# DIAGNOSTIC OF ELECTRICAL DEVICES WITH DISTRIBUTED PARAMETERS BY ANN AS A BUSINESS PERSPECTIVE

Tchaban Vasyl

University of Information Technology and Management in Przemysl, University of Rzeszów. Institute of Technics, 21/4 Pilsudski Av., Rzeszow, 35-074, Poland
e-mail: vtchaban@univ.rzeszow.pl

Tchaban Andrew

National University "Lviv Polytechnic", 95/34 Lubinska Str., Lviv, 79-054, Ukraine
e-mail: vtchaban@polynet.lviv.ua

**ABSTRACT**
The mathematical models of new generation connected with elements of artificial intelligence give good chances of development of new technologies in diagnostics of physical objects by not destructive methods. In the paper for example are shown two such significant problems – the diagnostic of electric devices laminated cores and measuring of disbalance in induction motors which creates the unhealthy lateral vibrations taking to consideration the variable air gap and one-sided forces of magnet attraction. In the paper we present results of experiments, that indicate on possibility to detect temperature and faults in laminated structure of electric device cores and eccentricity of induction motors taking into consideration steady-state current in magnetizing windings. As the tool of diagnostic method we used artificial neural networks. To obtain input signals for the ANN we used mathematical field model of the electric device. The results of computation are given.
Key words – detect faults in laminated cores, mathematical field model, artificial neural network.

## INTRODUCTION

The mathematical models of new generation connected with artificial neural networks (ANN) give a good chances of development of new technologies in diagnostics of physical objects by not destructive methods. Such solution of the problem must be as interest of business structures as profitable work in the future. In the paper is shown as mathematical models of two electric devices of new generation together with ANN give the possibility of diagnostics of such states of the devices which are beyond one's strength for another methods. We are worked the theoretical principle of building of ANN supervisors on base of mathematical modeling. As successful supervisors we use precision circuital, circuital-field and field mathematical models of real devices described by non-linear differential equations with ordinary and spatial derivatives. The ANN taught by such supervisor gives either diagnosis of concrete fault in a device. Bellow we give two examples for objects with distributed parameters.

We present results of experiments that indicate on possibility to detect faults in laminated structure of electric device cores and indicate on possibility to measure the temperature of laminated and solid conductor materials caused by eddy currents taking into attention steady-state current in magnetizing windings. That to obtain input signals for the ANN we used mathematical field models of the devices.

We present results of experiments that indicate on possibility to detect a work of vibrations of electromechanical devices taking into attention steady-state current in magnetizing windings too. That to obtain input signals for the ANN we used mathematical circuital model of the device with distributed variable air gap.

## 1. THE DIAGNOSTIC OF LAMINATED CORES BY ANN

Fault detection in magnetic laminated cores is present-day problem in electric devices exploitation. The short of the particular sheets is the defect, which appears most often. In the paper we present results of experiments, that indicate on possibility to detect faults in laminated structure taking into consideration steady-state current of magnetizing windings. As the tool of diagnostic method we used ANN. To obtain input signals for the ANN we used mathematical field model of the choke with laminated core.

### 1.1. The thoroidal choke's mathematical model

The choke consists of a thoroidal laminated core, magnetizing winding with sinusoidal electric voltage supplied. In the cylindrical system of co-ordinates the partial differential equation of the thoroid can be obtained from both Maxwell's equations and it can be written as [1]

$$\frac{\partial B}{\partial t}=\frac{1}{\gamma}\left(\frac{\partial^2 H}{\partial r^2}+\frac{\partial^2 H}{\partial z^2}+\left(\frac{1}{r}-\frac{1}{\gamma}\frac{\partial\gamma}{\partial r}\right)\frac{\partial H}{\partial r}-\frac{1}{r}\left(\frac{1}{r}+\frac{1}{\gamma}\frac{\partial\gamma}{\partial r}\right)H-\frac{1}{\gamma}\frac{\partial\gamma}{\partial z}\frac{\partial H}{\partial z}\right), \tag{1}$$

where: $B$, $H$ are angle components of magnetic flux density and Magnetic field intensity vectors; $\gamma$ is electric conductivity; $r$, $z$ are spatial coordinates.

Connection between components $H$ and $B$ in the ferromagnetic layers is determined by the materials equation $H=\nu(B)\cdot B$, where $\nu$ is the static reluctivity of electromagnetic material, which can be calculated using its magnetization curve. In non-magnetic layers $\nu=\nu_0$.

On the boundary of the ferromagnetic and non-magnetic two layers must be fulfilled boundary conditions: $\nu_0 B_0=\nu_f B_f$, where indexes 0 and $f$ indicates on non-magnetic and ferromagnetic layer adequately.

The electric conductivity is function of thermodynamic temperature $\theta$

$$\gamma=\frac{\gamma_0}{1+\alpha(\theta-\theta_0)+\beta(\theta-\theta_0)^2}, \tag{2}$$

where $\alpha,\beta$ are constant coefficients.

The differential equations of not stationary heat conduction are

$$\frac{\partial\Theta}{\partial t}=\frac{1}{\rho C}\left(\lambda\left(\frac{\partial^2\Theta}{\partial r^2}+\frac{\partial^2\Theta}{\partial z^2}+\frac{1}{r}\frac{\partial\Theta}{\partial r}\right)+\frac{1}{\gamma}\left(\left(\frac{\partial H}{\partial z}\right)^2+\left(\frac{\partial H}{\partial r}+\frac{H}{r}\right)^2\right)\right), \tag{3}$$

where $\lambda$ is thermal conductivity matrix; $C$ is heat capacity; $\rho$ is specific gravity.

In non-magnetic layers $\gamma=0$ and the equations (1) and (3) are simpliaied.

The area of integration (1), (3) is: $R_1\le 0\le R_2$; $0\le z\le a$, where $R_1$ is internal radius of thoroid, $R_2$ is external radius of thoroid, $a$ is dimension in $z$ direction.

Generally boundary conditions we write in form

$$H(R_1,z)=wi/2\pi R_1;\ H(R_2,z)=wi/2\pi R_2;\ \ H(r,0)=H(r,a)=wi/2\pi r;$$
$$\frac{\partial\Theta}{\partial r}\Big|_{r=R_1,R_2}=0;\quad \frac{\partial\Theta}{\partial z}\Big|_{z=0,a}=0, \tag{4}$$

where: $wi$ is magnetomotive force of winding.

Taken in the consideration the Ampere's circuital law we obtain the current equation

$$\frac{di}{dt}=L_s^{-1}\left(u-iR-w\int_{R_1}^{R_2}\int_0^a\frac{dB}{dt}dzdr\right), \tag{5}$$

where: $u$ is electric voltage supplied, $R$ is resistance of windings, $L_s$ is inductivity of dissipation.

Using matrix notation, we can create the column of unknowns:

$$x=(B_\Delta,i)_t, \tag{6}$$

where $B_\Delta=(B_2,B_3,...B_{n-1})_t$ is the sub-column of discrete values of the induction in spatial mesh nodes, with exception of border nodes.

According to (9), the system of equations (4), (8) can be written in the canonical form:

$$\frac{dx}{dt}=f(x,t), \tag{7}$$

where $f(x,t)$ is $T$-periodical.

The integration (7) from the initial condition $x_0$ is the initial-boundary (Cauchy) problem for ordinary differential equations. The result of such a problem determines the transient process of the considered device. We solved it using the explicit Euler's method.

To obtain steady-state process we assume in (7) additional condition of $T$-periodicity:

$$x(0) - x(x(0), T) = 0. \tag{8}$$

The common solution (7) and (8) constitutes the two-point boundary problem for ordinary differential equations. Its solution with absence of the constant component in periodical result can be obtained in an easy way using the naive algorithm [1]:

$$x(0)^{k+1} = x(T)^k - \frac{1}{2}\left(x_{\max}^k + x_{\min}^k\right), \tag{9}$$

where $x_{\mathrm{kmax}}$, $x_{\mathrm{kmin}}$ are columns of the maximum and minimum values $x(t)$ on interval $[0,T]$.

The algorithm stops when: $abs\left(x(0)^k - x(T)^k\right) \le \varepsilon,$ where ε is the column of accuracy of computations.

### 1.2. Some results of numerical simulations

Presented mathematical model was simulated on the personal computer. We tested the choke by some concrete parameters. On fig. 1 are shown the spatial distribution of magnetic induction $B$ for shorted two sheets in core structure and currents in magnetizing windings for normal, shorted and pressing-out structures. We obtained defected structure states by expansion range of electromagnetic field equation (1) on the discrete nodes, which normally belong to dielectric layer.

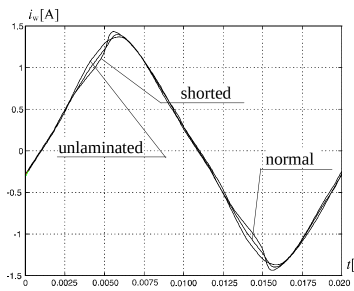


Fig. 1. Space distribution of magnetic induction $B$ in the thoroid with three ferromagnetic sheets if are shorted 2 sheets. Currents in magnetizing windings

We can observe that the current in the case of incorrect structure is different in opposite to the normal structure. These phenomena can be used as the signal about core structure.

Area of shorted sheets in the laminated structure of the core determines additional pats for eddy-currents. It causes different time-spatial distribution of the electromagnetic field vectors in comparison with the core without defects. On the other hand, this different time-spatial distribution influences - according to equation (5) – on the time-course of the current $i_w$. So, the current $i_w$ can be treated as the information signal about laminated structure condition of the magnetic core.

As the input signal for the neural network we used steady-state current of the magnetizing windings. To decrease length of input vectors we used preprocessing method, based on Fourier series distribution. Such method allows constructing input vectors for neural network, composed from amplitudes and phase angles of particular harmonics. In our experiments we tested supervised neural networks with back-propagation algorithm. Number of input neurons of the network was determined by number of amplitudes and phase angles of current harmonics.

In output layer we tested 3 nonlinear neurons. The goal of particular these neurons was to indicate correct state of magnetic core (neuron 1) and faults in laminated structure (neuron 2 and 3). Using these indicators we can determine faults areas with structure faults.

In the ANN learning process we assumed, that each neuron in output layer will be indicate to one of the three different states of laminated structure. In our experiments the neural network is responsible to recognize 3 different states, so the target vectors was constructed as follows: [1 0 0] for shorted structure, [0 1 0] – “unlaminated” structure, [0 0 1] – normal structure. We used sigmoid function of activation for output neurons, assuming that output neuron signal, which reaches value near of 1 will indicate state of structure. The others two neurons should generate signals near value of 0.

Artificial neuron networks with one hidden layer with tangensoid transfer function was tested. In the table 2 some result of experiments were presented.

In our experiments we tested 69 different signals. The neural network efficiency for assumed laminated structure was high and reached value of 0.9.

The proposed method is applicable for determination of temperature of ferromagnetic by artificial neural networks (ANN). As input signals are used the steady-state currents of magnet winding too. The results of computation are given.

Learning vector consists from amplitudes and phases of 1-, 3-, 5-th odd harmonics. For the improvement of ANN possibility to input signals are added noises. On fig. 2 are shown the scheme of ANN and dependence of learning error as function of epochs The sheme consists 6 receptors, 20 neurons in hidden layer with logsig transform and 1 autput neuron with linear transform.

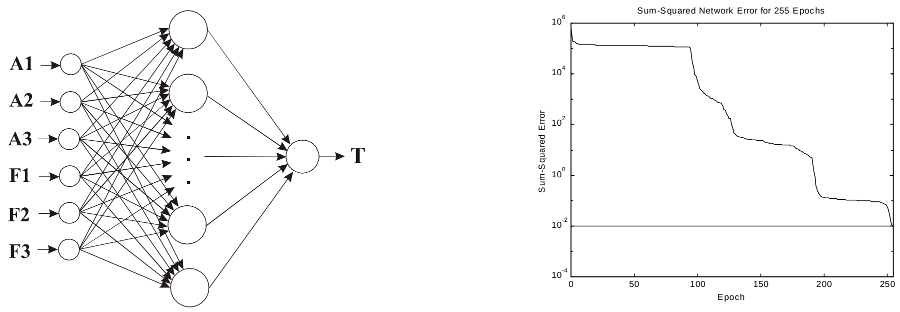


Fig. 2. Scheme of ANN and dependence of error as function of epochs number

The learned ANN was tested. For feebly noisy signals the precision was 98%. But if we have increase of noises the precision of ANN falls down/ For example by 50% noises the precision of ANN is 85 % only.

## 2. THE INVESTIGATION OF VIBRATIONS OF INDUCTION MOTOR

The diagnostic of induction motors by ANN needs natural experiments [1] or good mathematical models [2] as supervisors in ANN learning process. In this problem important is taking into account the motor vibrations. The simulation of vibration processes of induction motors are caused in the first turn by cros-swise and rotation oscillations of rotor. The difficult of calculation such processes is caused of calculation of requirements of changed air gap and one-sided forces of magnet attraction, which are caused by changed of this air gap in the time. All classical theory of electric machines is built by condition that air gap between rotor and stator is constant, therefore she is useless in practice in this case. To solve the problem give possibility only the method proposed in [1]. The mathematical model [1] of induction motor describe sufficient complicated of simultaneous crosswise and rotation oscillations of rotor and stator, which is attached to foundation by elastic supports. We simplify the problem in case of vibration pro-cesses of rotor only at stiff immovable stator, taken in consideration the susceptible mechanical links of fixation rotor to stator

### 2.1. Mathematical model

The rotor we consider as absolute hard body with mass $m$ and moment $J$ in relation to centre of mass. The construction disbalance we are taken into account by displacement of mass centre $m$ concerning his axis of rotation $c_R$ on the eccentricities$\varepsilon$. In immovable Cartesian coordinates $x$ and $y$ which coincide with geometrical stator centre $O$, coordinates of centre of rotor rotation $x_R$ and $y_R$ , and coordinates of centre of rotor mass are $x_m$ and $y_m$. The angle of turning-point of centre of rotor turning is $\gamma_R$ and the angle of rotor turning-point concerning of own rotation centre is $\gamma$.

The differential equations of induction motor we write in movable oscillation Cartesian coordinates

$\xi$ and $\chi$ ,which have common centre with immovable coordinate system $x$ and $y$. Axis $\xi$ choose so in order two she was passed for geometrical centre of rotor $c_R$.

The angle velocity of rotation of movable coordinates axes $\omega_R$ and angle of turning-point their $\gamma_R$ are connected by differential equation

$$\frac{d\gamma_R}{dt} = \omega_R; \quad \omega_R = \frac{x_R\left(\upsilon_{ym} - \omega\varepsilon\cos\gamma\right) - y_R\left(\upsilon_{xm} + \omega\varepsilon\sin\gamma\right)}{x_R^2 + y_R^2}, \tag{1}$$

where $\upsilon_{xm}$, $\upsilon_{ym}$ are velocities of movement of centre of rotor mass along of axes $x$ and $y$; $\omega$ is angle velocity of rotor,

$$\frac{dx_m}{dt} = v_{xm}; \quad \frac{dy_m}{dt} = \upsilon_{ym}; \quad \frac{d\gamma}{dt} = \omega; \tag{2}$$

The differential equations of electric contour of idealized machine in movable coordinates $\xi$ and $\chi$ have usually view

$$\begin{aligned} \frac{d\Psi_{S\xi}}{dt} &= u_\xi + p_0\omega_R\Psi_{S\chi} - r_S i_{S\xi}; \quad \frac{d\Psi_{R\xi}}{dt} = p_0(\omega_R - \omega)\Psi_{R\chi} - r_R i_{R\xi}; \\ \frac{d\Psi_{S\chi}}{dt} &= u_\chi - p_0\omega_R\Psi_{S\xi} - r_S i_{S\chi}; \quad \frac{d\Psi_{R\xi}}{dt} = p_0(\omega - \omega_R)\Psi_{R\xi} - r_R i_{R\chi}, \end{aligned} \tag{3}$$

where $\Psi$, $u$, $i$ are full linkage magnetic fluxes, voltages and currents; r are resistances of coils; $p_0$ is number of magnetic pole pairs (indexes S and R belong to stator and rotor and $\xi$ and $\chi$ belong to contours to separate electric contour). Stator voltages we find as $u_\xi = U_m\cos\left(\omega_0 t - p_0\gamma_R\right)$; $u_\chi = U_m\sin\left(\omega_0 t - p_0\gamma_R\right)$, where $U_m$, $\omega_0$ amplitude and angle frequency of input voltages;

$$i_{mk} = \alpha_m\left(\Psi_{mk} - \psi_k\right), \; m = S, R; \; k = \xi, \chi, \tag{6}$$

where $\alpha_S$, $\alpha_R$ are inverse inductance of stator and rotor, $\psi_\xi$, $\psi_\chi$ are main linkage magnetic fluxes

$$\psi_\xi = \alpha_S\left(a\Psi_{S\xi} + b\Psi_{S\chi}\right) + \alpha_R\left(a\Psi_{R\xi} + b\Psi_{R\chi}\right); \; \psi_\chi = \alpha_S\left(m\Psi_{S\xi} + n\Psi_{S\chi}\right) + \alpha_R\left(m\Psi_{R\xi} + n\Psi_{R\chi}\right), \tag{7}$$

at that

$$a = \frac{\left(1+TN\right)M - TS^2}{\Delta}; \; c = \frac{\left(1+TM\right)N - TS^2}{\Delta}; \; T = \alpha_S + \alpha_R + \frac{\pi p_0}{3w^2}\rho; \; \Delta = \left(1+TM\right)\left(1+TN\right) - TS^2;$$

$$M = b\int_0^{2\pi}\frac{\cos^2 p_0\eta}{\delta(\eta)}d\eta; \quad S = b\int_0^{2\pi}\frac{\sin p_0\eta\cos p_0\eta}{\delta(\eta)}d\eta; \quad N = b\int_0^{2\pi}\frac{\sin^2 p_0\eta}{\delta(\eta)}d\eta; \quad b = \frac{S}{\Delta}.$$

There $b = 3wa\mu_0/(\pi p_0)$ is constant coefficient; $\rho$ is magnetic resistance of main magnetic circuit of electric machine with the exception of resistance of air gap; $w$ is number of effective windings of phase stator; $\mu_0$ magnetic constant; $p_0\eta$ is angle coordinate of stator; $\delta(\eta)$ is function dependence of value of air gap from angle $\eta$

$$\delta(\eta) = \sqrt{x_R^2 + y_R^2 + R_1^2 - 2R_1\sqrt{x_R^2 + y_R^2}\cos\eta} - R_2, \tag{8}$$

what $R_1$ is inner radius of stator; $R_2$ is external radius of rotor.

Electromagnetic moment

$$M_E = \frac{3}{2}p_0\left(\psi_\xi i_{S\chi} - \psi_\chi i_{S\xi}\right). \tag{9}$$

The one-sided forces of magnet attraction in immovable co-ordinate axes will be

$$F_x = F_\xi\cos\gamma_R - F_\chi\sin\gamma_R; \quad F_y = F_\xi\sin\gamma_R + F_\chi\cos\gamma_R;, \tag{10}$$

where

$$F_{\xi} = c_0 \int_0^{2\pi} \frac{\varphi_{\eta}^2}{\delta(\eta)^2} \cos\eta d\eta; \quad F_{\chi} = c_0 \int_0^{2\pi} \frac{\varphi_{\eta}^2}{\delta(\eta)^2} \sin\eta d\eta \,; F_{\chi} = c_0 \int_0^{2\pi} \frac{\varphi_{\eta}^2}{\delta(\eta)^2} \sin\eta d\eta \,, \tag{11}$$

Here

$$\varphi_{\eta} = \left( \frac{3w}{\pi p_0} \left( i_{S\xi} + i_{R\xi} \right) - \frac{\rho\psi_{\xi}}{w} \right) \cos p_0\eta + \left( \frac{3w}{\pi p_0} \left( i_{S\chi} + i_{R\chi} \right) - \frac{\rho\psi_{\chi}}{w} \right) \sin p_0\eta, \tag{12}$$

where $c_0 = R_1 l \mu_0 / 2$ is constant coefficient; $l$ is length of stator.

The velocities of rotor movement we obtain from general equation of dynamic

$$\frac{d\upsilon_{xm}}{dt} = \frac{1}{m}\Big(F_x - c_x x_R - \nu_x \left(\upsilon_{xm} + \varepsilon\omega\sin\gamma\right)\Big); \; \frac{d\upsilon_{ym}}{dt} = \frac{1}{m}\Big(F_y - gm - c_y y_R - \nu_y \left(\upsilon_{ym} - \varepsilon\omega\cos\gamma\right)\Big);$$
$$\frac{d\omega}{dt} = \frac{1}{J}\left( M_E - M_M + m\frac{d\upsilon_{xm}}{dt}\varepsilon\sin\gamma - \left( m\frac{d\upsilon_{ym}}{dt} + mg \right)\varepsilon\cos\gamma \right), \tag{13}$$

where $M_M$ is resistance moment; $c_x$, $c_y$ are stiffness of rotor supports; $\nu_x$, $\nu_y$ are dissipation coefficients; g is gravitations constant.

The system of 11 differential equations (1), (3), (4), (13) is integrated simultaneous and joint. As result of integration we find full linkage magnetic fluxes $\Psi_{S\xi}$ , $\Psi_{S\chi}$ , $\Psi_{R\xi}$ , $\Psi_{R\chi}$, co-ordinates of centre of rotor mass $x_m$, $y_m$, angles of rotor turn $\gamma$ and movable co-ordinate system $\gamma_R$, linear velocities of movement of centre of rotor mass, $\upsilon_{xm}$, $\upsilon_{ym}$ and angle rotor velocity $\omega$.

Because of high frequency vibrations of mechanical system the differential equations are very stiff. They are integrated by implicit numerical Gear method including the formulas of 6-th order or as in [3]. For this

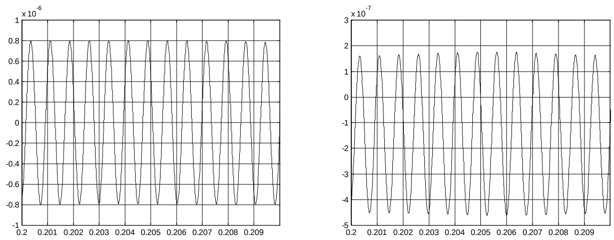

Fig. 3. Horizontal (above) $x_R = x_R(t)$ and vertical $y_R = y_R(t)$ vibrations of rotor on limited time interval of transient starting motor operation ($M_M = 0$)

aim we obtained the analytical formulas of Jacobi's matrix, because it is very complicated we here do not given.

### 2.2. Some results of numerical simulations

On fig. 3 are given the results of computation of induction motor starting on some period. The precision mathematical model may be as supervisor of network learning, consequently to replace very expensive experimental researches which not always may execute. Particularly if it is related to machines of big power.

The using of ANN by solution of some problem needs receiving of input signals for ANN which are sources about the prototype system. In case of analysis, which is realized in this paper (identification of value of load moment), is assumed that such signals are time of starting and angular velocity of induction motor in steady-state process which are received from given mathematical model. We are used unilateral ANN which consists three layers with one hidden layer with tansigmoidal transfer function (2 receptors, 6 neurons) and with 1 output neuron with linear transfer function representative the load moment value. In learning process is used the Levenberg-Marquardt's gradient method toghater with back propagation algorithm.

The using very small number of neurons in hidden layer of ANN disable of solution this problem. In a practical manner it disable the learning process. And vice versa of wary large number of neurons the ANN receive the grate possibility of transformation, as a result it learns such nuances in learning process which are inessential for the current task (table 2*).*

In order to certain that ANN may generalize we must make verification its functioning by independent assigning values process which present the same problem.

## CONCLUSION

Presented in the paper results of experiments show, that the mathematical model of induction motor celebrates as good supervisor in ANN learning process successfully

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