Using feed-forward back propagation for Rotor Flux Estimation of a Bearingless Induction Motor applied in the Speed Vector Control

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Abstract

This study presents the problem of rotor flux orientation control of induction-type bearingless motor. The key of this solution is the estimation of rotor flux. The neural network is able to estimate accurately the rotor flux magnitude or position. The bearingless induction motor model is used to obtain the training data and the learning technique used was investigated by computer simulation. The bearingless induction motor model characteristics were 3,75 kW, two pole-pair, 60 Hz, air-gap length 0.2 mm cage rotor is based on an input-output model. The adopted model have balanced three-phase currents and despised the viscous friction of the bearings. The software environment used for this simulation was MATLAB® R2010a. The motor equation were solved by using step-by-step numerical integration with an integration 10^{-5}s. The simulated results showed good performance. It was used a simulator based on the finite elements method for acquiring flux density for Bearingless Induction Motor model. This paper aims at compensating possible parametric variations of the motor caused by agents such as temperature or nucleus saturation and that neural network flux estimation may be a feasible alternative to other flux estimation methods. The results obtained by simulation confirm the effectiveness of the method.

Keywords : Neural network estimation, Rotor flux, Speed control, Bearingless induction motor, Vector control.

1. Introduction

Bearingless Induction Motor (BIM) combine the functionality of a motor and a magnetic bearing into a single electric machine (Severson, E.; Gandikota, S.; Mohan, N., 2015), (B. Liu, 2015). Flux estimation is an important part in induction machine control (Victor, V.F. et al., 2009). The flux information is used to control induction motors for the purpose of synchronous angle and synchronous speed estimations, flux regulation and torque regulation (Lopes, J. S. B. et al., 2014).

The vector control technique needs flux sensors to determine the exact magnitude and position values of the rotating flux. This limitation was resolved with the flux estimator based on vector machine model using as reference the rotor flux vector requiring only the stator phase currents and speed mechanics (Rodriguez, E.F.; Santisteban, J.A., 2011). Recently, the Neural Networks (NN) are widely used in power electronics and motion control systems.(B. Amarapur, 2013) and to identify and control nonlinear dynamic system because they can approximate a wide range of nonlineae functions to any desired degree of accuracy (K. Sedhuraman, S. Himavathi and A. Muthuramalingam, 2012).

The NN have the advantage of learning, i.e. to adapt to new situations even if these situations are not learned with the network during the training phase (Achkar, R., Nasr, C., Miras, J. D. and Charara, A., 2006). The use of the NN to identify and control nonlinear dynamic systems has been proposed because they can approximate a wide range of nonlinear functions to any desired degree of accuracy (K. Sedhuraman, S. Himavathi and A. Muthuramalingam, 2012).

Buro, N. G, (1994) showed an example of non-stationary rotor behavior with neural network in the filed of control for rotor dynamics. Jiang, Y. H., Zmood, R. B., and Qin, L. J. (1996) examined the operation of a magnetic bearing system using neural network controllers where the rotor was subjected to external periodic disturbances. Paiva de; J. A., Laurindo, M. A., Salazar, A. O. and Stephan (2008) develop in the ANSI C language a neural rotor flux observer compensates for parameter variations using a DSP numeric. Kun, L and Xiaofei, C. (2010) proposed a BP neural network controller for suspending control for magnetic suspended flywheel system. In Victor, V.F. et al. (2009) compare the performance of bearingless Induction machine with divided winding using two estimators based on NN versus the same system using conventional observers. A new control strategy is proposed to decouple the bearingless induction motor based on neural network αth-order inverse system approach and internal model control (Zheng-Qi WANG and Xian-Xing LIU, 2013). Other approaches to estimate speed use two different kinds of advanced flux observers are evaluated in the induction motor with a linear parameter varying observer and kalman filter with simulation results (I. Benlalaoui, S. Drid, L. Chrifi-Alaoui, D. Benoudjit, D. Khamari and M. Ouriagli, 2014).

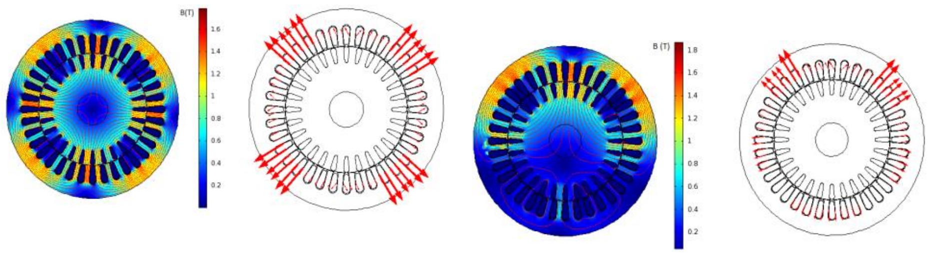
In this paper is proposed a solution to substitute the flux sensors. To replace the sensor, it is necessary estimate simultaneously the rotor flux position, the torque and the magnetization current using the Neural Network (NN) a single structure. It is used the Neural Networks to the motor parameters estimation in order to counterbalance the conventional observer limitations which is based on the model for an induction-type bearingless motor. The bearingless machines operates as an induction motor and as a magnetic bearing too, acting on the rotor levitation. This feature reduces the mechanical losses by friction and minimizes the number of machine maintenance (Paiva de; J. A., Laurindo, M. A. and Salazar, A. O., 2013). Thus, this research is an improvement of Victor, V.F. et al. (2009) that worked with two structures Neural Networks and continuation of the work of Victor, V.F. et al. (2012). The results simulated in the Matlab® of our work showed a good result to estimation of flux with excellent stabilization variation of parameters of the motor.

2. Bearingless Motor with Divided Windings

2.1 Behavior of the Flux density

It was used a simulator based on the finite element method for acquiring flux density for a model of BIM. Fig. 1 shows flux density distribution of the rotor in air gap to twice case different of current phase. The Fig. 1 (A) and (B) presents the behavior vector of air gap flux when the stator currents are balanced and the rotor is centralized. Rotor magnetic field analysis was realized by means of Maxwell tensor method (Victor, V.F. et al., 2012).

Fig. 1 (C) and (D) shows behavior of air gap flux when the stator currents are unbalanced in order to produce radial forces on the rotor to reposition it. For the flux estimation or conventional estimator, is being used the vector model of conventional induction machine (Victor, V.F. et al., 2009) and (Achkar, R., Nasr, C., Miras, J. D. and Charara, A., 2006). The operating the BIM with the centralized rotor was adopted to be equivalent to the conventional motor model. Thus, we consider that the rotor operated centralized with the goal to reduce the system complexity implemented using the estimated NN.



(A) (B) (C) (D)

Fig. 1 Rotor flux vector behavior (A) and (C) with Rotor magnetic field (B) and (D).

2.2 The Flux Model

The bearingless induction machines exhibit significant nonlinearities, creating the need for implementation of control systems that combine the classic control techniques with modern model observers (Paiva de; J. A., Laurindo, M. A. and Salazar, A. O, 2013). The parameters adopted in BIM were listed in Table 1. It includes some laboratory measured test parameters as (per phase) equivalent inductances or resistances (Victor, V. F. et. al. 2012) to be used in simulation models.

Table 1 Equivalent circuit parameters of the motor electric.

R1	Stator resistance	1.18 [Ω]
R2	Rotor resistance	1.42 [Ω]
J	Inertia moment	0.00995 [kg.m^2]
Ls	Stator inductance	6.56 [mH]
Lr	Rotor inductance	6.56 [mH]
Lm	Magnetizating inductance	0.14 [H]

The implemented system is based on the control vector technique that controls the induction machine similar to the direct control of the machine current (Leonhard, W., 2001). For the flux estimation or conventional estimator, is being used the vectorial model of conventional induction machine (Leonhard, W., 2001). The applied model can be described by the following equations (1-5):

$$\frac{di_{mR}(t)}{dt} = \frac{i_{sd}(t)}{T_R} - \frac{i_{mR}(t)}{T_R} \tag{1}$$

$$\frac{d\rho(t)}{dt} = n_p . \omega_{mec}(t) + \frac{i_{sq}(t)}{T_R i_{mR}(t)} \tag{2}$$

$$m_M(t) = k. i_{mR}(t) i_{sd}(t) \tag{3}$$

$$T_R = L_R / R_R \tag{4}$$

$$k = \frac{2}{3}(1-\sigma)L_s \tag{5}$$

where i_{mR} is the magnetizing current, $i_{sd}(t)$ and $i_{sq}(t)$ are the Park currents, $\rho(t)$ is the rotor flux position, $m_M(t)$ is the electric torque, $\omega_{mec}(t)$ is the rotor mechanical speed, n_p is par poles number, T_R is the rotor time constant, L_s is the stator inductance, L_R is the rotor inductance, R_R is the rotor resistance and σ is the scattering factor. The estimation of rotor variables was carried out using the rotor flux frame of reference, since it significantly simplifies the implementation of the digital system (Victor, V.F. et al., 2009).

The use of conventional vector model of induction machines in the study of the bearingless induction machine with divided windings was only possible due to the similarity between their stators structures. Such similarities are equivalent on both models allowing the implementation of the speed and radial positioning controllers (Ferreira, J. M. S., Zucca, M., Salazar, A. O., Donadio, L., 2005). To compensate the limitations imposed by observers based on models with fixed parameters, this work proposes a flux neural observer composed of one multilayer feedfoward neural networks.

3. System Description

Fig. 2 contains Bearingless motor system control which is composed by the current transformation blocks, PWM command, PIDs controllers, power inverter and other auxiliary circuit related. The rotor flux referential estimated to implement the speed controller. The block of Neural Networks Estimator represent complex systems by simple models (Narendra, K.S.; Mukhopadhyay, S., 1997).

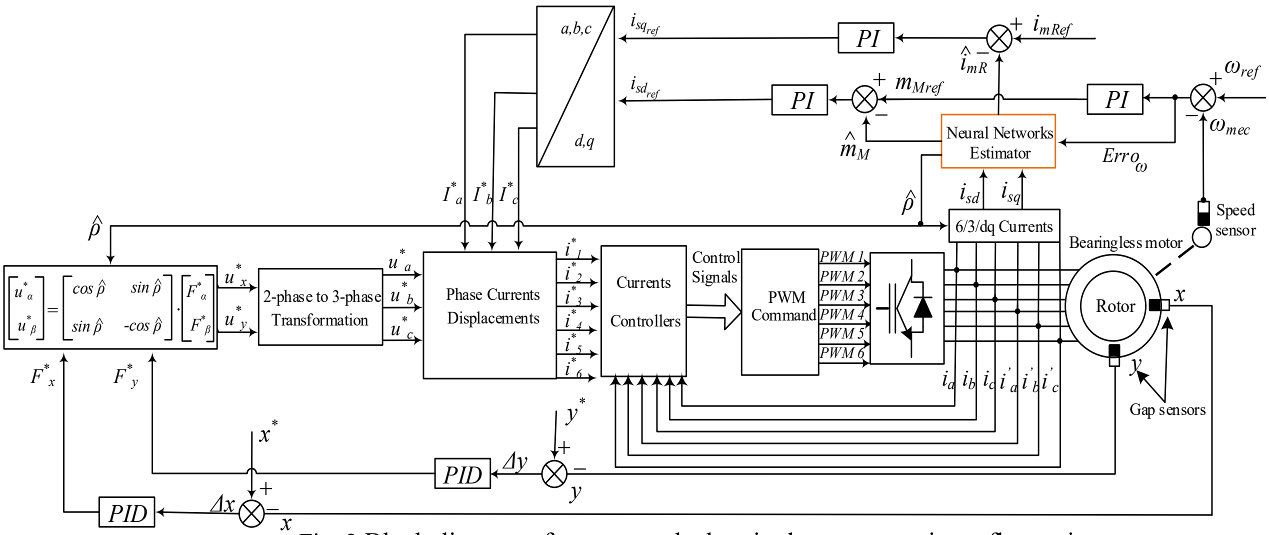


Fig. 2 Block diagram of system to the bearingless motor using a flux estimator.

Fig. 2 shows three closed-loop proportional-integral control that composes speed control, torque control, magnetizing current control and other PID blocks, which are the displacement controls. The controllers are in series with the speed controller; the torque control is responsible for generating the reference torque current; the third controls the magnetizing current, which is responsible for generating the current reference field (Paiva, J. Á., 2007).

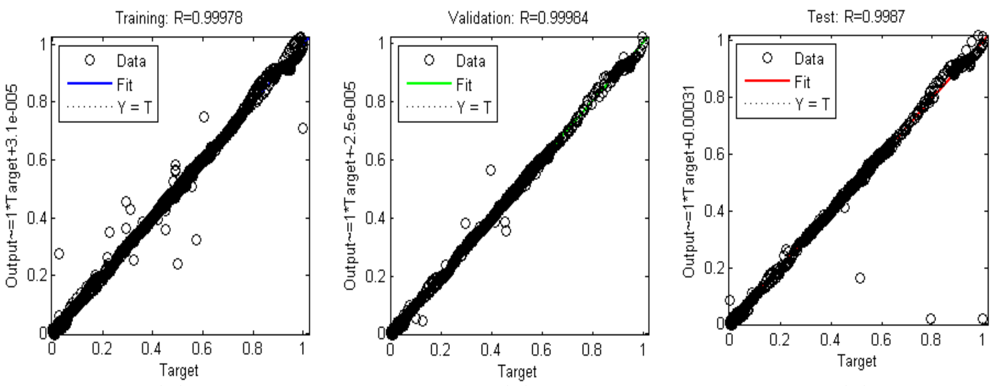
4. Design and analysis of Neural Network

The first step of an NN supervised training is to compile the input and output data set. The inputs and outputs are used to adjust the internal parameters of the network (T. H. dos Santos, A. Goedtel, S. A. O. da Silva and M. Suetake, 2011). The NN is fully connected. Besides, a bias signal is coupled to all the neuros of the hidden and output layers through a weight. The database has been developed for 20200 samples, which are obtained by varying based the criteria on Victor, V.F. et al., 2009. The training process was realized on the offline mode. During the training process was applied variations on the following parameters and signals: rotor time constant, torque electric and speed mechanical every 2 second step on a random basis. The time period of training was 40 seconds. The table 1 shows the parameters of the proposed network.

Table 1 Parameters of the proposed network.

Network architecture	Perceptron multilayer
Type of training	Supervised
Number of layer	3
Neurons of the input	3
Neurons of the 1st hidden layer	15
Neurons of the 2st hidden layer	10
Neuros of the output	3
Training algorithm	Levenberg-Marquardt backpropagation
Learning rate	$5e^{-2}$
Epochs	160
Square error goal	$7.4154e^{-6}$
Hidden layer activation function	Hyperbolic tangent
Output layer activation function	Linear

The Levenberg-Marquardt algorithm was chosen to training methods because provides the best accuracy for a given architecture (K. Sedhuraman, S. Himavathi and A. Muthuramalingam, 2012). It is very efficient when training networks have up to a few hundred weights(Jianbo Sun, Qionghua Zhan and Liming Liu, 2005). So it is chosen as the learning algorithm for Neural Network training in this paper. The proposed estimator is structured as shown in Fig. 2 where the input data $\{id(t), iq(t)\ and\ errow(t)\}$ and output data $\{mM(t), p(t)\ and\ i_{mR}(t)\}$. This topology was chosen after several performance tests with different numbers of layers and neurons per layer. Fig. 3 shows the training, validation and test performances given the training record.



(A) (B) (C)

Fig. 3 Represent the training (A), validation (B), and testing data (C).

Fig. 3, the R value is an indication of the relationship between the outputs and targets. The valeu R = 0.99978 indicates that there is a next relationship between outputs and targets. The weight and threshold of the network are saved. The change of the MSE factor in different epochs of the network is shown in Fig. 4.

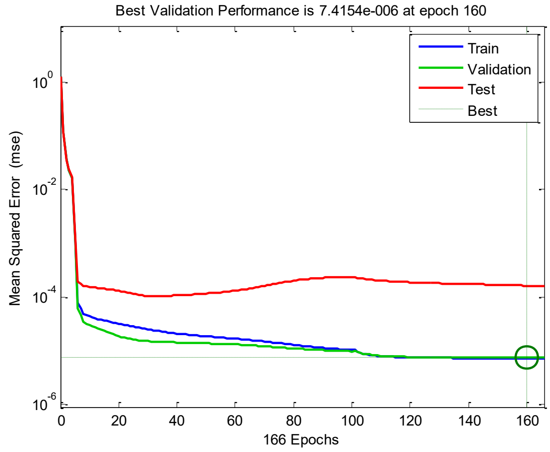


Fig. 4 The performance of the network for different epochs.

6. Simulation Results

The software environment used for this simulation was MATLAB® R2010a. The motor equation are solved using step-by-step numerical integration with an integration 10^{-5}s. It was used the Euler discretization method. Inputs and outputs were normalized to facilitate the process training data. To validate the performances of the proposed estimator NN, was provided a series of simulations for different references. The simulation tests involves the following operating sequences: the motor is required to reach the reference value $\omega_{ref} = 1800$ rpm in the interval of time$[0 - 3.367s]$, $\omega_{ref} = 1000$ rpm for $[3.368 - 6.734s]$ and $\omega_{ref} = 1400$ rpm for $[6.735 - 10s]$, Fig. 5 (A).

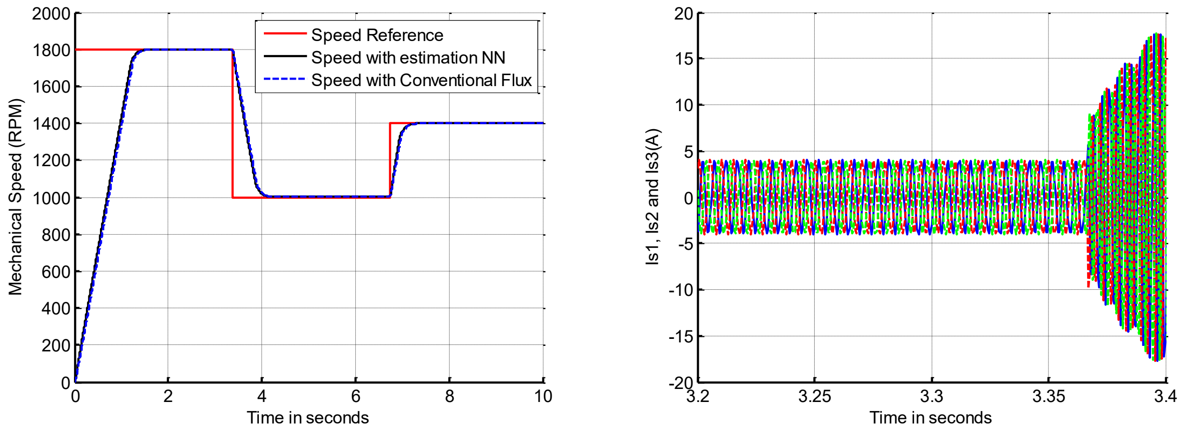


Fig. 5 Behavior of speed with conventional flux and NN (A) and current control (B).

The range of simulation time was 10 seconds. Fig. 5 (B) shows the signal of currents when changed speed reference. Fig. 6 shows comparative results between the motor torques.

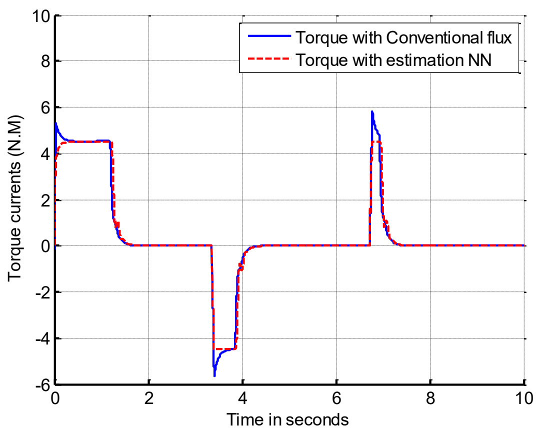


Fig. 7 and 8 show the current signal behavior $i_{sq}(k)$, $i_{sd}(k)$. The $i_{sd}(k)$ and $i_{sq}(k)$ currents tend to continuous and constant values, and the field current tends to the maximum amplitude of the phase currents. Fig. 9 shows the angular speed of the rotor flux.

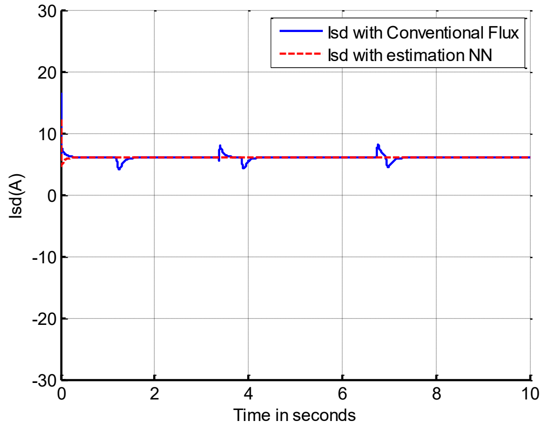


Fig. 7 Current signal behavior $i_{sd}(k)$.

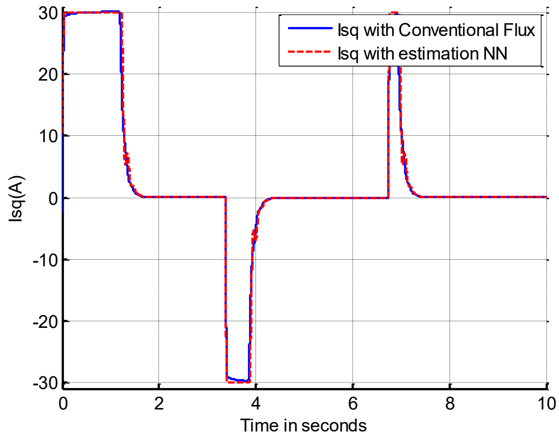


Fig. 8 Current signal behavior $i_{sq}(k)$.

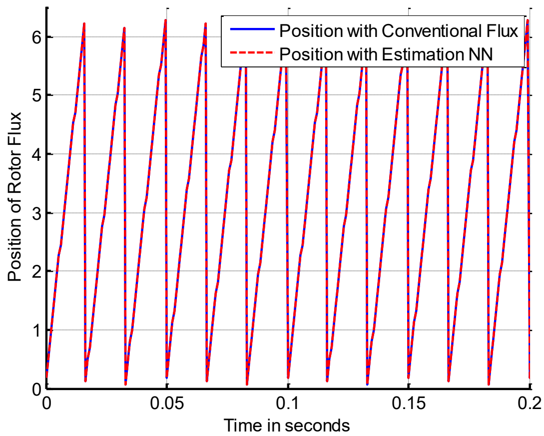


Fig. 9 Behavior of position of rotor flux.

Fig. 9 shows the angular position in a zoom range from 0 to 0.2 seconds. We observe this result timing of both $\rho(t)$ for the estimators. From these simulations, we can infer that the Neural Network estimator had good results on behavior. Thus, all motor's parameters are time varying, in particular, the rotor time constant which is extremely affected by the heating effect (Leonhard, W., 2001). In this study case, the T_R parameter changed its value at 10% of its value. So, Neural Network estimator don suffer parametric variations. Neural Network exhibits better results due to its learning capability.

7. Conclusion

This paper shows the implementation of a Neural Network allows the representation of the knowledge. The validity of the proposed estimator Neural Network is confirmed through the simulation results with supervised training process in off-line mode. We investigated the Neural Network estimator in a closed loop system with three controllers: speed control, torque control and the magnetizing current control – all of which are arranged in series. Accuracy fast estimation, simplicity of design and insensitivity to rotor time constant are the advantages of this method. We investigated the Neural Network estimator in a closed loop system with three controllers are arranged in series. Forthcoming researches will investigate estimator NN in an experimental prototype in the laboratory. Implementation on DSP of the NN and studying the behavior of all process.

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