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ARTIFICIAL NEURAL NETWORK AS A TOOL OF CYCLOCONVERTER DIAGNOSTIC

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1. Introduction

Consideration of identification problem with using artificial neural networks (ANN) allows to receive fast answer about structure of object and values of its components parameters. Such approach in non invading way shorten process of analysis. ANN are modern tool which can be using in diagnostic and identification [7, 8]. Such realization base on analysis of signal containing information about diagnosed object. However it requires appropriate design of net and learning of proper reactions. The learning process can be realized base on results of simulations obtained from mathematical model. Of course models must as faithfully as possible reflect real behavior of object. Moreover continuous signals obtained from mathematical model usually have to be submit for additional processing in order to receive data which can be used in ANN learning. In that paper identification of condenser capacity in cycloconverter by proper chosen neural network is presented. Net was learned using Levenberga-Marquardt'a method. Learning series was obtained by distribution current in orthogonal functions series. The purpose of this paper is presentation of ANN application in identification. Presented problems were part of University Grant, "Applying of artificial neural network to analysis, synthesis and diagnostics in electrical engineering", in 1998. Part of these solved problems were used in Ph. D. thesis. Future work should lead to design and build intelligent monitoring system of such electrical devices.

2. Model of cycloconverter

Model of cycloconvertor requires transformer and semiconductor elements description by mathematical formulas. The simple way to describe thyristors is make assumption that it is short-circuit when is in conduct state and open in non-conduct state. Transformer usually are modeled basing on equations obtained by analysis of electric circuit. Seems, that using theory of electro-magnetic circuits is more convenient. Advantage of such approach are simpler mathematical equations describing device. Mathematical model can be obtained

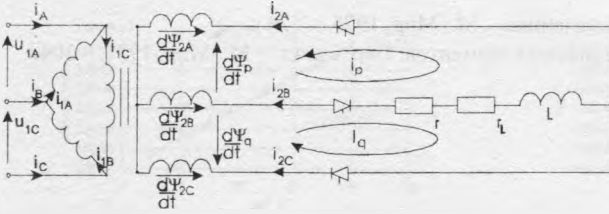


Fig. 1. Scheme of three-phase bridge rectifier in case where phases CB and AB are working

by writing equations for electric sub-circuit and for magnetic sub-circuit and carrying out analysis of different working states of three-phase rectifier.

The analysis of electric circuits shown on Fig. 1 allows to write down following formulas:

$$\frac{d\Psi_D}{dt} = \frac{d\Psi_D}{dt} + \mathbf{L} \frac{di_{2B}}{dt}, \quad \frac{d\Psi_D}{dt} = -\mathbf{R}_2 \mathbf{I}_D,$$

where: $\mathbf{L} = (L, L)^T$.

Using known dependences for three-phase transformer we get:

$$\frac{d\mathbf{X}}{dt} = \mathbf{B}(\mathbf{U} - \mathbf{R}\mathbf{I}),$$

where: $\mathbf{X} = (\Psi_A, \Psi_B, \Psi_C, i_p, i_q)^T$ - column matrix of associated flux and eye current of transformer secondary winding; $\mathbf{U} = (u_{1A}, u_{1B}, u_{1C}, 0, 0)^T$ - column matrix of voltage; $\mathbf{I} = (i_{1A}, i_{1B}, i_{1C}, i_p, i_q)^T$ - column matrix of windings current; $\mathbf{R} = \text{diag}(\mathbf{R}_1, \mathbf{R}_D)$ - matrix of resistances;

$$\mathbf{R}_D = \begin{bmatrix} r_{2A} + r_{2B} + r + r_L & r_{2B} + r + r_L \\ r_{2B} + r + r_L & r_{2B} + r_{2C} + r + r_L \end{bmatrix}; \quad \mathbf{B} = (\mathbf{D}, \mathbf{A}_2)^T \text{ - matrix of coefficients; } \mathbf{D} =$$

$(\mathbf{G}\alpha_1, \mathbf{G}\mathbf{H}_2\alpha_{21})$; $\mathbf{G} = (\alpha'' + \alpha_0\mathbf{Z} + \alpha_1 - \mathbf{H}_2\alpha_{22})^{-1}$; $\mathbf{A}_2 = (\alpha_{22}\mathbf{G}\alpha_1, \alpha_{21} + \alpha_{22}\mathbf{G}\mathbf{H}_2\alpha_{21})$; $\alpha'' = \text{diag}(\alpha_A'', \alpha_B'', \alpha_C'')$; $\alpha_1 = \text{diag}(\alpha_{1A}, \alpha_{1B}, \alpha_{1C})$; $\alpha_0 = \text{diag}(\alpha_{4B}, \alpha_{AC}, \alpha_{BC})$; $\alpha_{22} = \text{diag}(\alpha_{2A}, \alpha_{2B}, \alpha_{2C})$; $\alpha_{21} = \mathbf{H} \alpha_0 \mathbf{H}^T$; $\alpha_{22} = \mathbf{H}\alpha_0\mathbf{H}_1$;

$$\mathbf{H} = \begin{bmatrix} 1 & -1 & \\ & 1 & 1 \end{bmatrix}; \quad \mathbf{H}_1 = \begin{bmatrix} -1 & 1 & \\ 1 & & -1 \\ & 1 & -1 \end{bmatrix}; \quad \mathbf{H}_2 = \begin{bmatrix} 1 & \\ -1 & -1 \\ & 1 \end{bmatrix}; \quad \mathbf{Z} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}.$$

Magnetic circuit depicted on Fig. 2 can be described by dependence

$$\mathbf{I}_1 = \alpha \psi + \alpha_0 \mathbf{Z} \psi - \mathbf{H}_2 \mathbf{I}_D,$$

where: $\psi = (\Psi_A, \Psi_B, \Psi_C)^T$; $\alpha' = \text{diag}(\alpha_A', \alpha_B', \alpha_C')$.

The presented analysis describes only one of work state of device. Considering remaining six cases and adding second inversely affixed thyristor parallel to existing we can come to final form of formulas describing cycloconverter with LC load.

$$\frac{d\mathbf{X}}{dt} = \mathbf{M}\mathbf{Y}.$$

where: $\mathbf{X} = (\Psi_A, \Psi_B, \Psi_C, i_p, i_q, u)^T$ - column matrix of associated flux and eye current of transformer secondary winding and condenser voltage; $\mathbf{U} = (u_{1A}, u_{1B}, u_{1C}, -u, -u)$ - column

matrix of primary and secondary voltage of transformer; $\mathbf{Y} = (\mathbf{U} - \mathbf{R}\mathbf{I}, i_c)$; $\mathbf{I} = (i_{1A}, i_{1B}, i_{1C}, i_p, i_q)$ - column matrix of windings current; $i_c = i_p + i_q - u_c/r$ - condenser current; $\mathbf{M} = \text{diag}(\mathbf{B}, 1/C)$ - matrix of coefficients.

3. Data preprocessing

Direct learning of artificial neural network by data obtained from mathematical model is difficult and often practically impossible. It comes from fact that length of input vector is big therefore number of neurons in input layer and network size is also big. Moreover using data directly from model causes dependence on "moment of time" - calculations have to start always in the same moment of period. Application of method which will eliminate such inconvenience is necessary. If period T of analyzed signal is known that the most simple solution seems approximation that signal by orthogonal function system. In such system each of functions bring element which doesn't exist in another function of that system. Most often some first elements of orthogonal system already good enough approximate analyzed signal. Thus in network learning is enough to use parameters describing only these functions. In our investigations Fourier and Walsh series taking first seven harmonics were used. Number of harmonics was chosen after early testing.

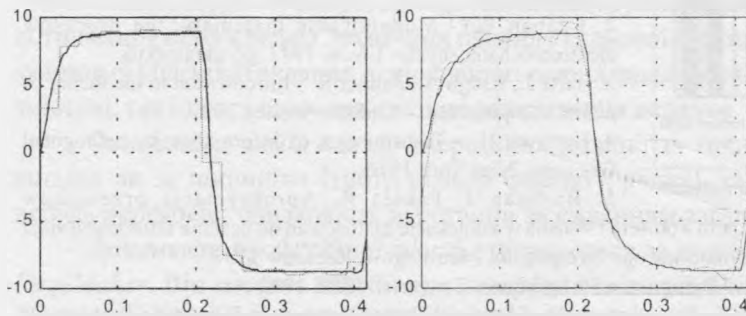


Fig. 3. Example distribution of analyzed current in Walsh and Fourier series

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3. Artificial neural network

Feedforward nets with one hidden layer learning backpropagation method were used in our investigations. Input layer consist of 15 neurons (number of elements in input vector) and output layer has 1 neuron because network recognized capacity of filtering condenser. ANN with 10, 15, 20, 25 and 30 neurons in hidden layer were tested. Neurons in hidden layer has tangent transfer function.

4. Results of experiments

Proper identification of condenser capacity in range from $10 \cdot 5$ to $9 \cdot 10^{-3}$ F is the task for artificial network. An assumption that net properly recognizes

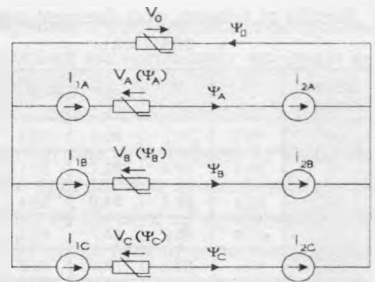


Fig. 2 Scheme of transformer magnetic sub-circuit

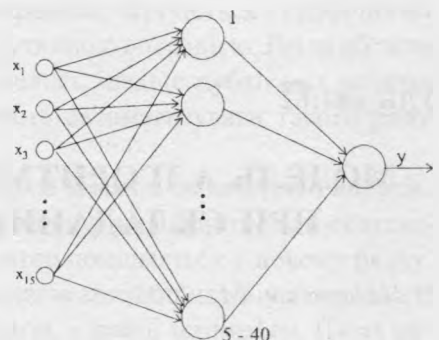


Fig. 4. Scheme of ANN designed to condenser capacity identification

Results of network work (percent of proper answers)

SSE no. neuron?w	10	15	20	25	30
10^5	73,2	77,7	88,5	73,3	38,2
10^6	81,1	87,3	92,7	87,1	40,4
10^7	82,9	92,3	94,0	88,4	42,2
10^8	72,9	85,2	84,7	83,4	41,9
10^9	67,5	83,1	77,4	73,2	38,8
10^{10}	62,0	80,5	75,7	67,4	34,0

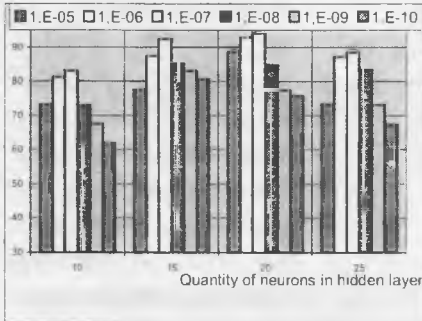


Fig. 5. Efficiency of artificial neural network

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МОДЕЛЬ АЛГОРИТМУ АВТОМАТИЗАЦІЇ ОПЕРАЦІЙ ПРИ СКЛАДАННІ ТЕЛЕВІЗІЙНИХ ПРОГРАМ

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