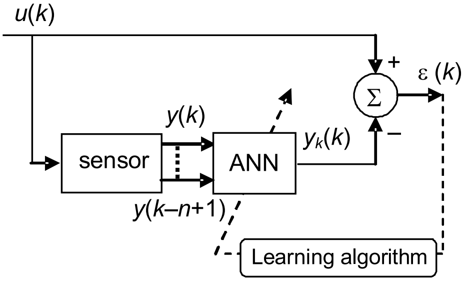

Fig. 4. Determination of ANN based corrector's model

The corrector defined in (10) was implemented by a feedforward MLP (*Multi-Layer Perceptron*) neural network and a moving window method [7, 10]. The backpropagation training algorithm and the Levenberg-Marquardt optimisation method were used to minimise the MSE cost function [1].

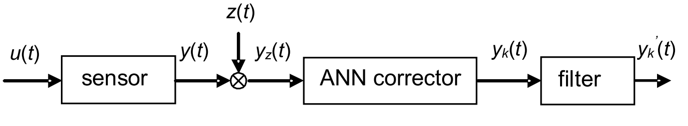

Fig. 5. Schematic diagram of the neural serial correction system with noise filtering

5. Experimentation

Verification of the ANN-based correction method was performed experimentally for two small Pt 100 industrial resistance temperature detectors in steel sheaths:

- TOPC 4: diameter d = 4 mm, length l = 115 mm, class B, range (–50÷200) ^{o}C,
- TOPI 6: parameters: d = 6 mm, l = 175 mm, class B, range (–200÷600) ^{o}C.

The sensors were tested in a thermostat in well stirred water. A series of experiments of sensor identification was performed using the step response method for various magnitudes of temperature step interrogations (as in Fig. 7). Each of the sensors was plugged into the thermostat and its output signal was acquired by a computerised measuring system [3]. The obtained experimental data was the basis for designing classical and neural correctors. Performances for these correctors were then compared.

Experimental results obtained in the thermostat in a well-mixed water in temperature range from 40 ^{o}C to 100 ^{o}C proved that dynamic properties of the sensors can be modelled with a good accuracy by linear equation (1) of second order (n = 2). The values of the sensor's thermal time constants are almost constant for TOPI 6 and change slightly for TOPC 4 (Fig. 6). Therefore their changes were neglected and the linear sensor model (1) was applied.

a) b)

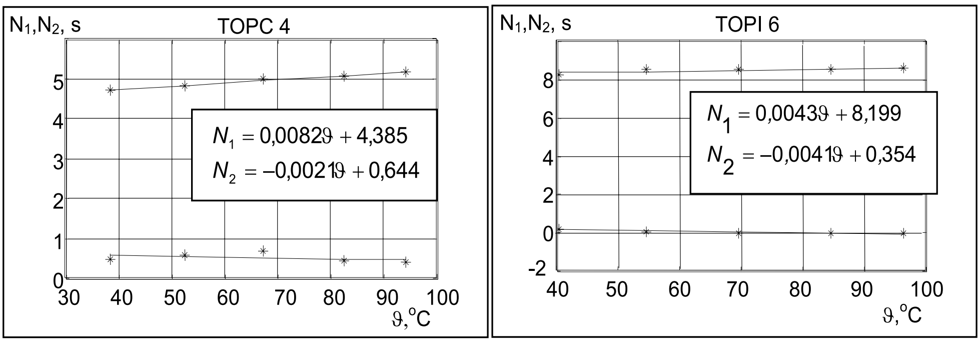

Fig. 6. Sensor time constants N_1 and N_2 versus water temperature:
a) for TOPC 4; b) for TOPI 6

The transfer function of the designed classical corrector is given in equation (3) for $N_k = N_1$ and k_k = 10. Correction performance was tested by calculating the dynamic error for the step response of the system sensor-corrector. The corrected temperature was computed using the both described computer algorithms based on classical method and by the use of neural correction.

The neural correctors were trained by applying the modelling scheme shown in Figure 4 and training data prepared in the way shown in Figure 7 for TOPC 4 sensor. For the both sensors from five step responses, four were used for the networks' training and the middle-one for the testing. Testing data was not applied to the networks' inputs during their training. Different structures of the FFN (*FeedForward neural Network*) were tested. For the both sensors the best results were obtained for the two-layer MLP network structure (6–12–1), i.e., six inputs, 12 neurons with a sigmoidal activation function in the hidden layer and one output. In that case, the network input vector consists of the current value of the signal from the sensor output $y(k)$ and five consecutive past signal samples. The corrected temperature value $y_k(k)$ is computed at the network output.

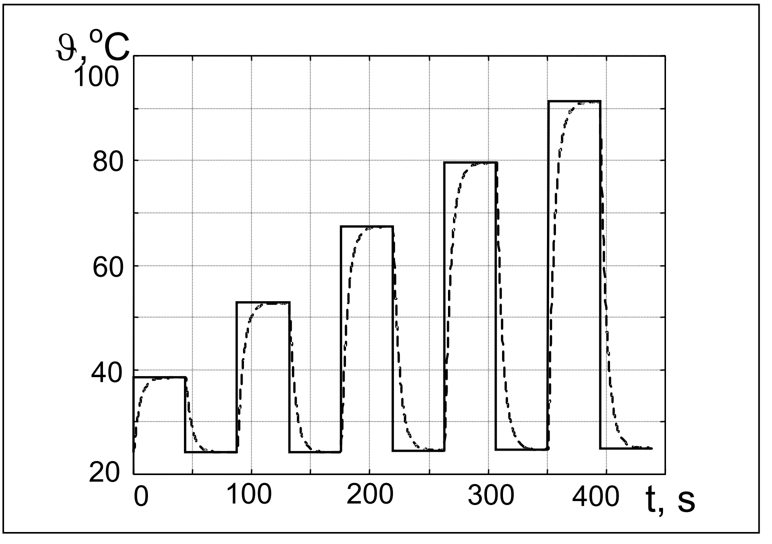

Fig. 7. Experimental data for networks' training and testing for the TOPC 4 sensor: temperature interrogation signal – solid line, sensor's output – dashed line

Additionally, digital moving average filters were implemented in the all the applied correction methods to reduce noise. In the case of classical correction method using convolution equation, filter I (before the corrector) of the tenth order was applied, as it is shown in Figure 3. In the case of ARX corrector and neural corrector, a moving average filter II (after the corrector) of the third order was applied. Type and number of filters and their order were verified experimentally with the aim to minimize the dynamic error.

Correction quality was tested on the basis of the step responses of the sensor-corrector systems. Results of the ANN-based correction, obtained for the testing data and compared to the classical methods, are shown in Figure 8 and in Figure 9 for the TOPC 4 sensor and in Figure 10 and in Figure 11 for the TOPI 6 sensor. Results without signal filtering are shown in Figure 8 and in Figure 10, and with filtering in Figure 9 and in Figure 11.

Quality of the applied correction methods was evaluated for the testing data by the following measures: Mean Sum Square Error (MSSE) and Mean Sum Absolute Error (MSAE), calculated for normalized step response, and $t_{0.05}$ – time after which the step response reaches a steady state with the accuracy less then 5%. The results are shown in Table 1 for TOPC 4 sensor and in Table 2 for TOPI 6 sensor.

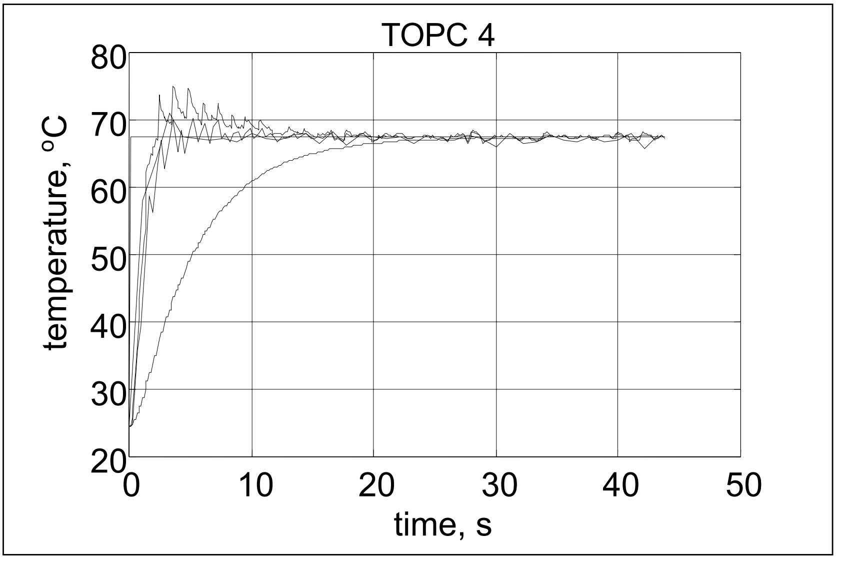

Fig. 8. Correction results for TOPC 4 sensor without signal filtering: sensor's step response – dashed dotted line, classical correction using convolution equation – dashed line, ARX corrector – dotted line, neural correction – solid line

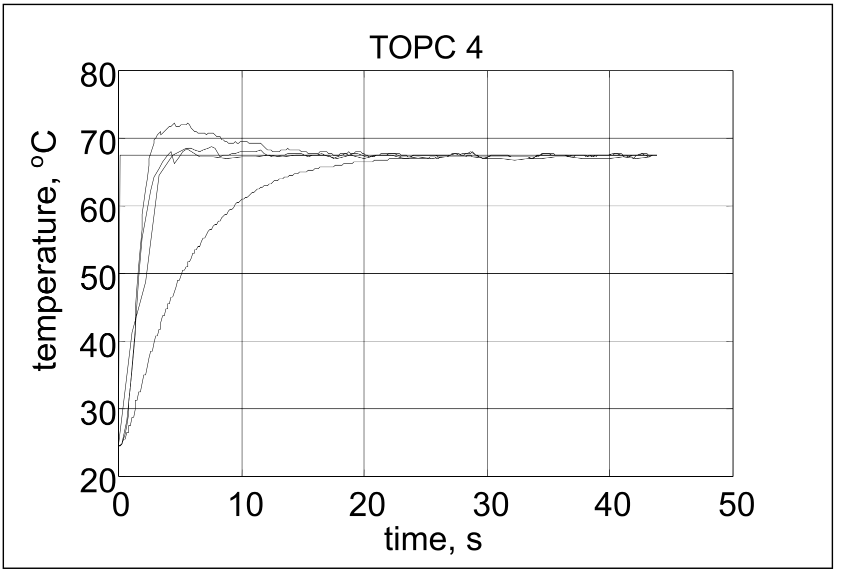

Fig. 9. Correction results for TOPC 4 sensor with signal filtering: sensor's step response – dashed dotted line, classical correction using convolution equation – dashed line, ARX corrector – dotted line, neural correction – solid line

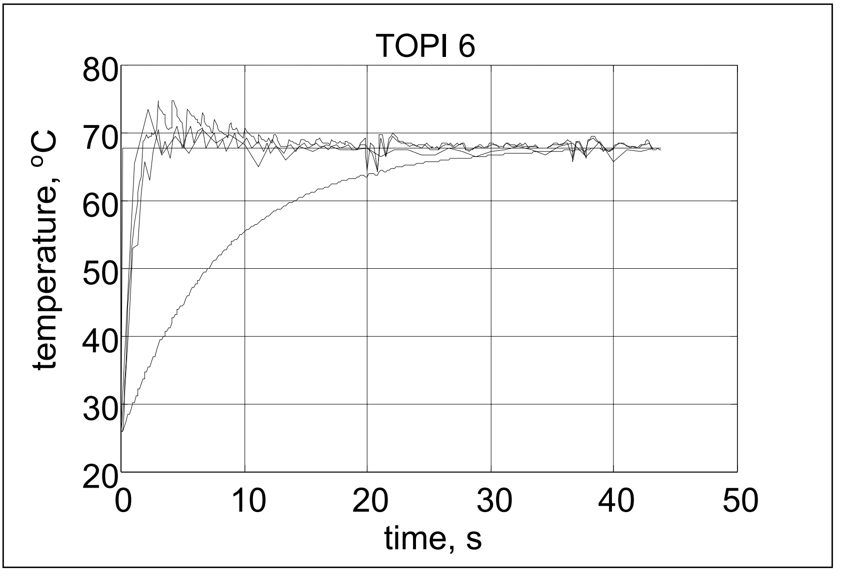

Fig. 10. Correction results for TOPI 6 sensor without signal filtering: sensor's step response – dashed dotted line, classical correction using convolution equation – dashed line, ARX corrector – dotted line, neural correction – solid line

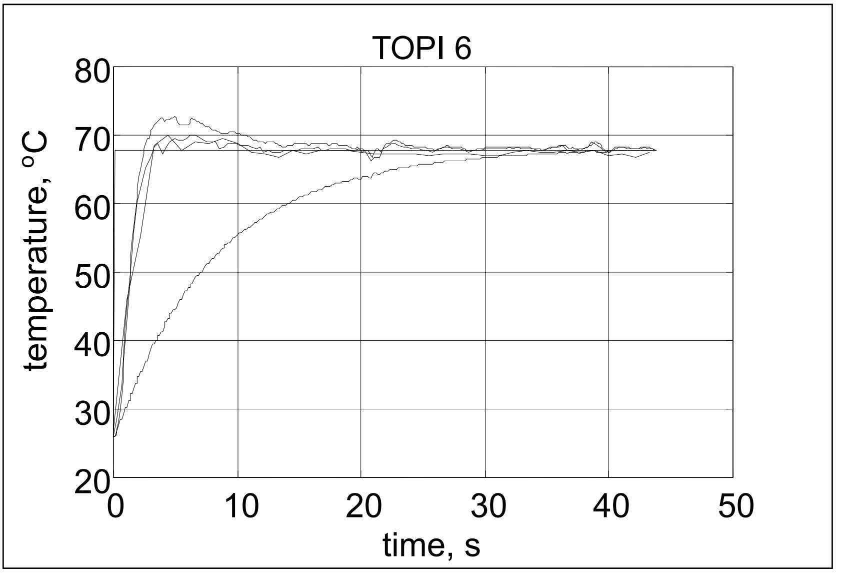

Fig. 11. Correction results for TOPI 6 sensor with signal filtering: sensor's step response – dotted dashed line, classical correction using convolution equation – dashed line, ARX corrector – dotted line, neural correction – solid line

Table 1
Quality of dynamic error correction for TOPC 4 sensor for different correction methods calculated for the step responses shown in Figures 8 and 9, step magnitude $\Delta\vartheta = 42.9\ ^{o}C$

Correction method	Filter	MSSE –	MSAE –	$t_{0,05}$ s
sensor without corrector	–	0.2450	0.1184	16.6443
neural correction, MLP ANN (6-12-1)	–	0.0420	0.0202	4.4385
	II*	0.1195	0.0347	4.4385
classical correction, convolution algorithm	–	0.1292	0.0417	10.8700
	I*	0.1627	0.0505	8.5700
classical correction, ARX algorithm	–	0.1306	0.0347	7.5800
	II*	0.1531	0.0380	3.2900

* – digital moving average filters: filter I – before the corrector, filter II – after the corrector,
MSSE – Mean Sum Square Error for the testing data, calculated for normalized step response,
MSAE – Mean Sum Absolute Error for the testing data, calculated for normalized step response,
$t_{0.05}$ – time after which dynamic error became to be less then 5% of signal value in steady state.

Table 2
Quality of dynamic error correction for TOPI 6 sensor for different correction methods calculated for the step responses shown in Figures 10 and 11, step magnitude $\Delta\vartheta = 41.8\ ^{o}C$

Correction method	Filter	MSSE –	MSAE –	$t_{0,05}$ s
sensor without corrector	–	0.2901	0.1770	26.6309
neural correction, MLP ANN (6-12-1)	–	0.0343	0.0242	12.2058
	II*	0.0970	0.0342	5.5481
classical correction, convolution algorithm	–	0.1120	0.0442	36.8000
	I*	0.1489	0.0521	10.7700
classical correction, ARX algorithm	–	0.1047	0.0327	21.0900
	II*	0.1303	0.0352	2.9700

* – digital moving average filters: filter I – before the corrector, filter II – after the corrector,
MSSE – Mean Sum Square Error for the testing data, calculated for normalized step response,
MSAE – Mean Sum Absolute Error for the testing data, calculated for normalized step response,
$t_{0.05}$ – time after which dynamic error became to be less then 5% of signal value in steady state.

6. Conclusions

Methods of temperature sensor dynamic errors correction based on analytical sensor model and on (ANN – *Artificial Neural Networks*) are proposed and discussed in this paper.

The methods were validated experimentally for two small platinum RTDs immersed in water. The best corrector's performances and the shortest correction time $t_{0.05}$ was achieved for the ARX corrector with digital moving average filter after the corrector. The results for the neural correctors are only slightly worse, and still very good. Generally, the correctors performances are comparable for the both methods. For the systems without filtering the best corrector's performances and the shortest correction time $t_{0.05}$ was achieved for the neural correctors. That indicates that the ANN-based method was less sensitive to noise interferences.

The described analytical correction methods can be applied for linear and stationary systems and the ANN-based method can be also used for non-linear and stationary systems.

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