Identification of DC Motor Parameters using Artificial Neural Networks

Jaroslava Žilková and Peter Girovský*

Department of Electrical Engineering and Mechatronics, Faculty of Electrical Engineering and Informatics, Technical University of Košice, Letná 9, 042 00

Košice, Slovakia jaroslava.zilkova@tuke.sk, peter.girovsky@tuke.sk

*Corresponding author

Abstract: *In this paper, a new off-line identification approach based on the structural similarity of a neural identifier and the identified system is introduced. This approach is illustrated by a simple neural network for parameters identification of a separately excited DC motor. The design of the neural identifier is based on the structural similarity of the system and the identifier, as the mathematical model of the system is known, as well as its structure. The unknown system parameters can be identified on basis of the measurable quantities such as the angular speed of the motor, stator voltage and stator current. Testing of the neural identifier is presented and simulation results are discussed in the conclusion of the paper. The results achieved by the presented approach of identification are good and the approach is suitable also for other systems. For the majority of the identified parameters the relative error proved to be lower than 0.5%.*

Keywords: parameter identification, neural network, DC motor

1 Introduction

In practice, there is often the need for highly precise and effective control of the output quantities of a particular system in both steady and transient states. The prerequisite for successful control of a given system is the knowledge of its parameters. That is why great attention is paid to the design of mathematical models of systems which are the basis for the application of particular control algorithms. Nowadays, mathematical models have crucial importance not only in systems control but also in most scientific disciplines, as they are not only a suitable form for expressing knowledge about the systems, but also, with technical devices, a very effective tool for further investigation of the properties of these systems. The created model, which should consider all the essential characteristics of the system, is described using a certain formal mathematical apparatus. The mathematical model of the system, which can often be not only very complex and time-consuming, can unfortunately be also inaccurate. In the process of mathematical model design the real object is simplified by excluding insignificant properties, while all essential properties are to remain intact. System identification involves the process of determining the mathematical description of real systems, and it can determine the structure and parameters of the system model.

The process of identification therefore involves:

- Structural identification
- Parametric identification

Structural identification deals with determining the structure of the system and parametric identification with determining the system model parameters.

Although real systems can be very complex, neglecting certain real properties and simplifying them can cause their description to be inaccurate. In addition, real-time systems are in constant interaction with their surroundings, and therefore, when designing models of systems, these are rather certain approximations of the real systems than precisely identical models of the systems.

Information about the system plays an important role in the identification process. The information can be:

- a posteriori
- a priori

A posteriori information is mostly quantitative and it is obtained through real system measurements. A priori information is qualitative and it includes knowledge obtained from previous study of entire classes of related systems, including the system under examination.

The identification of system parameters can be performed in two ways:

- on-line
- off-line

On-line identification is performed in real-time directly on the real-world system (Fig. 1). The advantage of off-line identification is that it is usually performed outside the investigated real system based on the processing of the measured quantities, thus limiting interventions into the existing system.

The most suitable identification techniques apply the approach in which the structure of the system model is based mainly on the mathematical and physical analysis of the real system and subsequently the model parameters are determined and specified empirically, using experimental methods. Often the procedure in which the analytical model is compared with the real system, through the data obtained by simulation of the mathematical model of the system with the data obtained by measurements of the real system is applied.

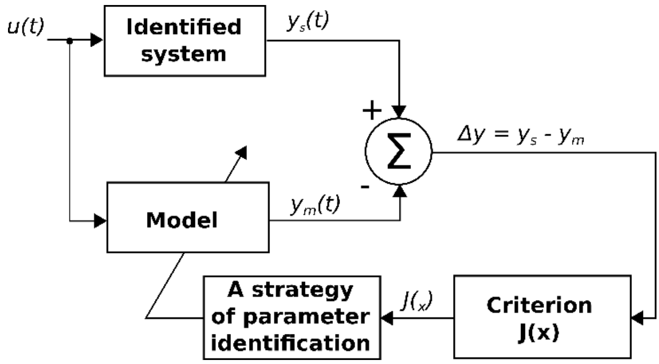

Figure 1
System parameters identification

In the analytical approach of identification, relations between the measured variables are obtained and, on their basis, the relations between the input and output variables of the system are determined. The advantage of the structural model obtained by this approach is that its individual relations correspond to the relevant parts of the system being identified. Since the model and the system structures are similar, there is a clear relationship between the model and the system parameters. In addition, in off-line identification, not only can the properties of the system be identified, even before it is implemented, but these properties can also, if necessary, be corrected.

Artificial intelligence currently represents a powerful tool for solving problems across various domains that cannot be addressed using analytical methods, which often rely on significant simplifications. In contrast, solutions based on artificial intelligence techniques can yield the expected results, as demonstrated in numerous published studies. Several approaches are used to identify or observe system parameters [1][32] and missing values [31]. One of the newer approaches utilizes artificial intelligence methods [4] which include fuzzy logic [5,7,26], artificial neural networks theory [6], evolutionary algorithms [11], as well as other methods, each of which has stronger and weaker sides. The main principle of artificial neural networks is the similarity with the activity of brain cells and the brain of living organisms. Artificial neural networks are exceptional thanks to their ability to learn - to adapt their parameters. By training [10] the neural network, the parameters of this network are adjusted so that it is able to extrapolate functional values also outside of the training set. Basic artificial neural networks (ANNs) theory can be found in [9]. Compared to other methods, thanks to their learning abilities artificial neural networks offer many benefits, including the ability to implicitly detect complex non-linear relationships between dependent and independently variable quantities. The ANNs are, due to this feature, predominantly used for modelling complex non-linear systems [12][29]. It can be said that there are currently many works that deal with artificial neural networks, their training rules and faster training rules, along with a multitude of applications in various fields of science. Artificial neural networks are researched and successfully applied in experimental and industrial systems and devices, including the area of electric drives and power electronics [21] of our interest, system modelling [18][30], drive control [2,6,14], quantities estimation [15-17] and identifying system parameters [3,8,19,27] as well as detecting motor and device failures [25].

In system parameters identification using neural networks [13][20] there is the problem of determining the optimal structure and size of the neural network, as well as that of selecting suitable inputs and other network parameters, e.g. the type of transfer functions for the given neural network.

The approach illustrated in this paper introduces a mode that can be applied when the structure of the system being identified is known. In such case it is possible to divide a complex system into simpler subsystems and for each of these subsystems design a simple neural network structure analogically to the system structure. Also the inputs and the type of transfer functions for the neural network needed for identifying the system parameters are based on the known information about the system.

In this paper, an off-line system parameters identification approach based on the theory of artificial neural networks is presented on the example of parameter identification of a separately excited DC motor. The design of the neuro-identifier structure, choice of training sets, tests of the neuro-identifier and evaluation of the achieved results are presented and discussed.

Compared to published approaches for parameter identification, this article introduces a novel method to system parameter identification, based on the integration of physical knowledge directly into the learning process of a neural network. A key feature of this approach is the use of a highly simplified neural network architecture, that mirrors the structure of the identified system, along with a significantly reduced requirement for experimental data.

2 Methodology of Identification Process Using ANN

Conventional methods for system parameters identification, especially in the field of electric drives, are based primarily on measuring the response of a system to a suitable test signal. However, the increase in computing performance has allowed automatic identification to be extended, bringing significant benefits. Some of them are outlined below:

- Possibility to generate complex testing signals
- Sophisticated identification algorithms
- Possibility of on-line identification
- Continuous use of identification results to improve system control

When designing structures for system parameters identification based on ANNs, two approaches are typically applied:

- Parameter identification based on the approximation of the dependence of the searched for parameter on measurable variables. In this case, identification is based on large ANNs (Fig.2). The training of these ANNs takes place on the basis of a selected training set of test signals, mostly offline [9].
- The parameter values searched for are derived from the ANN's structure analogy with the structure of the identified system, and the ANN is used as a parallel or serial-parallel model of the system. ANN has a very simple structure in this case, with a small number of neurons. For the training of the neural network, the rapid training algorithm is used and the values of the identified parameters usually correspond to the ANN parameters directly or are obtained indirectly - by calculation from the adapted network parameters [22-24].

Each of the approaches described above has certain advantages and disadvantages.

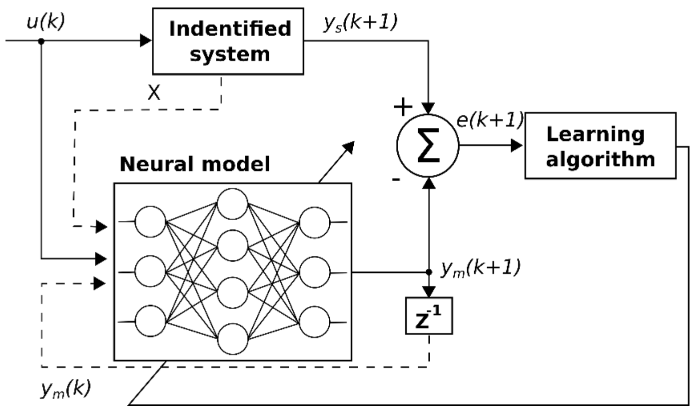

Figure 2

The main view of the process of identifying a large ANN through a parallel neural model

In the first case, that of large neural networks, the problem is the selection of input network quantities, of learning samples, but also the selection of the optimal network structure. The advantage is the possibility of using a classical verified training algorithm without high demands on the speed of the training algorithm.

In the second case, the advantage is that due to the analogy of the neural network structure with the structure of the identified system it is not only the neural network inputs but also the structure of the neural network that is clearly defined. However, in the case of on-line use, there are high demands on the speed of the training algorithm. Our previous works were focused on identification using the second approach, where online identification was used, with the input signal being a signal created specifically for this purpose [18][19].

In this paper, knowledge of the system is used to identify system parameters. In line with the second approach, the neural network analogy with the system structure is used, but as learning is going off-line, a common training algorithm can be used as in the first case, where the requirements for the speed of identification are not high.

2.1 Identification of DC Motor Parameters

A separately excited DC motor is a multi-parameter nonlinear system whose input quantities are the input voltages u_a, u_b and the output quantities can be angular speed, motor torque, armature current or motor shaft position. The mathematical model of a separately excited DC motor is based on the general model of DC machines, with the usual simplifying assumptions.

The dynamic model of a separately excited DC motor can be divided into two subsystems: electromagnetic and mechanical.

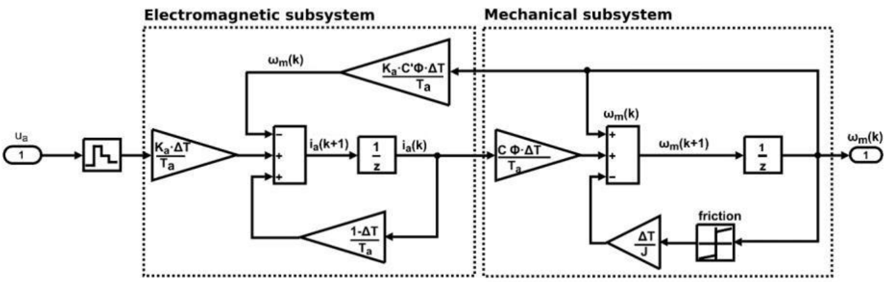

Figure 3
Discrete model of a separately excited DC motor

The electromagnetic system of a motor includes an excitation circuit and an armature circuit of the motor. If magnetic flux stabilization is ensured, i.e. the magnetic flux and the current in the excitation circuit are constant both in static and dynamic modes of operation of the motor, the DC motor will be a motor with constant excitation.

In view of the necessity of identifying the parameters of a DC motor with constant magnetic flux, it is considered that the DC motor will only be loaded by the actual and external friction torque m_f, while the exponential component of the viscous friction will be neglected:

$$m_f = sgn(\omega_m) M_C + b\omega_m \tag{1}$$

where,

M_C - is Coulomb's friction
b - is the slope of the linear component of the viscous friction
ω_m - is the angular speed of the rotor shaft

The main motivation for addressing the proposed approach for parameter identification, was to align the DC motor model with the structure of the designed neural network. Therefore, we derive the individual variable derivatives from equations (1) - (4), in a manner analogous to the formulation of the state-space model of a DC motor.

$$\frac{di_a}{dt} = \frac{u_a - R_a \cdot i_a - C\emptyset \cdot \omega_m}{L_a} \tag{2}$$

$$\frac{d\omega}{dt} = \frac{M_m - M_f}{J} \tag{3}$$

After modifying equations (2) and (3), we obtain the following expressions:

$$\frac{di_a}{dt} = \frac{K_a}{T_a} u_a - \frac{C\emptyset.K_a}{T_a} \omega_m - \frac{1}{T_a} i_a \tag{4}$$

$$\frac{d\omega}{dt} = \frac{C\emptyset.i_a - sgn(\omega_m).M_C + b.\omega_m}{J} \tag{5}$$

Subsequently, equations (4) and (5) are transformed into their discrete form, which serves as the basis for constructing the discrete model of the DC motor.

$$i_a(k+1) = i_a(k) + \frac{K_a \cdot \Delta T}{T_a} u_a(k) - \frac{C\emptyset \cdot K_a \cdot \Delta T}{T_a} \omega_m(k) - \frac{\Delta T}{T_a} i_a(k) \tag{6}$$

$$\omega_m(k+1) = \omega_m(k) + \frac{C\emptyset \cdot i_a(k) \cdot \Delta T}{J} - \frac{-sgn(\omega_m(k)) \cdot M_C \cdot \Delta T}{J} + \frac{b \cdot \omega_m(k) \cdot \Delta T}{J} \tag{7}$$

where,

- i_a - is the armature current
- u_a - is input armature voltage
- C - is the motor constant
- J - is the moment of inertia
- ϕ - is the magnetic flux
- K_a - is the rotor gain
- T_a - is the electrical time constant

Rotor gain K_a, electrical time constant T_a and the motor constant C' are expressed by the following equations:

$$K_a = \frac{1}{R_a} \qquad T_a = \frac{L_a}{R_a} \qquad C = \frac{pN_m}{2\pi a} \tag{8}$$

where,

- R_a - is the armature resistance
- L_a - is the armature inductivity

p - is the number of pole pairs
N_m - is the number of turns of armature winding
a - is the number of parallel paths of armature winding

(Eq. 6-8) represent the basic equations of the discrete model of DC motor with separate constant excitation.

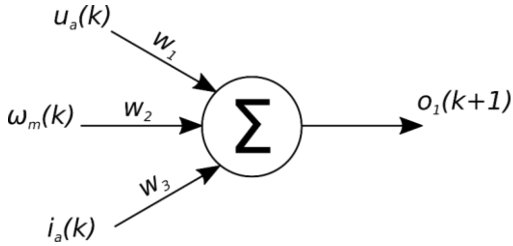

Figure 4
Neural parameters identifier of the motor: electromagnetic part - N_1

Since the neural model (Fig.4) of the parameter identifier of the electromagnetic system is designed according to (Eq. 6), the output of the neuron $o_1\ (k+1)$ can be, based on the equation, expressed by the formula presented below:

$$o_1(k+1) = w_1(k) \cdot u_a(k) + w_2 \cdot \omega_m(k) + w_3 \cdot i_a(k) \tag{9}$$

Where the parameters of the electromagnetic part of the motor are incorporated into individual weights of the N_1 neuron:

$$w_1 = \frac{K_a \cdot \Delta T}{T_a} \tag{10}$$

$$w_2 = -\frac{K_a \cdot c\emptyset \cdot \Delta T}{T_a} \tag{11}$$

$$w_3 = 1 - \frac{\Delta T}{T_a} \tag{12}$$

Based on (Eq. 10-12), it is possible to determine the values of the parameters of the electromagnetic subsystem of the motor, namely the motor armature gain K_a, electrical time constant of the motor armature T_a, and excitation $C'\Phi^*$. After training, when $o_1(k+1) \doteq i_a(k+1)$, the parameters are determined as follows:

$$C\phi^* = -\frac{w_2}{w_1} \tag{13}$$

$$T_a{}^* = \frac{\Delta T}{1-w_3} \tag{14}$$

$$K_a{}^* = \frac{w_1\, T_a{}^*}{\Delta T} = \frac{w_1}{1-w_3} \tag{15}$$

Whilst the armature resistance value R_a* is obtained from the identified gain value K_a* according to (Eq. 8) and the armature inductivity value L_a* is also obtained from (Eq. 8), from the identified electrical time constant of the motor T_a*.

The second part of the identifier for identifying parameters of the mechanical part of the motor will be made analogous to the mechanical part of the motor shown in (Fig. 5).

If:

$$\omega 2_m = \mathrm{sign}(\omega_m) \tag{16}$$

by adjusting (Eq. 7) the equation of angular speed will be:

$$\omega_m(k+1) = \frac{C\emptyset.\Delta T}{J} i_a(k) + \left(1 - \frac{b \cdot \Delta T}{J}\right) \omega_m(k) - \frac{M_C \cdot \Delta T}{J} \omega 2_m(k) \tag{17}$$

The second part of the identifier for identifying the parameters of the mechanical part of the motor consists of one neuron with a linear transmission function according to the scheme in (Fig. 5), which is analogous to the mechanical part of the motor shown in (Fig. 3).

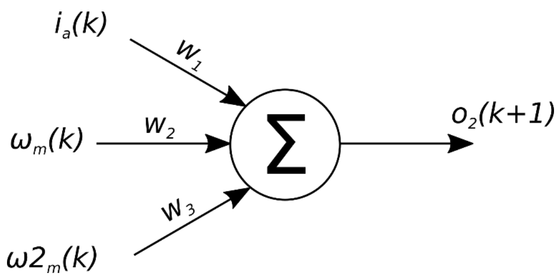

Figure 5

Neural parameters identifier of the DC motor: mechanical part – N_2

According to (Fig. 5) the output of neuron N_2: $o_2\ (k + 1)$ can be expressed in line with (Eq. 17) in the form:

$$o_2(k+1) = w_1(k) i_a(k) + w_2 \omega_m(k) + w_3 \omega 2_m(k) \tag{18}$$

Where the searched for parameters of the motor mechanical part are incorporated in individual weights of neuron N_2:

$$w_1 = \frac{c\emptyset \cdot \Delta T}{J} \tag{19}$$

$$w_2 = -\frac{M_C \Delta T}{J} \tag{20}$$

$$w_3 = 1 - \frac{b \cdot \Delta T}{J} \tag{21}$$

If, after training, the output of neuron N_2: $o_2(k+1) \doteq \omega_m(k+1)$, then, based on (Eq. 19-21), values of the motor mechanical part parameters, namely the moment of inertia J, coefficient of friction b and Coulomb's friction M_c, can be calculated using the following mathematical formulas:

$$J^* = \frac{c\emptyset^* \cdot \Delta T}{w_1} \tag{22}$$

$$M_c{}^* = -\frac{w_2 \cdot J^*}{\Delta T} \tag{23}$$

$$b^* = \frac{(1-w_3) \cdot J^*}{\Delta T} \tag{24}$$

3 Results and Discussion of Parameters Identification

The structure of the neural network for the identification of electromagnetic and mechanical parameters of the separately excited DC motor consists of two neurons that are trained separately. The DC motors parameters that were used to identify motor parameters in simulations are shown in Table 1. Parameters selected as reference values for verification by simulation were friction coefficient b and Coulomb friction M_c.

Table 1

Parameters of the separately excited DC motors used in identification

Parameter	Value of motor 1	Value of motor 2	Unit
P_n	36700	2300	W
U_{an}	420	220	V
I_{an}	97	12.3	A
ω_n	239.8	293.2	rad.s^{-1}
R_a	0.208	1.6	Ω
L_a	0.0081	0.016	H
CΦ	0.8	0.7	V.s
J	0.0346	0.0315	kg.m^2
M_c	0.8	1.0	N.m
b	1	0.3	N.m.s.rad^{-1}

The data sets used for neural training were created on the basis of simulated waveforms of the DC motor model, where the neuron N_1 inputs shown in (Fig. 4) are selected on the basis of (Eq. 2) and the neuron N_2 inputs, shown in (Fig. 5), are selected on the basis of (Eq. 17), whilst the value ΔT corresponds to the sampling period of individual signals. The shape of the input signals plays a crucial role in the accuracy of the identified parameters. Therefore, the simulation included testing input signals with varying amplitudes and frequencies (Fig. 6). For the actual motor parameter identification, signal profiles that produced the best results were used (Fig. 7, Fig. 8).

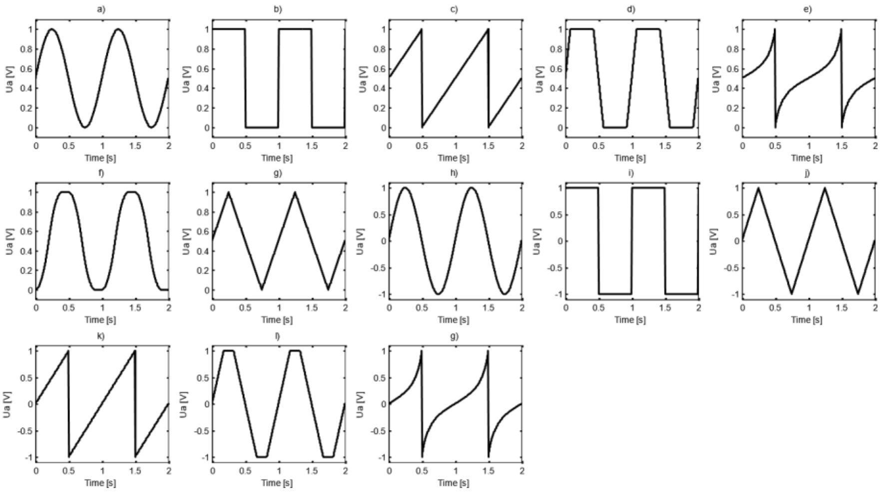

Figure 6
Examples of tested input signals

The best results in parameter identification were obtained using a sinusoidal waveform input voltage signals with a frequency of 0.5 Hz and amplitude of 110 V. For determining the mechanical parameters, a saw-tooth input signal with a frequency of 1 Hz and amplitude of 43V was applied.

The learning process in the proposed approach can be explicitly formulated as an optimization problem. The objective of learning is to minimize the discrepancy between the outputs of the neural identifier and the corresponding outputs of the DC motor model, i.e., the armature current and angular speed in the next sampling step. The cost function used for training is the mean squared error (MSE), computed over the training dataset:

$$J(\theta) = \frac{1}{N}\sum_{k=1}^{N}\big(y(k+1) - \hat{y}(k+1)\big)^2 \tag{25}$$

Where, $y(k+1)$ represents the measured (or simulated) system output and $\hat{y}(k+1)$ is the output of the neural identifier. The neural identifier consists of two neurons corresponding to the electromagnetic and mechanical subsystems of the DC motor. Their outputs are defined as:

$$o_1(k+1) = w_1(k) \cdot u_a(k) + w_2 \cdot \omega_m(k) + w_3 \cdot i_a(k)$$

$$o_2(k+1) = w_1(k) i_a(k) + w_2 \omega_m(k) + w_3 \omega 2_m(k)$$

where, these equations directly correspond to (9) and (18) in the manuscript. The decision variables in the optimization process are the synaptic weights of the neural network (i.e., w_1, w_2, w_3 for each neuron). Due to the structural analogy between the neural network and the physical model of the DC motor, these weights directly represent the system parameters (e.g., armature gain, time constant, inertia, friction coefficients). The training is performed using the Levenberg–Marquardt algorithm, which iteratively updates the weights to minimize the defined cost function.

Implicit constraints of the learning/optimization process are, however, given by the structure of the neural network, which is derived from the known physical model of the system. This structure ensures that the identified parameters have physical meaning and are consistent with the system dynamics.

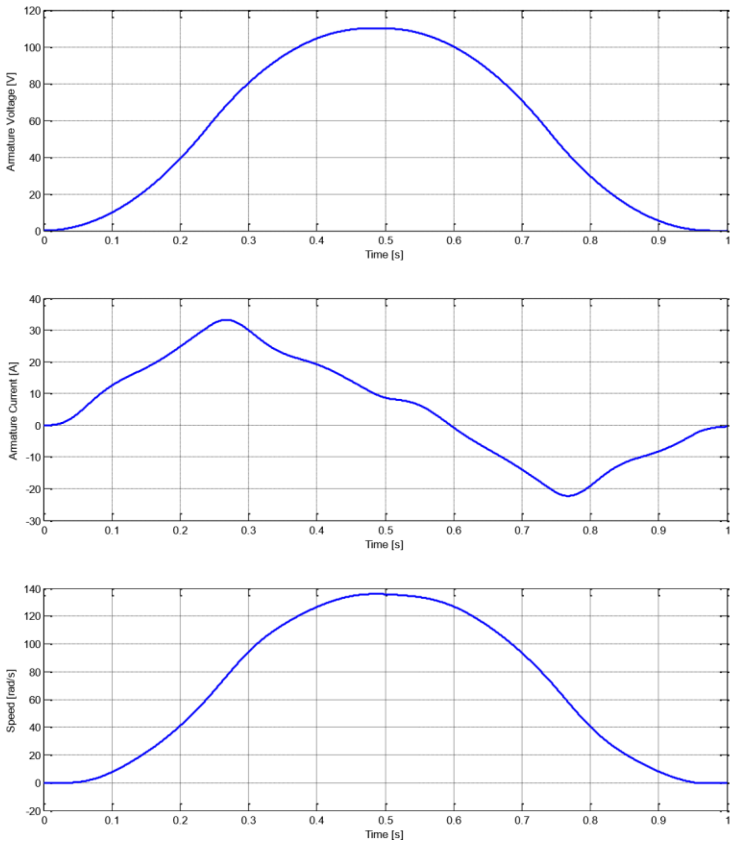

Figure 7
The waveforms of quantities used to create training sets for N_1 neuron

The waveforms of armature voltage, armature current and speed, used in the preparation of the training sets for N_1 neuron are shown in (Fig. 7) and in the preparation of the training sets for N_2 neuron are shown in (Fig. 8).

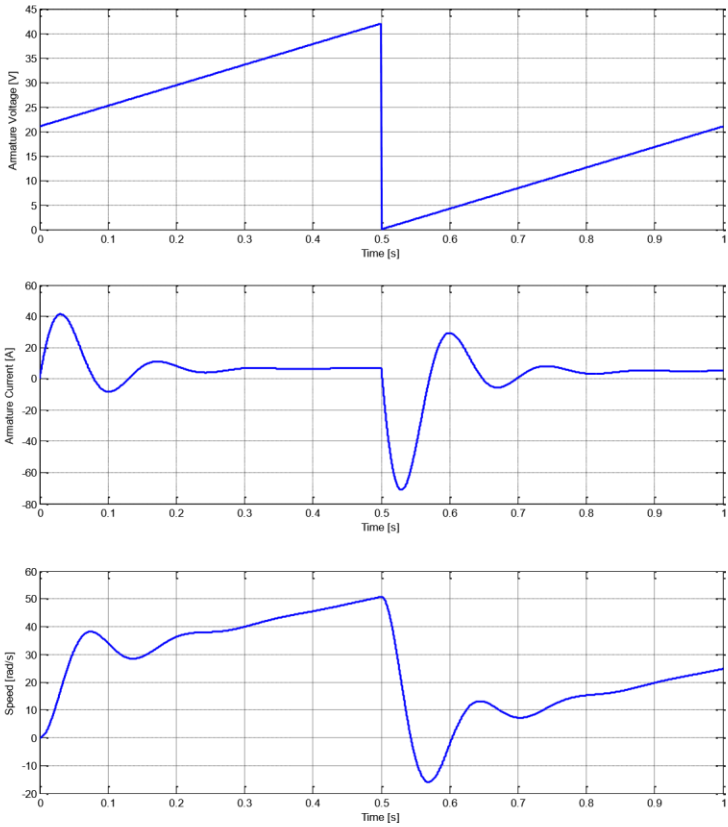

Figure 8

The waveforms of quantities used to create training set for N_2 neuron

Another key parameter for identification is the sampling period of the signal. Figures 9 and 10 illustrate the identification accuracy of individual parameters of the electromagnetic and mechanical subsystems for various sampling periods, where MSE represents the mean squared error.

To evaluate the accuracy of the identified parameter Ra in comparison to the actual armature winding resistance, the relative deviation was calculated in percentage terms according to Eq. (26). The same approach was used to compute the relative deviations for all other identified parameters of the DC motor.

$$\delta R_a = \frac{|R_a^* - R_a|}{R_a^*} \cdot 100 \quad [\%] \tag{26}$$

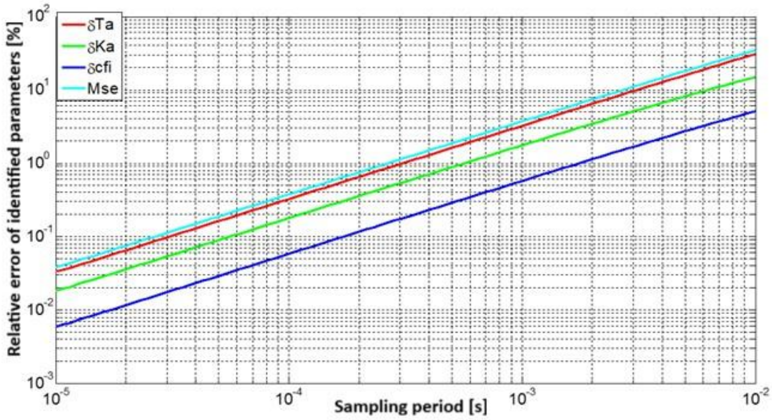

Figure 9

Accuracy of electromagnetic system parameter identification as a function of the sampling period

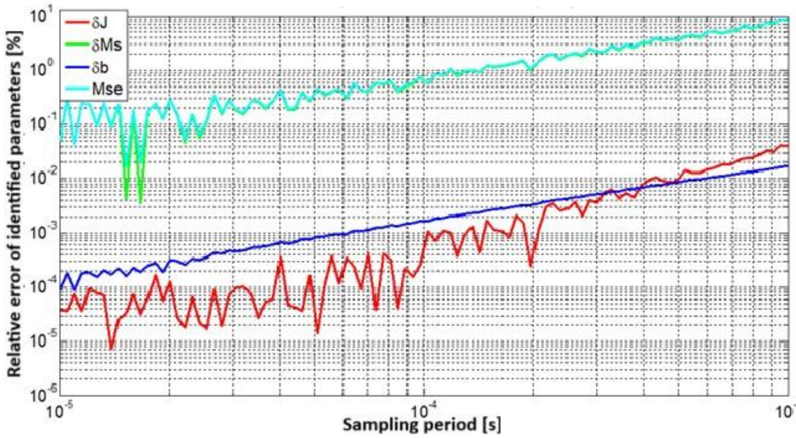

Figure 10

Accuracy of mechanical system parameter identification as a function of the sampling period

Table 2 presents the obtained electromagnetic parameters and Table 3 presents the obtained mechanical parameters of the motor. The tables show the comparisons with the reference values and present the relative errors obtained in the process of identification of the individual parameters. In several works [14,22-24] dealing with parameters identification of e.g. DC motors, relative errors which would enable a better expression of the accuracy of the achieved results are not presented. In [28] the relative error in the obtained results is not smaller than 6%. In [28], also the results obtained using the MATLAB system identification toolbox are presented, and these are even less accurate. In [19][20], in on-line identification of parameters of an induction motor, the relative errors of the obtained results are mostly in the range of 0.5% to 4%. Compared to these results, the parameters of the DC motor electromagnetic subsystem (Table 2) were determined with error less than 0.5% and parameters of the mechanical subsystem (Table 3) with error in the range 0.17% to 0.74%.

Table 2
Identified electromagnetic parameters

Parameter	Reference value of motor 1	Identified value of motor 1	Relative error
L_a	0.0081 H	0.0081 H	0.1865 %
R_a	0.2080 Ω	0.2089 Ω	0.4443 %
CΦ	0.8000 V.s	0.7988 V.s	0.1448 %
K_a	4.8077 Ω^{-1}	4.7864 Ω^{-1}	0.4443 %
T_a	0.0389 s	0.0388 s	0.3148 %
Parameter	**Reference value of motor 2**	**Identified value of motor 2**	**Relative error**
La	0.0160 H	0.0160 H	0.4186 %
Ra	1.6000 Ω	1.6083 Ω	0.3938 %
CΦ	0.7000 V.s	0.6990 V.s	0.1500 %
Ka	0.6250 Ω-1	0.6218 Ω^{-1}	0.5168 %
Ta	0.0100 s	0.0100 s	0.4000 %

Table 3
Identified mechanical parameters

Parameter	Reference value of motor 1	Identified value of motor 1	Relative error
J	0.0346 kg.m2	0.0346 kg.m2	0.0005 %
b	1.0000 N.m.s/rad	0.9927 N.m.s/rad	0.7366 %
M_c	0.8000 N.m	0.7988 N.m	0.1697 %
Parameter	**Reference value of motor 2**	**Identified value of motor 2**	**Relative error**
J	0.0315 kg.m2	0.0317 kg.m2	0.5397 %
b	0.3000 N.m.s/rad	0.3029 N.m.s/rad	0.9667 %
M_c	1.0000 N.m	0.9973 N.m	0.2740 %

The parameter identification method for the separately excited DC motor was also tested experimentally on Motor 2, and the identification profiles of the electromagnetic and mechanical subsystems are shown in Fig. 11 and Fig. 12.

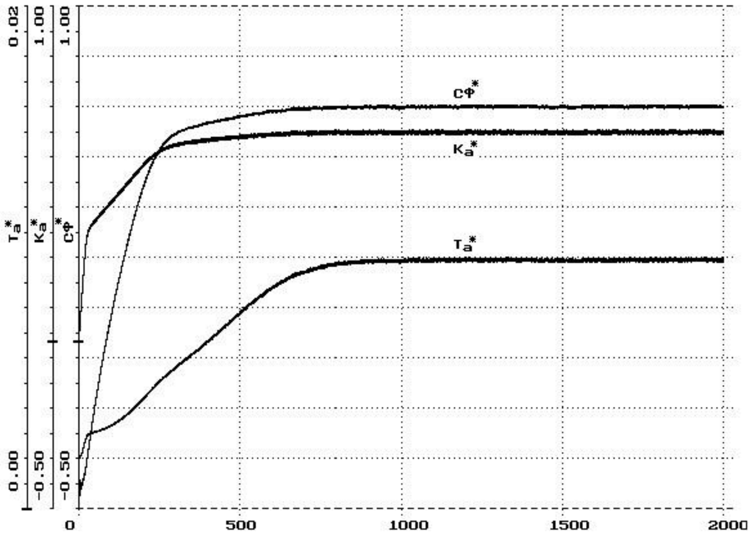

Figure 11

Identification process of the electromagnetic system parameters of Motor 2

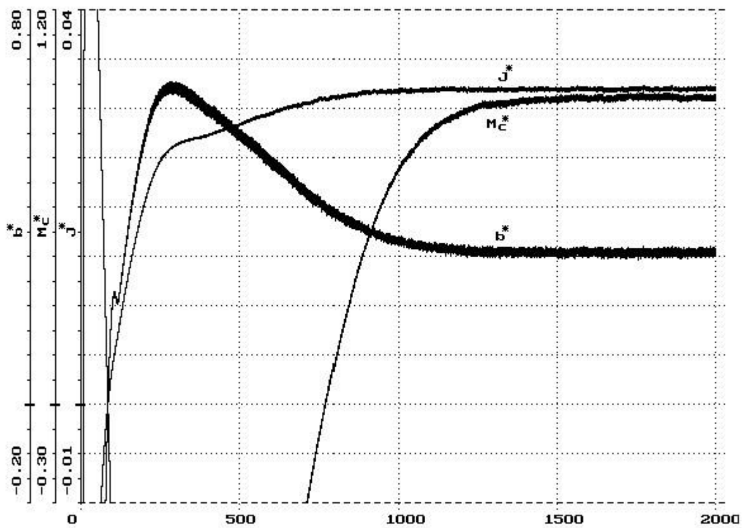

Figure 12

Identification process of the mechanical system parameters of Motor 2

4 Conclusions

This paper presents an approach of system parameters identification, based on a simple artificial neural network and presented as a separately excited DC motor example. The structure of the neural system parameter identifier is based on the analogy of the neural network and the real system, of which, the structure is known.

Since the system consists of two subsystems, two separate parts are used in the identification structure. The first part is the electromagnetic subsystem and the second part is the mechanical subsystem of the motor. For both parts independent neural identifiers were created, represented by neurons with linear transmission functions. The inputs and outputs of the neural identifiers were selected in accordance with the known equations describing the two subsystems. Unknown parameters of both motor subsystems were identified on basis of readily measurable variables such as input voltage, motor armature current and angular speed.

Training sets were prepared separately for both neurons, based on the waveforms of these quantities. The accuracy of parameter identification also depends on the amplitude and frequency of the input signal. The desired electromagnetic and mechanical parameters of the DC motor were determined from the individual synaptic weights of the neurons after the training of the neural networks by the Levenberg-Marquardt method. The identified parameters of the DC motor system are the values of the parameters of the electromagnetic subsystem of the motor, namely armature inductivity La, armature resistance Ra, motor armature gain Ka, electrical time constant of the motor armature Ta and excitation $C\Phi^*$, and the values of the parameters of the mechanical part of the motor, namely the moment of inertia J, friction coefficient b and the Coulomb friction M_c.

The comparison of the obtained results with the actual DC motor parameters revealed that the relative error was less than 0.5% for most of the identified parameters, with the exception of the viscous friction coefficient, which was less than 0.8%.

The presented approach of identification is suitable for further application. It is appropriate in cases when a great deal of information about the system is available and it is possible to create a simple network or a multiple network system, with a structure analogous to the structure of the identified system.

Acknowledgements

This work was supported by the Slovak Research and Development Agency under the contract No. APVV-19-0210 and No. APVV-23-0521.

This work was supported by the Scientific Grant Agency of the Ministry of Education of the Slovak Republic under the project VEGA 1/0363/23 and VEGA 1/0584/24.

Funded by the EU NextGenerationEU through the Recovery and Resilience Plan for Slovakia under the project No. 09I05-03-V02-00018.

References

[1] Ljung L (2008) Perspectives on System Identification, IFAC Proceedings Volumes, Vol. 41, Issue 2, pp. 7172-7184, https://doi.org/10.3182/20080706-5-KR-1001.01215

[2] Lin Ch, Zhenbo W, Fanghua J, Junfeng L (2021) Adaptive neural network control of nonlinear systems with unknown dynamics, Advances in Space Research, Vol. 67, Issue 3, pp. 1114-1123, https://doi.org/10.1016/j.asr.2020.10.052

[3] Naing NN, Min Khaing Z, Naing ZM (2020) Development of Methodology for System Identification of Non-linear System Using Radial Basis Function Neural Network, In: IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus), St. Petersburg and Moscow, Russia, pp. 2390-2394, DOI: 10.1109/EIConRus49466.2020.9039297.

[4] Vaščák J, Jakša R (2015) Artificial intelligence (in Slovak). TU, Košice

[5] Piegat A (2001) Fuzzy modeling and control. Springer-Verlang Berlin Heidelberg GmBH

[6] Bose BK (1994) Expert System, Fuzzy Logic and Neural Network Applications in Power Electronics and Motion Control. In: Proceedings of the IEEE vol 82, no. 8, pp 1303 – 1323, https://doi.org/10.1109/5.301690

[7] Passino KM, Yurkovich S (1998) Fuzzy control. Menlo Park, Calif., Addison-Wesley

[8] Perduková D, Palacký P, Fedor P, Bober P, Fedák V (2020) Dynamic Identification of Rotor Magnetic Flux, Torque and Rotor Resistance of Induction Motor. In: IEEE Access : practical innovations, open solutions. - Piscataway (USA): Institute of Electrical and Electronics Engineers Vol. 8 (2020), pp 142003-142015, https://doi.org/10.1109/ACCESS.2020.3013944

[9] Vas P (1999) Artificial-intelligence-based electrical machines and drives, New York: Oxford University Press

[10] Wang HC, Song F, Wen FW (2013). An Improved BP Algorithm and its Application. In Advanced Materials Research Vol. 765–767, pp. 489–492.

Trans Tech Publications, Ltd. https://doi.org/10.4028/www.scientific.net/amr.765-767.489

[11] Brandstetter P, Dobrovsky M, Kuchar M (2014) Implementation of Genetic Algorithm in Control Struc-ture of Induction Motor AC Drive. Advances in Electrical and Computer Engineering. vol 14, Issue 4, pp 15-20, ISSN 15827445

[12] Žilková J, Timko J, Girovský P (2012) Modelling and control of tinning line entry section using neural networks. International Journal of Simulation Modelling. vol 11, no 2, pp 97-109, https://doi.org/10.2507/IJSIMM11(2)3.203

[13] Brandštetter P, Škuta O (2008) Rotor time constant adaptation using radial basis function network. In 13th International Power electronics and motion control conference EPE-PEMC. 1375-1381, https://doi.org/10.1109/EPEPEMC.2008.4635460

[14] Rubaai A, Kotaru R (2000) Online identification and control of a DC motor using learning adaptation of neural networks. IEEE Transactions on Industry Applications. vol 36, pp 935-942, https://doi.org/10.1109/28.845075

[15] Girovský P, Timko J, Žilková J, Fedák V (2010) Neural estimators for shaft sensorless FOC control of induction motor. 14th International Power Electronics and Motion Control Conference (EPE-PEMC,) Ohrid, Macedonia

[16] Girovský P, Timko J, Žilková J (2012) Shaft Sensor-less FOC Control of an Induction Motor Using Neural Estimators. Acta Polytechnica Hungarica. vol 9, no 4, pp 31-45

[17] Kaminski M, Orlowska-Kowalska T (2011) Clustering in Optimization of RBF-Based Neural Estimators for the Drive System with Elastic Joint. 20th IEEE International Symposium on Industrial Electronics (ISIE), https://doi.org/10.1109/ISIE.2011.5984449

[18] Balara D, Timko J, Žilková J (2013) Application of neural network model for parameters identification of non-linear dynamic system. Neural network world. vol 23, no 2, pp 103-116, https://doi.org/10.14311/nnw.2013.23.008

[19] Balara D, Timko J, Žilková J, Lešo M (2017) Neural networks application for mechanical parameters identification of asynchronous motor. Neural network world. vol 27, no 3, pp 259-270, https://doi.org/10.14311/NNW.2017.27.013

[20] Hadef M (2009) Parameter identification of a separately excited DC motor via inverse problem methodology. Turk J Elec Eng & Comp Sci. vol 17, pp 99-106, https://doi.org/10.3906/elk-0805-5

[21] Bose BK (2007) Neural Network Applications in Power Electronics and Motor Drives. IEEE Transaction on Industrial Electronics. vol 54, pp 14-33, https://doi.org/10.1109/TIE.2006.888683

[22] Rahim NA, Taib MN, Yusof MI (2003) Nonlinear system identification for a DC motor using NARMAX approach. Asian Conference on Sensors. AsiaSense 2003. pp 305-311,

https://doi.org/10.1109/ASENSE.2003.1225038

[23] Saab SS, Kaed-Bey RA (2001) Parameter identification of a DC motor: an experimental approach, In: ICECS 2001. 8th IEEE International Conference on Electronics, Circuits and Systems, pp 981-984, https://doi.org/10.1109/ICECS.2001.957638

[24] Shaw SR, Leeb SB (1999) Identification of induction motor parameters from transient stator current measurements. IEEE Transactions on Industrial Electronics. vol 46, no 1, pp 139–149, https://doi.org/10.1109/41.744405

[25] Vas P (1993) Parameter estimation, condition monitoring and diagnosis of electrical machines. Oxford University Press, Oxford

[26] Josephine RL, Suja S (2014). Experimental Investigations with Fuzzy Controller for PV Fed DC Motor Incorporating SEPIC Converter as Efficient Power Interface. In Applied Mechanics and Materials Vol. 550, pp. 110–125, https://doi.org/10.4028/www.scientific.net/amm.550.110

[27] Wei Wu (2012) DC Motor Parameter Identification Using Speed Step Responses. Modelling and Simu-lation in Engineering, vol 2012, Article ID 189757, 5 pages. https://doi.org/10.1155/2012/189757

[28] Wang S, Li GD (2012) On-Line Parameter Identification and Active Disturbance Rejection Control of Permanent Magnet Synchronous Motor. In Advanced Materials Research, Vol. 588–589, pp. 479–483

[29] C. Pozna, R.-E. Precup (2012) Aspects concerning the observation process modelling in the framework of cognition processes, In Acta Polytechnica Hungarica*,* Vol. 9, No. 1, pp. 185–202

[30] V. Grosu, E. David, L. Goras, G. Pelz (2024) On the modelling possibilities of integrated circuits behavior using active learning principles, In Romanian

Journal of Information Science and Technology (ROMJIST), Vol. 27, No. 2, pp. 183–195

[31] L. Yan, T. Zhao, X. Xie, R.-E. Precup (2024) An online semi-supervised ensemble fuzzy system for data streams learning with missing values, In Expert Systems with Applications, Vol. 255, p. 124695

[32] A.-I. Szedlak-Stinean, R.-E. Precup, E. M. Petriu, R.-C. Roman, E.-L. Hedrea, C.-A. Bojan-Dragos, (2022) Extended Kalman filter and Takagi-Sugeno fuzzy observer for a strip winding system, In Expert Systems with Applications, Vol. 208, p. 118215