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Comparison Neural Networks and Ossanna Circle Diagram for Asynchronous Motors Performance Analysis

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Abstract: The aim of the steady-state analysis of induction motors is to do performance estimating in the design part. The designer firstly develops a model with the simplest designing rules and then calculates the performance of the machine with previous estimating analysis. The analysis should be quite rapid and should give optimum result. In this study, it is put forward that neural networks can firstly be used in the performance analysis of asynchronous motors.

Key words: Asynchronous motor, neural networks, performance analysis

INTRODUCTION

Asynchronous motors are exited machines used in a lot of areas in industry because of the features like the simpleness of the structure, the easiness of the control and the necessarily of the fewer care. One of priority reasons of induction motors is that the speed adjusting can easily be done by wide ranges by means of the developing of solid-state technology. The aim of the steady-state analysis of induction motors is to do performance estimating in the design part. The designer firstly develops a model with the simplest designing rules and then calculates the performance of the machine with previous estimating analysis. If these values give the desired characteristics, it can be said that design is appropriate. If it isn't so, it is required to calculate the performance with necessary adjusting again. Because of this, the analysis should be quite rapid and should give optimum result. The classic design analysis is based on a steady-state phase equivalence circuit (Fig. 1).

Recently, Fuzzy logic and neural network techniques are now being increasingly applied to power electronics and electrical machines[1-3]. The principal advantages of these methods are fast convergence with adaptive step size of control parameters. The neural network adds the advantage of fast control implementation, either by a dedicated hardware chip or by DSP-based software[4,5].

This study describes that the performance of the induction motor can be done by high accuracy and in a simple way using neural networks.

Ossanna circle diagram: Ossanna circle diagram is the well-known method to obtain induction motor characteristics. It is necessary to do that experiment for drawing Ossanna circle diagram.

- The experiment of no-load working
- The short circuit experiment with locked rotor
- The measuring of winding resistances

P_0 is found with no-load working experiment (on s=0 working point). For this experiment, motor is fed normal voltage for no-load working. I_0 phase is drawn from a start point and the position, which will do θ_0 angles with vertical axis. Thus, P_0 point is found.

In short circuit experiment, the short circuit current phase from which will be obtained V_0 normal voltage is drawn with ϕ_{kd} angle. The tips of I_0 and $(Ikd)_0$ current phases are on the circle. It is united the tips of the phases. So, the drawn plank on the middle passes centre of the circle.

Winding resistance is measured in the heat condition (for detection of f point in the diagram). It is detected the scales of the various sizes with this mathematical equations:

$$ef = \frac{R_{ort}\,(I_{kd})_0}{V_0 \text{ Current Scale}} \quad (1)$$

where, V_0 is nominal phase-Notre voltage. de distance in short circuit situation is the total copper loss in rotor and stator. df and ef distances are proportional with rotor and stator losses. A_{ff} line (torque

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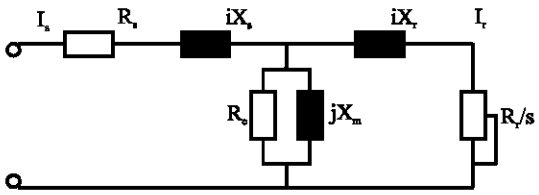

Fig. 1: A phase equivalent circuit of asynchronous motor

axis) is obtained by f point. It is called mechanic power axis to A_d line. For the detection of slip (s) points by going down wards from P_0 point (also by taking away the de distance down words) is found H point. It is drawn a new line which is parallel to P-H and cutting P_0H and HP_k lines. The point of the line which cuts P_0H on s=0, by drawing any I phase, if the tip is showed by g:

$$\text{motor efficiency} = \frac{gh}{gj} \tag{2}$$

where, gh is the mechanic power, which motor ensures and gj is the total of fixed and changeable losses, is determined with this ratio:

$$\text{Cos}\phi = \frac{gj}{og} \tag{3}$$

$$s = \frac{hk}{gk} \tag{4}$$

According to these values ossanna circle diagram is depicted in Fig. 2. So we can see the points, which are determined in equations above.

Artificial neural networks: Recently, it has been shown that neural networks have abilities to solve various complex problems. On the other hand, the multilayered feed-forward network has a better ability to learn the correspondence between input patterns and teaching values from many sample data by the error back-propagation algorithm. Therefore, in this paper, we used three-layered feed-forward neural networks and taught them by error back-propagation. Figure 3 shows a general structure of a neural network used in this study.

The output O_{ij} of each unit ij is defined by:

$$O_{ij} = f(net_{ij}),\ net_{ij} = \sum_i w_{ij} O_i + \theta_j \tag{5}$$

where, O_i is the output of unit i, w_{ij} is the weight of the connection from unit i to unit j, θ_j is the bias of unit j, $\sum_i$ is a summation of every unit ij whose output flows into unit j and f (x) is a monotonously increasing function. In generally, sigmoid function f (x) = 1/(1+exp(-x)) is used. When the set of m-dimensional input patterns $\{i_p = (i_{p1}, i_{p2}, \ldots, i_{pm}); p \in P\}$ where, P denotes set of presented patterns and their corresponding desired n-dimensional output patterns $\{t_p = (t_{p1}, t_{p2}, \ldots, t_{pm}); p \in P\}$ are provided, the neural network is taught to compute ideal patterns as follows. The squared error function E_p for a pattern p is defined by:

$$E_p = \frac{1}{2} \sum_{j \in \text{output}} (t_{pj} - O_{pj})^2 \tag{6}$$

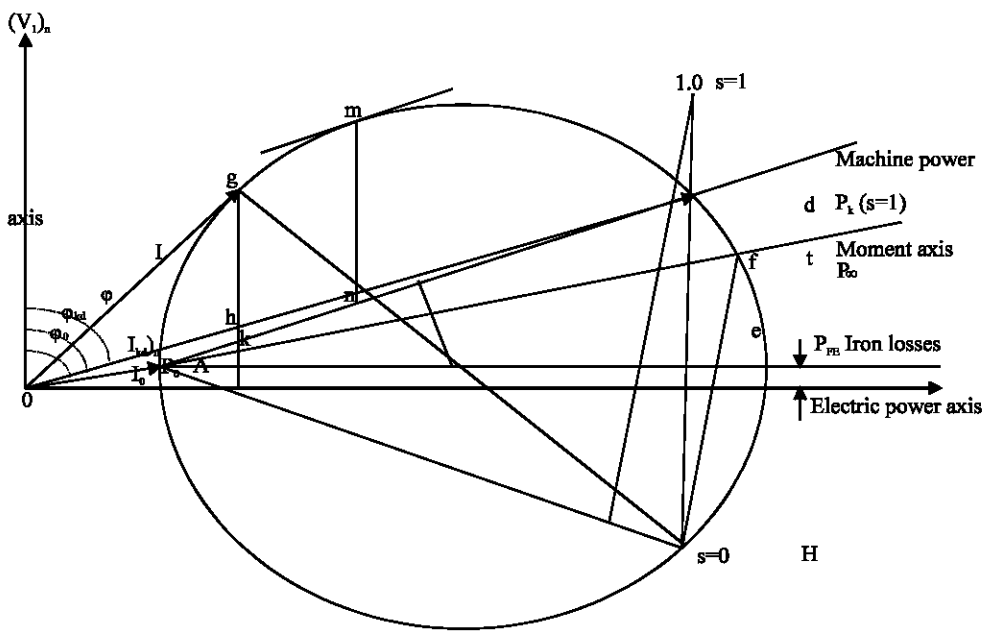

Fig. 2: Ossanna circle diagram

The purpose is to make $E = \sum_p E_p$ small enough by choosing appropriate w_{ji} and θ_j To realize this purpose, a pattern $p \in P$ is chosen successively and randomly and then w_{ji} and θ_j are changed by:

$$\Delta_p w_{ji} = -\epsilon\,(\partial E_p / \partial w_{ji}) \quad (7)$$

$$\Delta_p \theta_j = -\epsilon\,(\partial E_p / \partial \theta_j) \quad (8)$$

where, ϵ is a small positive constant. By calculating the right hand side of (7) and (8), it follows that

$$\Delta_p w_{ji} = \epsilon\, \delta_{pj} O_{pi} \quad (9)$$

$$\Delta_p \theta_j = \epsilon\, \delta_{pj} \quad (10)$$

where:

$$\delta p = \begin{cases} f'(net_j)(t_{pj} - O_{pj}) \\ f'(net_j)\sum_k w_{kj}\delta_{pk} \end{cases} \quad (11)$$

Note that k in the above summation represents every unit k whose output follows into unit j. In order to accelerate the computation, the momentum terms are added on (9) and (10):

$$\Delta_p w_{ji}(n+1) = \epsilon\, \delta_{pj} O_{pi} + \alpha \Delta_p w_{ji}(n) \quad (12)$$

$$\Delta_p \theta_j(n+1) = \epsilon\, \delta_{pj} + \alpha\, \Delta_p \theta_j(n) \quad (13)$$

where, n represents the number of learning cycles and α is a small positive value.

RESULTS

The architecture of ANN consists of 2:4:4 structure which has 2 nodes of input layer, 4 nodes of hidden layer and 4 nodes of output layer (Fig. 3).

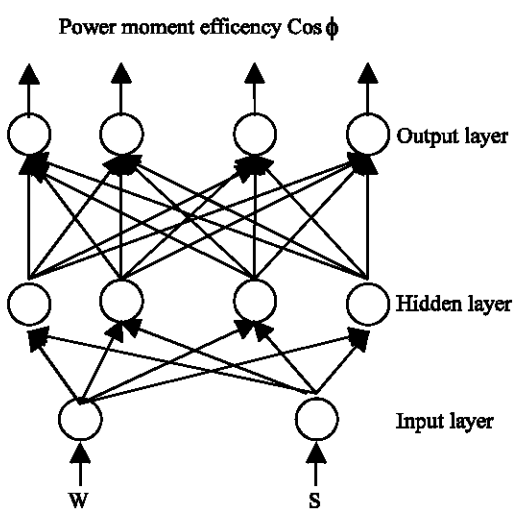

Fig. 3: Used neural network architecture

Table 1: Comparison neural networks and ossanna circle diagram

Input	Experimental results				ANN test results			
Speed (r/min)	Power (kW)	Moment (kg m)	Effici -ency	Cos (φ)	Power (kW)	Moment (kg m)	Effici -ency	Cos (φ)
1495	0.00	0.00	0.0	0.10	0.18	0.34	5.41	0.12
1475	0.98	1.02	75.0	0.45	0.69	0.74	70.5	0.42
1440	1.10	1.95	80.5	0.64	1.40	1.83	86.2	0.67
1410	3.17	2.23	82.3	0.72	2.82	2.26	87.0	0.71
1350	3.85	4.16	78.0	0.74	3.90	4.29	80.3	0.72
1275	4.38	4.92	72.3	0.71	4.39	4.84	72.0	0.70
1200	4.34	5.15	66.0	0.66	4.35	4.98	65.1	0.67
1050	3.65	4.89	54.4	0.57	37.6	4.68	53.8	0.59
900	2.83	4.35	43.8	0.50	2.83	4.29	42.8	0.50
750	2.04	3.77	33.7	0.45	2.00	3.87	34.9	0.44

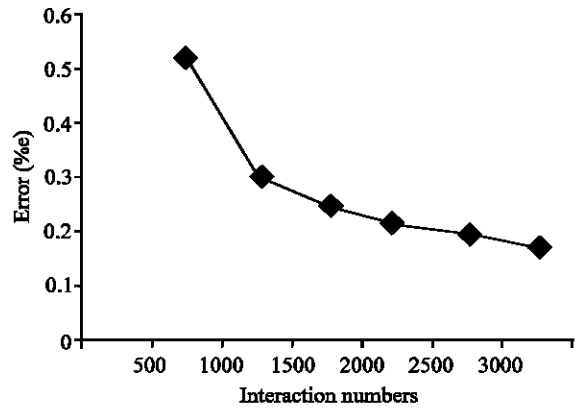

Fig. 4: Total errors for changing iteration

This Multi Layer Perceptron (MLP) network has been trained by the back-propagation algorithm. The input data of the ANN was not normalized, but the output data of ANN was normalized.

For the generalized Delta Rule Learning rule, optimum the momentum coefficient and the learning rate have found α=0.96, ϵ=0.6, respectively. The ANN software was developed by using Turbo Pascal. Figure 4 shows the MSE error according to iterations.

Then we obtained experimental results of working characteristics in the laboratory using Ossanna circle diagram for a 3, 3 kW 220/380 V asynchronous motor. These experimental results were compared with the testing values of ANN (Table 1).

This study has described a neural-network-based motor analysis. This method was compared with a well-known method named Ossanna circle diagram. These results explain that neural network based method is efficient like the ossanna circle. But preparing ossanna circle diagram needs experience and takes time. In addition, ANN based method is very suitable for fast control implementation, either by a dedicated hardware chip or by DSP-based software.

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