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An ANN based Rotor Flux Estimator for Vector Controlled Induction Motor Drive

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Abstract

Field Oriented Control (FOC), also known as vector control of induction motor drives is very useful technique to obtain high performance speed response. Implementation of field oriented control requires the value of the instantaneous magnitude and position of the rotor flux. The magnitude and position of the rotor flux is approximated based on flux measurements in the direct FOC scheme and estimated in the indirect FOC scheme. In this paper a novel flux estimator, in the form of a two stage neural network flux estimator, is presented. The neural network is able to accurately estimate the rotor flux magnitude and position for line-start operation of an induction motor. Its ability to estimate flux response that lies outside of the neural network training data set is one of its strengths. Our preliminary work indicates that neural network flux estimation may be a feasible alternative to other flux estimation methods like programmable DSP kit. The comparative performance of both has been presented in this work.

Keywords: FOC, Vector Control, Induction Drive, Neural Network, Back Propagation.

Introduction

In order to control an induction motor requiring high dynamic performance, an accurate knowledge of the magnitude and position of the rotor flux of the induction motor is necessary, irrespective of the operating point. Both direct Field Oriented Control (FOC), and indirect FOC, has been successfully established in theory and practice. In both control strategies the stator current components, responsible for the flux and torque production, are decoupled. This achieves independent control of torque and flux. Since its introduction in the early 70's the direct FOC scheme has been regarded as less practical[1], because sensors are needed to obtain information about the machine variables. The sensors include the search coils, coil taps, or Hall effect sensors. Sensors often impose limitations on the machine's operating range (particularly at the low speed end) and also increase the overall cost of the machine. However, with the introduction of indirect FOC, the hardware requirements are much simpler, resulting in better overall performance. In order for such a scheme to work, the accurate estimation of rotor flux magnitude and position is vital. There are a few schemes available today [2-8]; most of which are based on adaptive control while others use digital signal processing (DSP) for the estimator implementation. In this paper an artificial neural network is described, as used for the estimation of the instantaneous magnitude or position of rotor flux during line-start operation of an induction motor. The design of a two hidden layer neural network is discussed. The learning requirements of the design are evaluated by developing the back-propagation learning technique for the flux estimator.

In balanced three-phase systems, the two axis (d-axis and q-axis) model is used for dynamic modeling of an induction motor [9-12]. The d-q model of an induction motor can be expressed in either a stationary or a rotating reference frame. In stationary reference frame [10], the reference d and q axes are fixed on the stator. In synchronously rotating reference frame, the d-q axes rotate at the synchronous speed. Fig. 1 shows the block diagram of a FOC Scheme in stationary reference frame for the estimation of feedback signals such as rotor flux Ψr, and unit vectors (Sinθ, Cosθ), using DSP as well as ANN. The feedback signals can be calculated using the machine voltages and currents by using the following equations.

$$\Psi ds = \int (vds - Rs\ ids)dt \quad (1)$$

$$\Psi qs = \int (vqs - Rs\ iqs)dt \quad (2)$$

$$\Psi qm = \Psi qs - Ls\ iqs \quad (3)$$

$$\Psi dm = \Psi ds - Ls\ ids \quad (4)$$

$$\Psi qr = (Lr / Lm)\Psi qm - Lr\ iqs \quad (5)$$

$$\Psi dr = (Lr / Lm)\Psi dm - Lr\ iqs \quad (6)$$

$$\Psi r = \sqrt{[(\Psi qr)2 + (\Psi dr)2]} \quad (7)$$

$$Cos\theta = (\Psi dr / \Psi r) \quad (8)$$

$$Sin\theta = (\Psi qr / \Psi r) \quad (9)$$

All signals indicate that they are in stationary reference frame.

The integrations in equation (1) & (2) can be merged with low corner frequency Low Pass Filter [1] as represented in Fig. 1. Both DSP and ANN receive voltage and current magnitude signals vds, vqs, ids and iqs and then estimate rotor flux using equations (1 to 9). The DSP based estimator output is used for comparison of the ANN based estimator performance.

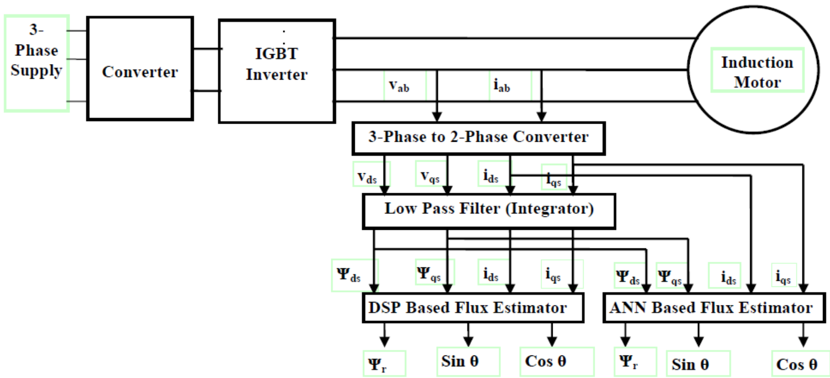

Figure 1: Block diagram of a direct FOC scheme

Artificial Neural Networks in Vector Controlled Drive

Most control techniques of squirrel cage Induction Motor (IM) require speed feedback signal from the shaft encoder and these devices have various disadvantage and are undesirable in many applications. In order to control an IM requiring high dynamic performance, an accurate knowledge of the magnitude and position of rotor flux is necessary. Vector controlled induction motor drive operates like a separately excited dc motor using the d-q axis dynamic equations of the induction motor [11-12]. Rotor flux magnitude and position are estimated using stator current and voltage measurement in various operating conditions of the induction motor. Various methods in control system theory have been applied to improve the robustness of a motor control system. In order to make an intelligent motion control system, we require soft computational methods such as fuzzy logic and ANN (artificial neural network).

This paper presents an application of ANN to estimate rotor flux and position. The ANN is an interconnection of many nonlinear computational neurons capable of high speed nonlinear computation due to its parallel structure [13-15]. The input of each individual neuron sums N weighted inputs and passes the result through an activation function, to give an output. Three common types of activation functions are hard limit, threshold and sigmoid. The input weights of each neuron are adjusted during training to improve performance. Hence, ANN uses a self learning process. The ANN computing differs from traditional computing; as neural nets generate their own rules by learning from examples. While traditional computing systems are rendered useless by even a small amount of damage to memory, neural nets are fault tolerant.

Proposed ANN Structure

Back propagation (BP) neural network structure is used for estimation of vector controlled induction motor parameter such as torque, speed and flux magnitude and position, because in BP network each unit receives inputs from preceding layer. The significance of this is that the information going into the hidden layer units reorder into an internal representation and outputs are generated by internal representation rather than by inputs. The input signals are then converted by the ANN according to the connection weights. In learning process, connection weights update in a direction to minimize error between desired outputs and ANN outputs. These errors are then back-propagated.

Rotor flux and position estimated using single ANN structure give better result but contain more harmonics compared to two ANN structure. This paper proposes two ANN structure, one ANN structure estimates stator d-axis and q-axis flux as in equations (1) & (2), while second ANN structure estimates rotor d-axis and q-axis flux as represented by equations (5) & (6). Rotor flux and position are then estimated using equation (7), (8) & (9).

The block diagram of proposed ANN structure is shown in Fig. 2; the first ANN Structure consists 4 layers (4-12-28-2) and uses ‘tansig’ and ‘purelin’ as activation functions and Levenberg-Marquardt algorithm is used for training data. The maximum no. of iterations is 120 epochs and mean square error is 0.001at a learning rate of 0.04.The Second ANN structure also consist 4 layers (4-16-32-2) using ‘tansig’ and ‘purelin’ as activation functions and Levenberg-Marquardt algorithm is used for training data, the maximum iteration is taken as 60 epochs and target mean square error is 0.001 at learning rate of 0.04 to estimate rotor d-axis and q-axis fluxes. Input-output training data may be generated by using TMSLF 2407 DSP kit with the help of intelligent power module (shown in Fig. 3).

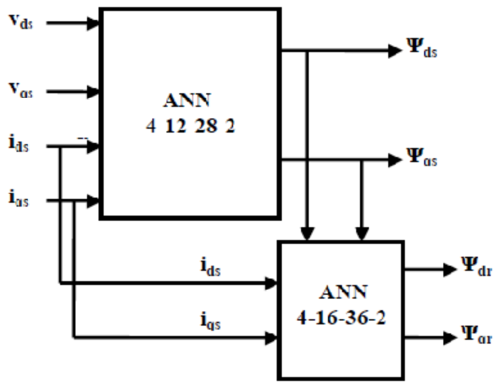

Figure 2: Block diagram of proposed ANN structure.

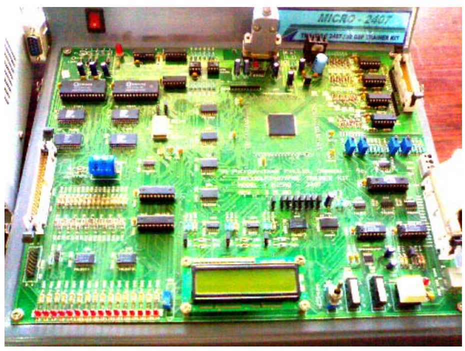

Figure 3: TMSLF 2407 programmable DSP kit

Results and Discussions

In this paper, application of ANN for the estimation of rotor flux and rotor position is suggested for vector control of an induction motor drive. Various layers of BP ANN structure have been trained with help of Neural Network Toolbox for Matlab-Simulink program. The real system data in the form of three-phase voltage and current were obtained for a 1 hp, 50 Hz, 3-phase squirrel cage induction motor drive and processed with the help of the programmable DSP kit (TMSLF 2407). The preliminary measured parameters were Vd, Vq, id and iq; the DSP kit is capable of converting the three phase voltage and current data obtained from the practical drive system into corresponding d-q components by using Park's Transformation [9]. These d-q data for voltages and currents are in turn used to estimate the other parameters with the help of the programming features of the kit with the help of equations (1) to (9). The values obtained thus for a known set of inputs (Vd, Vq, id and iq) give the known output values for flux, which serve as target values in training the Neural Network of Fig. 2. A comparative study was then conducted between the DSP estimator and the proposed ANN estimator.

Fig. 4 shows, estimated value of stator d-axis flux at 3-N-m load torque. The ANN based d-axis flux and DSP based d-axis flux reach peak value of 2.4 Wb at the same time of 0.01sec. In the case of ANN based estimator, the peak value of flux is maintained constant throughout the operation, and its value is slightly higher as compared to DSP based peak flux of 2.38 Wb. As load torque is increased from 3-Nm to 5-Nm, ANN estimated d-axis flux as well as DSP estimated d-axis flux match more closely as shown in Fig. 5. In ANN based estimator, the peak value of flux is 2.4 Wb and has a constant peak while in DSP based estimator the peak value of flux has some harmonics.

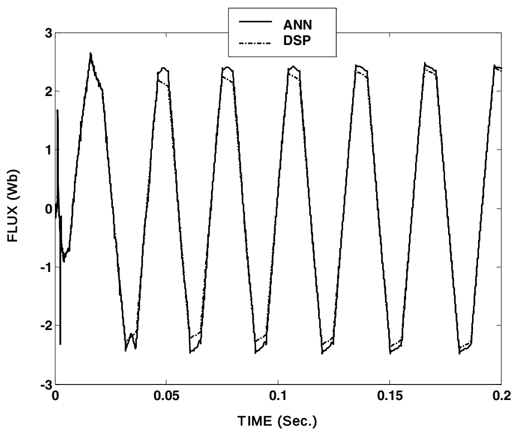

Figure 4: Stator d- axis flux at torque 3-Nm

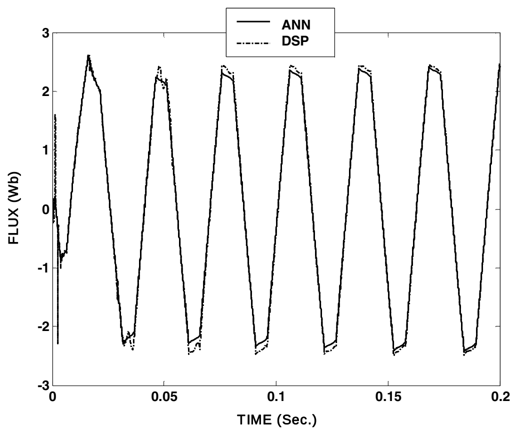

Figure 5: Stator d- axis flux at torque 5-Nm

Fig. 6 shows the stator q-axis flux at load torque of 3-Nm. ANN based estimation of stator q-axis flux and DSP based estimation of flux reach the peak value of 2.8 Wb after 0.02 sec. Both the estimated values have close resemblance but ANN based peak flux is slightly higher than DSP based peak flux. As the load torque is increased from 3-Nm to 5-Nm, ANN based stator q-axis flux as well as DSP based q-axis flux responses track very closely as shown in Fig. 7. Both ANN and DSP based stator d-axis flux have the peak value as 2.8 Wb and remains constant for complete operation.

Rotor d-axis and q-axis flux and position are estimated using above estimated d-axis and q-axis stator flux. Fig. 8 shows rotor d-axis flux at load torque of 3-Nm as estimated by both ANN and DSP; which produce nearly same results. In the case of ANN based estimator, rotor d-axis peak flux (2.4 Wb) is reached after 0.05 sec and remains constant. On the other hand, for the DSP based rotor d-axis flux, the peak flux is slightly lower (2.35 Wb) in the beginning. After 0.17 sec. its value is same as ANN based estimator. As load torque is increased from 3-Nm to 5-Nm, both ANN and DSP based rotor d-axis flux match quite closely, as shown in Fig. 9. In case of ANN based estimator at load torque 5-Nm, rotor d-axis flux reaches its steady state value (with peak of 2.4 Wb) after 0.05 sec. In case of DSP based estimator, rotor d-axis flux is slightly lower (with peak as 2.33 Wb) in magnitude in the beginning. After 0.17 sec its value is same as ANN based estimator (2.4 Wb).

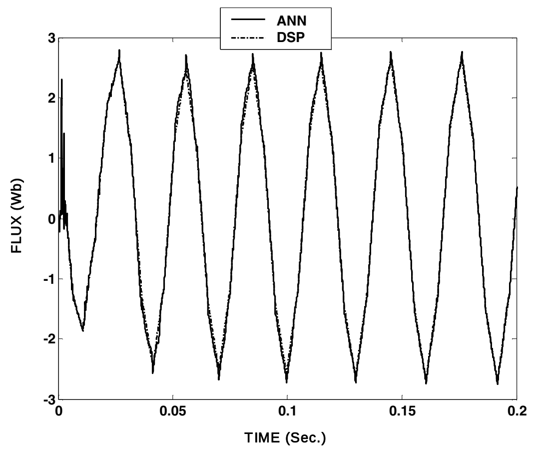

Figure 6: Stator q- axis flux at torque 3-Nm.

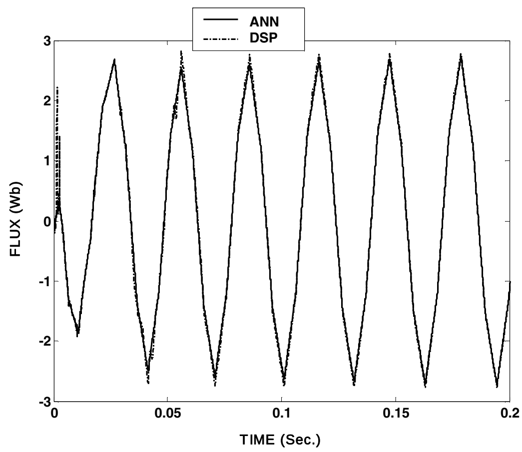

Figure 7: Stator q- axis flux at torque 5-Nm

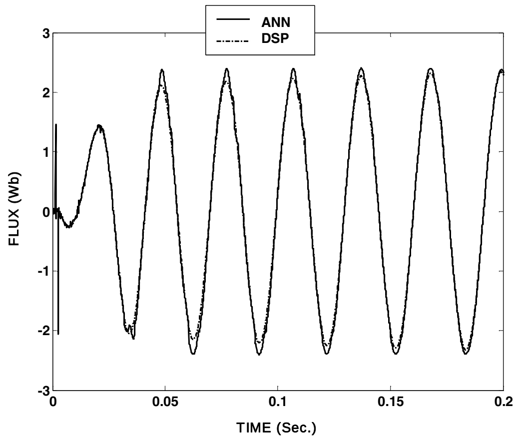

Figure 8: Rotor d- axis flux at torque 3-Nm

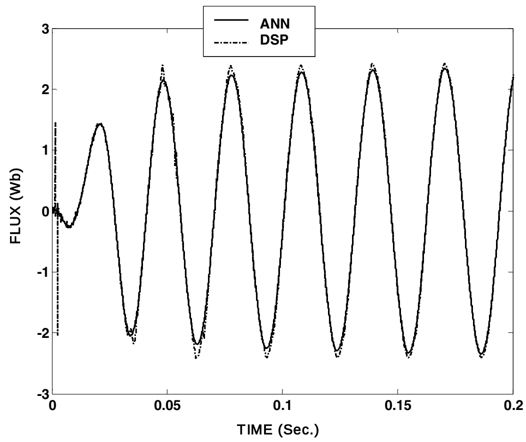

Figure 9: Rotor d- axis flux at torque 5-Nm

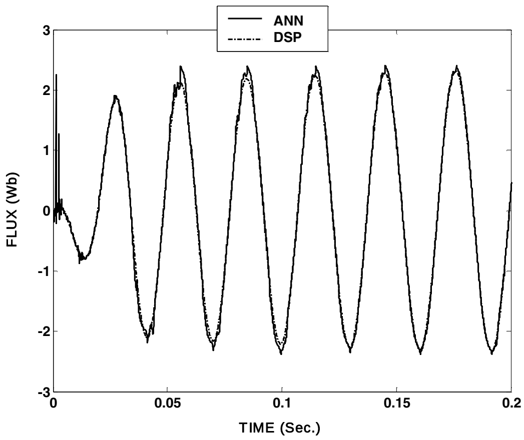

Figure 10: Rotor q- axis flux at torque 3-Nm

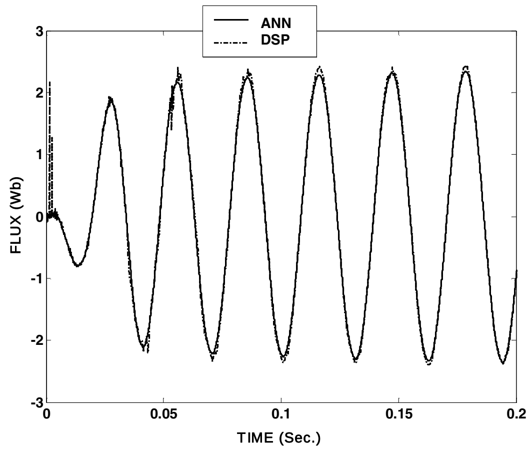

Figure 11: Rotor q- axis flux at torque 5-Nm

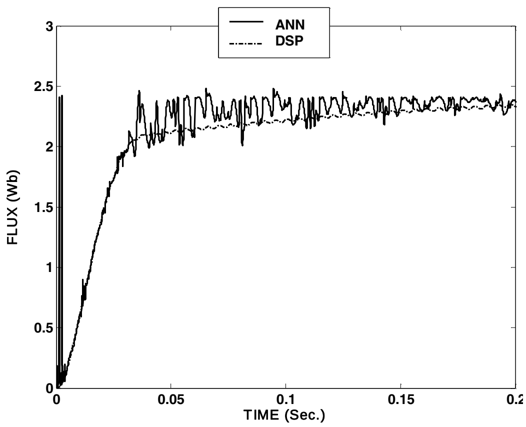

Figure 12: Rotor flux at torque 3-Nm

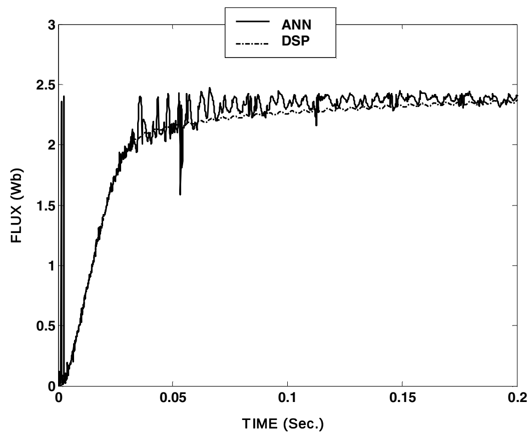

Figure 13: Rotor flux at torque 5-Nm

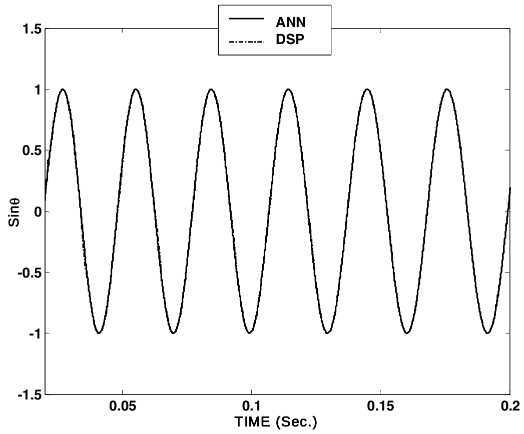

Figure 14: Rotor position at torque 3-Nm

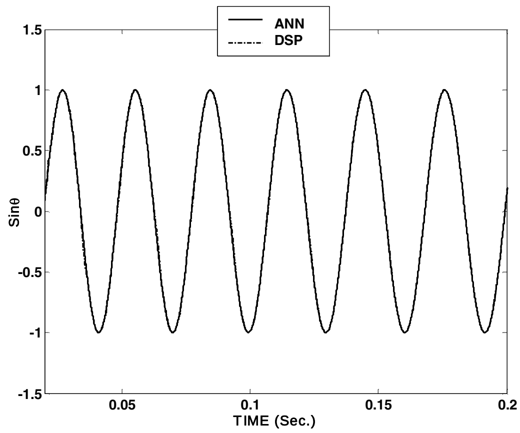

Figure 15: Rotor position at torque 5-Nm

Rotor q-axis flux at load torque 3-Nm as estimated by both ANN based and DSP based schemes produce nearly same results shown in Fig.10. In ANN based estimation of rotor q-axis flux, the peak value of flux (2.4 Wb) is reached after 0.05 sec and remains constant thought the operation. In the case of DSP based estimation on the other hand, the peak value of flux is slightly lower initially and becomes same as ANN based estimation subsequently. As the load torque is increased from 3-Nm to 5-Nm, ANN based rotor q-axis flux as well as DSP based rotor q-axis flux track very closely as shown in Fig.11, with the peak value of flux as 2.4Wb. The steady state flux is established after 0.05 sec for both DSP and ANN based estimation.

Now, the rotor flux magnitude is estimated; the target values for the known inputs were obtained using equation 7. In case of ANN based estimation of rotor flux magnitude at load torque 3-Nm, the peak value of rotor flux 2.4 Wb is reached after time 0.03 sec while in DSP based estimation, the peak value of rotor flux magnitude is reached after time 0.2 sec. as shown in Fig.12. As a load torque increased from 3-Nm to 5-Nm, the estimation of rotor flux magnitude using ANN and DSP based estimators, are shown in Fig.13.

The rotor position is estimated using equations (8) and (9) and its results at load torques 3-Nm and 5-Nm are shown in Figs. 14 and 15 respectively. The ANN based estimator outputs are compared with the corresponding outputs of DSP based estimator; which show good accuracy, fast response and ANN based estimator also shows harmonic-immune performance.

Concluding Remarks

This paper describes a vector-controlled induction motor drive that incorporates a feedforward-neural-network for estimation of rotor flux and position. Simulations for ANN estimation have been carried out using MATLAB, to verify the effectiveness of the proposed method. Flux reference is set to its rated value of 2.4 Wb; speed reference is set as 150 rad/s, and the load torque is varied between 3- Nm to 5-Nm. The real system data for a 1 hp, 3-phase squirrel cage induction motor drive were obtained and processed with the help of the DSP kit (TMSLF 2407) and a comparative study was conducted with the proposed ANN estimator. The results obtained demonstrate the successful application of ANN in the estimation of rotor flux and position for a vector controlled induction motor drive system. A four-layer feedforward neural network has been trained for estimation of stator d-axis and q-axis flux, which are supplied as inputs to another neural network of similar structure (with different number of neurons) in order to estimate the rotor d-q axis flux. This two stage ANN structure is found to give very efficient and accurate results with comparatively less computation burden in training of neurons. The performance of the proposed neural net estimator is found to be very good as compared to programmable DSP based estimator.

Appendix

Table 1: Parameters of the Practical Induction Drive

S.No	Parameter	Symbol	Value
1	Power Supply	3 Φ	
2	Supply Frequency	f	50 Hz
3	Power Rating	P	746W
4	Voltage	V	415
5	Connection Type	Y	
6	Stator Resistance	R_s	6.03 Ω
7	Stator Inductance	L_s	29.9 mH
8	Rotor Resistance	R_r	6.085 Ω
9	Rotor Inductance	L_r	29.9 mH
10	Magnetizing Inductance	L_m	489.3 mH
11	Moment of Inertia	J	0.011787 kgm^2
12	Damping	B	0.0027 Nm/rad/sec
13	Number of Poles	P	4

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