BACK-EMF BASED ROTOR POSITION ESTIMATION FOR LOW COST PMSM DRIVE USING FULLY CONNECTED CASCADE ARTIFICIAL NEURAL NETWORKS

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I. INTRODUCTION

Permanent Magnet Synchronous Motors (PMSMs) are widely employed due to their high torque per volume, high efficiency and low maintenance cost, among other advantages. To perform vector control on the motor, the feedback of rotor speed and stator currents is necessary, which can be obtained directly or by using a mechanical device attached to the motor shaft, increasing the drive system volume and its maintenance cost. To overcome such disadvantages, many sensorless methods for speed estimation have been proposed. Among those methods, various strategies based on Artificial Neural Networks (ANNs) can be found. This paper presents a back-electromotive force estimator based on Fully Connected Cascade ANNs (FCC-ANNs). From the estimator, rotor position and speed can be obtained. Simulation and experimental results using automatically generated C code functions for the FCC-ANNs using fixed sample point notation provided rotor position estimation with simple implementation.

Keywords – Artificial Neural Networks, Back-EMF Estimation, Permanent Magnet Synchronous Motor, Position Estimation.

 NOMENCLATURE

\(v_{\alpha, \beta}\) \(\alpha\) and \(\beta\) axis voltages.
\(v_{a,b,c}\) \(a, b\) and \(c\) phase voltages.
\(i_{\alpha, \beta}\) \(\alpha\) and \(\beta\) axis currents.
\(i_{a,b,c}\) \(a, b\) and \(c\) phase currents.
\(E_{\alpha, \beta}\) \(\alpha\) and \(\beta\) axis back-EMFs.
\(E_{a,b,c}\) \(a, b\) and \(c\) phase back-EMFs.
\(\omega_r\) Rotor electric angle frequency.
\(\omega_m\) Rotor mechanical angle frequency.
\(\theta_r\) Rotor electric angle position.
\(L\) Phase inductance.
\(T_L\) Load torque.
\(L_M\) Phase mutual inductance.
\(T_r\) Electromagnetic torque.
\(R\) Phase resistance.
\(P\) Number of poles.
\(h\) Viscous friction coefficient.
\(J\) Total inertia.
\(k_{e,f}\) Back-EMF and torque coefficients.

Abstract – Permanent Magnet Synchronous Motors (PMSMs) are widely used mainly due to their high torque per volume, high efficiency and low maintenance cost, among other advantages. To perform vector control on rotor speed and stator currents, the feedback of those variables is necessary, which can be obtained directly or by estimation. Measuring rotor position and speed directly requires the use of a mechanical device attached to the motor shaft, increasing the drive system volume and its maintenance cost. To overcome such disadvantages, many sensorless methods for speed estimation have been proposed. Among those methods, various strategies based on Artificial Neural Networks (ANNs) can be found. This paper presents a back-electromotive force estimator based on Fully Connected Cascade ANNs (FCC-ANNs). From the estimator, rotor position and speed can be obtained. Simulation and experimental results using automatically generated C code functions for the FCC-ANNs using fixed sample point notation provided rotor position estimation with simple implementation.

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Manuscript received 17/04/2017; first revision 06/06/2017; accepted for publication 19/08/2017, by recommendation of Editor Marcelo Cabral Cavalcanti.

Eletró. Potên., Campo Grande, v. 23, n. 1, p. 69-77, jan./mar. 2018

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can be found in literature. One example is the application of diagonal recurrent neural networks, used to compose the observer [2]. In such work, two neural observers and a position estimation correction block are used. One neural observer is used to estimate stator current and the second observer is used to estimate speed from measured stator currents and voltages. The estimated rotor speed is then integrated for obtaining rotor position.

A review on sensorless control techniques for non-sinusoidal PMSM (the Brushless DC motor) drive can be found in [5]. Among the presented estimation techniques, the ANN approach is mentioned. The authors comment on the ANN capability for approximating nonlinear functions and cite some applications in motor drives, such as online parameter (resistance and inductance) and torque estimation in vector-controlled induction motor drives, which can be also applied in PMSM drives.

Another ANN-based rotor position estimation, for a 8/6 solid rotor switched reluctance motor, is presented in [10]. Such type of motor is utilized mainly due to its robustness and fault tolerance. ANNs are used to estimate rotor position from phase flux linkage and phase current input data. The utilized drive consists in four different operating regions. Thus, four ANNs are utilized, one for each operating region. The authors comment on an important characteristic of the ANN approach, which is the automatic consideration of nonlinear effects, such as mutual inductance and eddy currents effects, in the input-output mapping.

In addition to acting as observers, ANNs have also been used within the control algorithm for nonlinear control of electric machinery. In [11], an ANN was combined with a fuzzy logic to develop a speed controller for a non-sinusoidal PMSM. The obtained dynamic response was compared to other controllers, such as the conventional proportional-integral and other fuzzy strategies. The authors commented that the proposed ANN-fuzzy controller outperformed the others in terms of dynamic characteristics, as settling time and overshooting. Another model-based ANN control approach using ANN is presented in [12]. Two ANNs are used in the control loop of a DC motor drive, in which one network is used to estimate the drive dynamics and the other is used to generate voltage input signals to the drive. Different applications of ANNs in engineering include system identification, fault detection and power electronics applications, among others [13]–[15].

Although methods used in previous works present satisfactory results, the objective of this paper is to present a simpler ANN-based observer, providing the used training data, simulation and experimental results, without using online training. The main idea of the work presented here is to estimate rotor position for then obtaining the speed estimation, in a manner that the estimator has low computational cost and be of easy implementation, exploiting the advantages of ANNs mentioned in the literature to obtain a simple, fast and straightforward estimator. Without using integration of estimated speed to obtain the electrical position, the position correction block is eliminated. Based on a Luenberger observer, which takes the voltages and currents in the $\alpha\beta$ reference-frame (stationary) to estimate the $\alpha$ and $\beta$ back-electromotive forces (back-EMFs), the use of an ANN for estimate each back-EMF is proposed [16]. Using such estimations, it is possible to obtain the estimated rotor angle position. After training the networks, C code functions using fixed point notation with integer bases are automatically generated and the implementation consists in uploading such functions to the microcontroller. Thus, the ANNs are coded as black-box functions, which take as inputs the measured stator currents and applied voltages and return the estimated back-EMFs.

Another objective of this work is to present the application of Fully Connected Cascade (FCC) ANNs, which can achieve, with fewer hidden neurons, the same performance of a typical Multi Layer Perceptron (MLP) network, thus reducing the computational burden.

The procedure for training the ANN is to apply several speed reference steps, using an encoder to measure rotor position, and organizing the acquired data to train the ANNs. With the trained ANNs, the encoder can be replaced by the ANN-based estimator. It is interesting for a sensorless method that parameter tuning be as less manual as possible, reducing installation time [4]. The proposed estimation method in this work has this advantage. Once the ANN architecture and a minimal number of neurons is defined, the procedure for training the ANN-based estimator for other different PMSM is similar. As mentioned before, another advantage of an ANN approach is the automatic treatment of the drive nonlinearities. Thus, it is possible to highlight the main features of the presented observer as:

- Use of FCC topology, reducing the number of connections and computational burden if compared to classical MLP networks [17];
- The PMSM parameters do not need to be identified individually;
- The position estimation does not depend directly on the signals amplitude, since it is obtained based on the position of the estimated back-EMFs in $\alpha\beta$ notation, which is useful for dealing with load disturbances and nonlinearities;
- C code functions using fixed point notation are automatically generated after training, which simplifies implementation on a low cost microcontroller (see Figure 27 in Appendix section for an example of automatically generated code).

The use of an encoder in the training process is necessary since the alternative would be to utilize another estimator to generate the data for training, which would require an entire tuning process. Additionally, in industry applications, the encoder is also utilized for tuning other types of observer, because it is necessary not only to identify model parameters but also to validate the results from the observer with a reliable sensor. Thus, the use of the encoder in training process of the method described in the present paper does not represent a drawback in comparison to other observer methods applied industrially.

In Section II, the dynamic model for the PMSM is presented. The design and implementation aspects of the estimator are presented in Section III. Simulation results are
shown in Section IV the experimental results in Section V. Conclusions are discussed in Section VI.

II. SINUSOIDAL PMSM DYNAMICS

The electrical dynamics for a balanced three-phase wye-connected sinusoidal PMSM can be written by terms of phase variables as [18]:

\[ v_a = R_i a + (L - L_m) \frac{di_a}{dt} + E_a \]  
\[ v_b = R_i b + (L - L_m) \frac{di_b}{dt} + E_b \]  
\[ v_c = R_i c + (L - L_m) \frac{di_c}{dt} + E_c \]

where \( E_a, E_b \) and \( E_c \) are the phase back-EMFs, given by:

\[ E_a = k_e \omega_r \sin(\theta_r) \]  
\[ E_b = k_e \omega_r \sin(\theta_r - 120^\circ) \]  
\[ E_c = k_e \omega_r \sin(\theta_r + 120^\circ) \]

in which \( \omega \) is the rotor electrical speed and \( \theta_r \) is the rotor electrical position.

The conversion of a set of balanced three-phase variables \( f_\alpha, f_\beta \) and \( f_0 \) to two-phase variables \( f_a \) and \( f_\beta \) is made using Concordia’s Transform [19], to eliminate lineary dependent variables:

\[
\begin{bmatrix} f_\alpha \\ f_\beta \\ f_0 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\ 0 & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} f_a \\ f_b \\ f_c \end{bmatrix}.
\]

The opposite process is made through the inverse of the transformation matrix utilized in (7).

Considering the \( \alpha \beta \) reference-frame and using (7), the following equations can outline the electrical dynamics of the PMSM:

\[ v_\alpha = R_i a + (L - L_m) \frac{di_\alpha}{dt} + E_\alpha \]  
\[ v_\beta = R_i b + (L - L_m) \frac{di_\beta}{dt} + E_\beta \]  
\[ v_0 = R_i c + (L - L_m) \frac{di_0}{dt} + E_0 \]

The produced torque can be written in terms of phase currents and back-EMFs as:

\[ T_e = \left( \frac{kt}{ke} \right) \left( \frac{P}{2} \right) \frac{E_\alpha i_\alpha + E_\beta i_\beta + E_c i_c}{\omega_r} \]

The mechanical dynamics are given by:

\[ J \frac{d\omega_m}{dt} = T_e - T_L - h\omega_m \]

where \( h \) is the friction coefficient of the mechanical coupling.

The relation between the electrical frequency and the mechanical frequency is given by:

\[ \omega_r = \frac{P}{2} \omega_m. \]

III. BACK-EMF ESTIMATOR USING FCC ARTIFICIAL NEURAL NETWORKS

In this section, the used estimator based on FCC-ANNs is presented. Firstly, the estimation strategy is presented, indicating the role of the ANNs in such strategy. Then, the ANN architecture, topology and other parameters are commented.

A. Estimation Strategy

A flowchart for the proposed position and speed estimator is shown in Figure 1. The method consists in performing the back-EMFs estimation in the \( \alpha \beta \) system to first obtain the position and then speed. The observer is composed by a pair of neural networks. Each network receives as inputs the voltages and currents \( \alpha \) and \( \beta \), and estimates each one of the back-EMFs. The estimated back-EMFs are calculated by an arc-tangent algorithm. The angular frequency, namely speed, is then estimated by the position variation rate.

The derivative terms in (8) and (9) are not used in the training process. This was done because of the ANNs capability of estimating the back-EMFs without such terms, due to their memorization characteristics. Also, the derivative terms insert a high noise level in practice.

As the electrical dynamics of the motor is fast, compared to the mechanical dynamics, the information of lead/lag and relative amplitude between voltage and current are sufficient for the back-EMFs estimation. Information of phase and amplitude difference of the voltage and current signals due to inductances and resistances are implicitly learned by the network during the training. This way, one of the advantages of using neural networks is evident, which is the parameter independency. In other words, the estimation can be performed from experimental data without knowing the motor parameters, such as phase equivalent resistance and inductance.

B. ANNs for the Estimator

The utilized neural network architecture is the FCC-ANN, trained with Neuron by Neuron (NBN) algorithm [17]. Each hidden layer in a FCC-ANN has only one neuron. The output of each neuron is connected to all of the forward neurons. Such architecture was used for having better performance with a lower number of neurons and synaptic connections if compared to the traditional MLP, provided that the training is adequate [20]. The reduced number of neurons and connections contributes with the implementation in a microcontroller device, given the limited memory and processing performance of the device. The topology consist in 4 data inputs plus 1 bias input, 4 hidden neurons and

![Fig. 1. Estimator flowchart. Based on [16].](image-url)
one output neuron. The activation is the Symmetric Elliot’s function, mainly for being of easy implementation in fixed point notation, given by:

\[
Elliot(x) = \frac{2ax}{1 + |ax|}.
\]  

In the simulations with floating point, the Symmetric Sigmoid function presented the best performance, but it takes approximations or iterative calculations to be implemented in the utilized hardware, which prevented its use. The parameter \(a\) represents the function steepness and \(x\) is the activation potential (inputs weighted sum with the synaptic weights of the neuron inputs). The implementation was made using SuperNN library [21].

The training was performed using the measurements of the \(\alpha\) and \(\beta\) voltages and currents and rotor position and speed using an encoder. Such data was acquired with the mechanical speed varying from 30 RPM to 120 RPM. The back-EMFs signals for the training are obtained through the product of the sines and cosines of the position and the measured speed, taking the back-EMF constant unitary. The back-EMF coefficient value is not necessary once the position is given by an arctangent function which takes the ratio between the two back-EMFs. However, it is necessary to generate the back-EMFs amplitude variating with the speed for the network to be trained appropriately. The experimental training data set and the simulation training data set were assembled with approximately 3000 samples each.

Figure 2 shows the ANNs structure. Note that each of the ANNs produces only one output, \(E_\alpha\) or \(E_\beta\). Using only one ANN with two outputs highly increased the number of necessary neurons and connections to achieve a similar performance than with two separated ANNs.

![Image of ANNs FCC topology](image)

**Fig. 2. ANNs FCC topology.**

**IV. SIMULATION RESULTS**

The motor parameters are given in Table I. It is a motor utilized in washing machines, with a high number of poles, in a manner that the operating mechanical rotation is relatively low comparing to the drive frequency.

| Parameter | Value | Unit |
|-----------|-------|------|
| \(R\) | 15.5 | \(\Omega\) |
| \(L\) | \(76 \times 10^{-3}\) | \(H\) |
| \(L_m\) | \(38 \times 10^{-3}\) | \(H\) |
| \(J\) | 0.1566 | \(Kg \times m^2\) |
| \(\beta\) | \(0.98 \times 10^{-3}\) | \(N \times s/m\) |
| \(P\) | 48 | - |
| \(k_e\) | 0.117 | \(V \times s/rad\) |
| \(k_i\) | 0.117 | \(N \times m / A\) |

The simulated data for training was obtained by controlling the simulated motor dynamics over several speed reference steps, with and without load. To consider the presence of noise in currents and voltages, to verify the estimator robustness, a random relative noise of 40% was added to the measured voltages and currents.

**A. Simulations without Load**

The back-EMFs estimation for the motor rotating at frequencies of 30 RPM, 50 RPM and 100 RPM are depicted in Figures 3, 4 and 5, respectively. In all three cases it can be observed that the \(\alpha\) and \(\beta\) estimated back-EMFs have a 90° phase shift, with amplitude variations caused by the inserted noise in current and voltage. The amplitude and the frequency of the signals increase proportionally with the speed.

From the estimated back-EMFs, rotor electrical position can be obtained. Simulation results are shown in Figures 6, 7 and 8.

**Fig. 3. Simulation: back-EMF estimation at 30 RPM.**

**Fig. 4. Simulation: back-EMF estimation at 50 RPM.**

**B. Simulations with Load**

Simulations with the application of a 2 Nm load step, at \(t = 2.5\) s were performed to evaluate the estimator under load...
Comparing to the drive frequency, utilized in washing machines, with a high number of poles, in set and the simulation training data set were assembled with to be trained appropriately. The experimental training data back-EMFs amplitude variating with the speed for the network signals for the training are obtained through the product speed varying from 30 RPM to 120 RPM. The back-EMFs using an encoder. Such data was acquired with the mechanical point notation, given by:

\[ \text{Back-EMFs} = \text{E}_{\alpha}, \text{E}_{\beta} \]

The training was performed using the measurements of the back-EMFs, rotor electrical position from the estimated back-EMFs have a 90° disturbance. Figures 9, 10 and 11 present the estimated and simulated positions at mechanical speeds of 30 RPM, 50 RPM and 100 RPM respectively. At the insertion of the load, it is possible to observe oscillations in the estimated position, which were stabilized with time. After stabilization, the simulated positions at mechanical speeds of 30 RPM, 50 RPM up to 120 RPM. Due to hardware limitations in the acquisition system, only four variables could be obtained simultaneously. The chosen variables are: \( \beta \) voltage, \( \beta \) current, electrical position and speed. The \( \alpha \) variables are then obtained by shifting the \( \beta \) variables by 90°. Figure 12 shows the assembled data set for voltages while Figure 13 shows the data set for currents. The value ranges are related to internal microcontroller variables. The ANN topology is the same as the mentioned in Section III, Subsection B, with 4.

### V. EXPERIMENTAL RESULTS

Experimental results were obtained using a PMSM drive with vector control. The ANNs were executed along with the readings of an encoder, to verify the results. In this section, training procedures are first presented, followed by experimental results obtained in the execution phase.

#### A. Training

Several speed reference steps were applied to obtain a data set with information of the motor behavior from 30 RPM up to 120 RPM. Due to hardware limitations in the acquisition system, only four variables could be obtained simultaneously. The chosen variables are: \( \beta \) voltage, \( \beta \) current, electrical position and speed. The \( \alpha \) variables are then obtained by shifting the \( \beta \) variables by 90°. Figure 12 shows the assembled data set for voltages while Figure 13 shows the data set for currents. The value ranges are related to internal microcontroller variables. The ANN topology is the same as the mentioned in Section III, Subsection B, with 4.
hidden neurons. Training was performed through 300 epochs with NBN algorithm.

C. Tests without Load

Figures 16, 17 and 18 show the back-EMF estimations for the motor rotating at 30 RPM, 50 RPM and 100 RPM, respectively. It can be noticed that both the distortion level in the waves amplitudes and harmonic distortions reduce as the rotor speed increases. This is due to the relative noise level in the currents which is reduced as the speed increases.

B. Execution

The proposed estimation system was tested experimentally in a set composed by a PMSM with parameters given by Table I, a STM32F103C8T6 microcontroller and an 220V, 200W inverter. The ANNs were trained with floating point variables and exported to C codes with fixed point variables using multiplications by integer bases. Next, tests without load are firstly presented, followed by tests with the application of load torque steps. The utilized experimental setup is shown in Figure 15.

B. Execution

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Position estimations from the back-EMFs shown in Figures 16, 17 and 18 are depicted in Figures 19, 20 and 21, respectively. It is possible to observe that for a rotation of 100 RPM, the estimation performance is better than in lower speeds, due to the networks inputs noise level.

Figure 22 shows the error per sample. Table II shows the absolute mean and the squared mean estimation errors. For both cases, the estimation error is lower at 100 RPM. Considering the mean squared error, the estimator performed better at 50 RPM than at 30 RPM. Considering the absolute squared error, however, the estimator performed better at 30 RPM than at 50 RPM. Roughly speaking, this means that at 50 RPM, the estimation error has smaller peak values than at 30 RPM, which can be interpreted as a more behaved estimation, but with a larger dc error, which can be associated with the training process.

TABLE II

| Error/Speed | 30 RPM | 50 RPM | 100 RPM |
|-------------|--------|--------|---------|
| Squared     | 112.37 | 92.47  | 38.22   |
| Absolute    | 7.95   | 8.78   | 4.96    |

From the estimated position, rotor speed is estimated. A test at speeds of 50 RPM, 100 RPM and 30 RPM is shown in Figure 23. It can be observed that the real speed converges to the reference speeds. The estimated speed, however, presents a high noise level due to derivative calculations, with the occurrence of an offset around 30 RPM.

D. Tests with Load

The load for the following tests were generated by inserting a DC current of approximately 1.5 A in a three-phase induction machine through two phases, with the third phase blocked, which generates a load torque of approximately 2 Nm. The load was inserted in each test by applying a step from a voltage source, after the PMSM reached the reference speed.

Figure 24 presents the measured and estimated positions at a reference speed of 30 RPM. The load torque was inserted at time \( t = 2.65 \) s, approximately. In the position curves it can be observed that the motor speed was decreased during the transient caused by the load step, and returns to the initial speed. The estimated position remained close to the measured position even during the load insertion. A similar behavior can be observed in Figure 25, with the application of load at \( t = 1.82 \) s for a 50 RPM reference speed, and Figure 26, with the application of load at \( t = 2.04 \) s for a 100 RPM reference speed. Comparing to the simulation results, it is possible to observe that in the experimental results smaller oscillations were observed. This can be attributed to the load steps being filtered by the electric current transient response of the induction machine, since a step voltage is applied.
Among such advantages, the lack of construction and maintenance cost, increase of physical robustness of the drive system and reliability can be mentioned. The mentioned advantages are specifically important in PMSM applications such as in white good appliances, where the reduced volume is a requirement, and in hermetic compressors, in which the motor is drowned in oil, which could compromise the functionality of the mechanical sensor. Simulation and experimental tests could be performed with the use of automatically generated C code functions, making it practical to embed the trained FCC-ANNs in a fixed point microcontroller. Such approach shows up as an option for position estimation in low cost PMSM drive systems, such as for washing machines applications, with easy tuning and implementation.

ACKNOWLEDGEMENTS

The authors acknowledge Santa Catarina State University, Brazilian Federal Agency for Support and Evaluation of Graduate Education (CAPES) and EMBRACO.

APPENDIX

Figure 27 presents excerpts from the generated C code for $E_\alpha$. Firstly, the necessary variables are declared as 32 bit integers and the inputs are scaled. The propagation starts with applying the weighted inputs to all neurons. From the second layer on, the activation function value is calculated and the neuron outputs are propagated forward. The numeric values are the synaptic weights generated from training.

```c
void neural_run_ealpha(int32_t V_Alpha, int32_t V_Beta, ...){
   int 32_t mem[10], from_min[5], from_max[5], ...
   ...
   //layer 2
   ...
   e_alpha_temp = (((from_max[4] - from_min[4])*(mem[9] - ...
   *e_alpha = (int16_t) e_alpha_temp; }
```

Fig. 27. Excerpts from generated code. The “...” symbol stands for omitted code.

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Concerning to the quality of the estimated information, there were networks trained using an open source library and performed from a data set taken with varied speed. The obtained networks are executed in a microcontroller automatically exported to C codes in the form of functions. Simulation and experimental results are indicative of the functionality of the mechanical sensor. Simulation and experimental results are indicative of the functionality of the mechanical sensor. 

VI. CONCLUSION

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BIographies

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