

Performance Improvement of Field oriented Controlled Permanent Magnet Synchronous Motor Based Electric Vehicle Drives by ANN Controller

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Abstract. The present work represents the design and testing of artificial neural network controllers for permanent magnet synchronous motor drives applied in electric vehicles along with the conventional controller. This control methodology intends to leverage the power of adaptive learning offered by artificial neural networks (ANN) to overcome the challenges of electric vehicle propulsion, such as varied operating conditions, time-varying parameters, and nonlinear dynamics of systems. Simulation studies indicated that ANN controllers outperformed conventional PI-based field-oriented control methods for all the aspects of speed regulation, ripple reduction in torque, and robustness against perturbation. Real-time modifications of the neural network model to changes in load and outside noise improve performance without the need for complicated decoupling or tedious tuning. These results demonstrate that the ANN technique for the control of PMSMs is quite suitable for electric vehicles and easily integrated into them. It can help in driving by improving efficiency, making runs smoother, and could adapt to various needs of multimodal transportation with further improvements.

Keywords: EV, ANN, FOC, PMSM, PI

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1 Introduction

Electric vehicles (EVs) can benefit from the advantages of full power density and compact size provided by PMSMs, making PMSMs the best choice for EV propulsion because PMSMs provide significantly more efficient and higher power density than all other electric vehicle motors. One of the most appealing attributes of PMSMs for electrified vehicle applications is their high torque to inertia ratio, providing a compact motor with a high energy density. Although PMSMs provide many advantages, their nonlinear characteristics (i.e., magnetic saturation and cross-coupling) create many challenges in control applications. Additionally, PMSMs will change in performance over time due to aging and temperature variations [1]. FOC and DTC control systems generally used with PI controllers to generate accurate baseline reference points for controlling the functioning of PMSMs. Conventional Controllers typically do not respond quickly to sudden changes in their operating environment because of their relatively slow response times. Besides, they do not have the necessary level of flexibility to be able to effectively handle the nonlinear characteristics of PMSMs [11]. Recent trends in intelligent control techniques indicate that artificial neural network controllers may be an effective way to control permanent magnet synchronous motor drives. Moreover, Artificial Neural Networks have the capability to learn the non-linear complexities involved in the motor in real-time using input/output information from the system, which is an entirely new development compared with conventional control applied to Permanent Magnet Synchronous Motors [2] [3]. An ANN controller also possesses flexibility inbuilt within the controller that can handle uncertainties in parameters like stator resistance/rotor flux. Therefore, artificial neural network controllers assure far superior speed and torque control performance compared with conventional control techniques, coupled with significant reduction in torque ripple effects that occur during conventional controller operation [4]. Moreover, recent works have evidenced that the robustness level of ANN controllers with regard to internal faults and external disturbances due to additional loads brings significant enhancement in dependence and reliability of EV drive systems that plays an important part in protecting passengers. A considerable amount of research work proves that ANN controllers work effectively. They definitely enhance dynamic performance by ensuring efficient reduction in torque ripple effects, which further brings decrease in mechanical disturbance, vibrations, noise, speed setting, and improved acceleration and deceleration for the operator. In particular, one of the most important emerging technologies for control systems is the use of artificial neural networks for control techniques [7]. These modern control techniques render unnecessary the use of expensive mechanical sensors such as encoders by successfully predicting the rotor speed and position based on the terminal voltages and currents. This makes the system cheaper, smaller, and

less complicated with no single point of failure. These emerging trends point out the tremendous possibilities of control techniques with artificial neural networks to modernize the PM synchronous motor drive technology under the tough conditions set by the demands for efficiency, flexibility, and robustness for the electric mobility challenge.[12].

2 Components of Drives and Mathematical Modelling

In order to control a permanent magnet synchronous motor, one must work with a three-phase system and convert it into a two-axis system, called a rotating reference frame (dq frame). While this technique involves some complex workings, it allows for easier control.[6]

2.1. The equations for voltage, when placed in the synchronous rotating reference frame, take on the following forms:

Stator voltage equations:

$$v_d = R_s i_d - \omega_e L_q i_q + L_d \frac{di_d}{dt} \quad (1)$$

$$v_q = R_s i_q + \omega_e (L_d i_d + \lambda_f) + L_q \frac{di_q}{dt} \quad (2)$$

Whereas:

R_s = Stator resistance(Ω)

L_d = d – axis inductance(H)

L_q = q – axis inductance(H)

i_d = d – axis current(A)

i_q = q – axis current(A)

v_d = d – axis voltage(V)

v_q = q – axis voltage(V)

These equations model the motor's electromagnetics by decoupling the d-axis, which produces the flux, from the q-axis, which produces the torque. This is the basic concept of Field Oriented Control.

2.2. Generation of Electromagnetic Torque

The electromagnetic torque of the PMSM is generated by the interaction of the currents in the stator and the magnetic flux in the rotor. For the case of a surface-mounted PMSM in which $L_d = L_q$, the torque equation becomes significantly simpler:

Electromagnetic Torque Equation

$$T_e = \frac{3}{2} p \lambda_f i_q \quad (3)$$

For interior PMSM configurations where $L_d \neq L_q$, the complete torque equation includes the reluctance torque component:

Electromagnetic Torque Equation

$$T_e = \frac{3}{2} p [\lambda_f i_q + (L_d - L_q) i_d i_q] \quad \dots\dots\dots (4)$$

Whereas:

λ_f = Permanent magnet flux linkage(Wb)

ω_e = Electrical angular speed(rad/s)

ω_m = Mechanical speed(rad/s)

p = Number of pole pairs

T_e = Electromagnetic torque(Nm)

This formulation demonstrates how torque control can be achieved primarily through q-axis current regulation, while d-axis current is typically set to zero in surface-mounted PMSMs to maximize torque per ampere.

2.3. Mechanical dynamics

The mechanical subsystem outlines how the motor rotates in conjunction with the loads placed on the vehicle. Mechanical dynamics uses Newton's second law pertaining to rotation:

$$J \frac{d\omega_m}{dt} = T_e - T_L - B\omega_m \quad (5)$$

Whereas:

T_L = Load torque(Nm)

J = Moment of inertia(kg · m²)

B = Viscous friction coefficient(N · m · s)

The mechanical and electrical speeds relate as such:

$$\omega_e = p \omega_m \quad \dots\dots\dots (6)$$

2.4. Clarke transformation

For implementation of Field Oriented Control, coordinating transformations are required to switch between different reference frame measurements. The Clarke transformation takes three-phase stationary abc coordinates and converts them to two-phase stationary αβ coordinates:

$$\alpha = i_a \quad \dots\dots\dots (7)$$

$$\beta = \frac{1}{\sqrt{3}}(i_b - i_c) \quad \dots\dots\dots (8)$$

Park Transform

The Park transformation then takes stationary αβcoordinates and converts them to the rotating dq coordinates

$$i_d = \alpha \cos \theta_e + \beta \sin \theta_e \quad \dots\dots\dots (9)$$

$$i_q = -\alpha \sin \theta_e + \beta \cos \theta_e \quad \dots\dots\dots (10)$$

Whereas:

θ_e = Electrical angle(rad)

i_a, i_b, i_c = Three – phase currents(A)

α, β = Two – phase stationary frame currents

2.5. Field Oriented Control Strategy

To control Field Oriented Control, control of torque and flux is decoupled. The control strategy typically follows control of the currents in the dq-axis as:

2.5.1. Outer Loop (Speed Control): A PI controller computes the speed error and generates reference q-axis current:
Outer Speed Control Loop Equation

$$i_q^* = K_{p,\omega}(\omega^* - \omega) + K_{i,\omega} \int (\omega^* - \omega) dt \quad \dots\dots\dots (11)$$

where ω^* is the reference speedand $K_{p,\omega}, K_{i,\omega}$ are the proportional and integral control gains respectively

ω^* = Reference speed
 $K_{p,\omega}, K_{i,\omega}$ = PI controller gains

2.5.2. Inner Loop (Current Control): PI controllers are used to control the d-axis and q-axis currents independently. For surface-mounted PMSMs, the d-axis current reference is typically set to zero ($i_d^* = 0$) to maximize efficiency:

$$V_d^* = K_{p,d}(i_d^* - i_d) + K_{i,d} \int (i_d^* - i_d) dt \quad (12)$$

$$V_q^* = K_{p,q}(i_q^* - i_q) + K_{i,q} \int (i_q^* - i_q) dt \quad (13)$$

The modulator then takes the voltage references and projects them back to three-phase coordinates before implementing them through SVPWM.

2.6. Space Vector Pulse Width Modulation (SVPWM)

Sinusoidal PWM is often outperformed by SVPWM in terms of bottom-line efficiency due to its ability to utilize the DC bus voltage (by about 15%) and minimize harmonic distortion. In SVPWM, the voltage is sectioned into 6 sectors and one of the reference voltage vectors is synthesized by combining two adjacent active vectors with one or two of the zero vectors.

$$T_1 = T_s \frac{|V_{ref}|}{V_{dc}} \sin\left(\frac{\pi}{3} - \alpha\right) \quad (14)$$

$$T_2 = T_s \frac{|V_{ref}|}{V_{dc}} \sin(\alpha) \quad \dots (15)$$

$$T_0 = T_s - T_1 - T_2 \quad (16)$$

Where T_s is the switching period, V_{dc} is the DC bus voltage, and alpha is the angle within the sector. This technique ensures minimum switching losses while maintaining excellent voltage regulation for the PMSM drive.

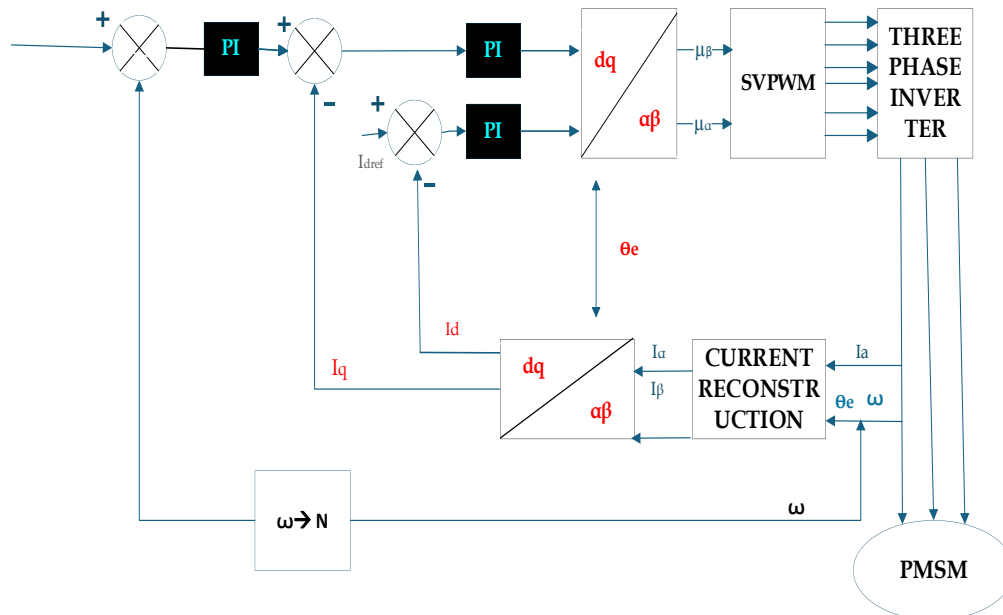


Fig. 1. FOC controlled PMSM drive

3. Modelling and Simulation

Modelling traditional PI controllers using components and equations above leads to results based on Field-oriented control (FOC) splitting the current into different parts so you can very precisely control a motor's speed and torque. It uses algebra, such as Clarke and Park transformations, to turn three-phase voltages and currents into a two-axis reference frame. In this system, you can control the direct-axis (I_d) and quadrature-axis (I_q) currents separately. Individuals often use PI controllers to change the I_d and I_q currents. After the control operation in the d-q frame, the reference signals are turned back into three-phase

control signals. A motor that uses permanent magnets proportional controllers most of the time, integral controllers are used in both the inner current control loops and the outer speed control loop of a Field-Oriented Control system.[2]

If the I_d reference is set to zero, the direct-axis current part doesn't make any torque. FOC is only in charge of controlling the I_q current that creates torque in this mode. FOC makes sure that I_q is just right so that the motor is magnetized correctly. This leads to reliable and effective operation. As shown in Fig. 1, the motor can either keep a constant speed or be controlled from the outside, even if there isn't a current that makes torque.

3.1. Speed controller with a PI controller

The P part of the PI controller is proportional, and the I part is integral. The proportional term gives an output that is directly related to the error at that moment, which is the difference between the expected output and the actual output. The integral part makes an output based on how many mistakes happen over time. This helps get rid of mistakes that don't change.

The main job of the PI controller in motor drives is to make the motor respond better to changes. This means that the system's output should be the same as the reference's input. When the load torque or speed changes a lot, for example, PI controllers work well.

3.2. Controller Using an artificial neural network

There are usually three types of layers in an artificial neural network: an input layer, one or more hidden layers, and an output layer. The input layer gets data from outside the network, the hidden layers do most of the math inside the network, and the output layer sends the final answer to the network.[9]

Each neuron in the input layer stands for an input value X_j and is linked to neurons in the next layer by a set of weights W_{ij} . To get a weighted total, the inputs are added together with weights. An activation function in the hidden and output layers then processes this total. This activation function makes the network non-linear, which helps it find and understand complex relationships in the data.

The artificial neural network (ANN) model is developed and trained primarily using MATLAB as the main software platform. The Levenberg–Marquardt backpropagation learning method is generally used in this current study to enhance the performance of our selected network. Since this procedure can result in a more precise value of the assets for nonlinear functions that are widely used in engineering calculations, it was chosen to be carried out.

Parameters decided based on the already selected experimental data shown in table 1.

Table 1. Parameter of the PMSM.

Parameter [1]	Value
Stator phase resistance R_s	2.875 Ω
d-axis inductance L_d	8.5 H
q-axis inductance L_q	8.5 H
Flux linkage of rotor magnets λ_f	0.18 V·s
Pole pairs P	2
DC-link voltage V_{dc}	400V
Reference speed	1500 rpm

4. Simulations and Results

The experimental results show that the PI-ANN controller is much better than the traditional PI setup, especially when it comes to dynamic response. We saw a clear improvement in settling time, which means that the system stabilizes much faster when controlled by the neural network. It's interesting that this increase in speed didn't cause the instability we might have thought it would. In fact, the overshoot was lower than with the standard controller, not a trade-off. The PI-ANN did show a little more pre-shoot, but the overall performance shows that we can get a faster response without losing stability. This makes the hybrid

strategy a better choice. Further we can improve by using numerous hybridized techniques to overcome our flaws in the represented systems.

We made a feedforward neural network with a 3–20–10–1 architecture that looks at d/q-axis currents and mechanical speed to figure out electromagnetic torque in real time. The model has two hidden layers of 20 and 10 tanh neurons, and then a linear output. This is how it simulates the motor's complex, non-linear dynamics. The network uses the Levenberg-Marquardt algorithm. The system got a nearly perfect correlation of $R = 0.9948$ and an unusually low error ($MSE = 4.678 \times 10^{-4}$) with data that had been normalized and tested a lot with a 70/15/15 split. This highly accurate digital twin makes sure that the ANN-assisted FOC implementation stays accurate and responsive in a variety of operational situations.

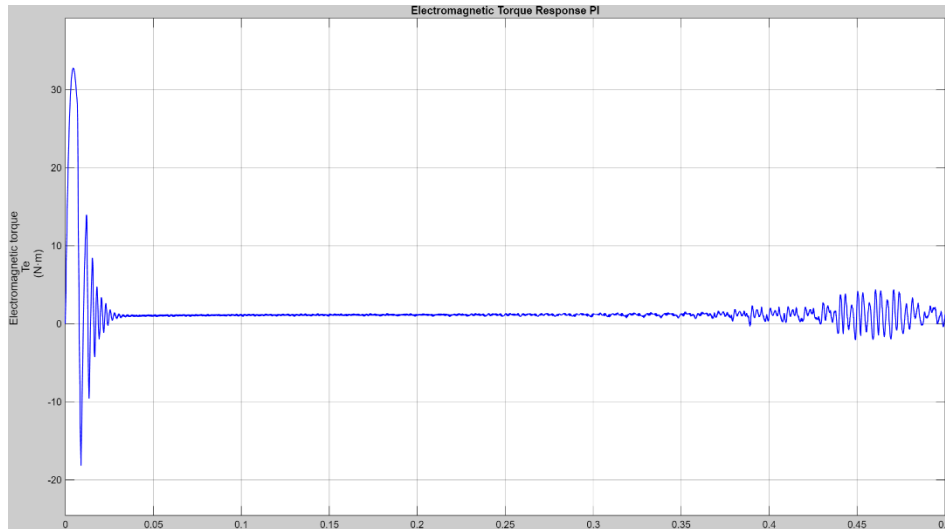


Fig. 2. Electromagnetic Torque Response of FOC-PI

Therefore, while the ANN is more capable of speed and torque transitions than the PI Controller, the need for additional damping and tuning to prevent the over-aggressiveness of the braking response may need additional development with the ANN Controller.

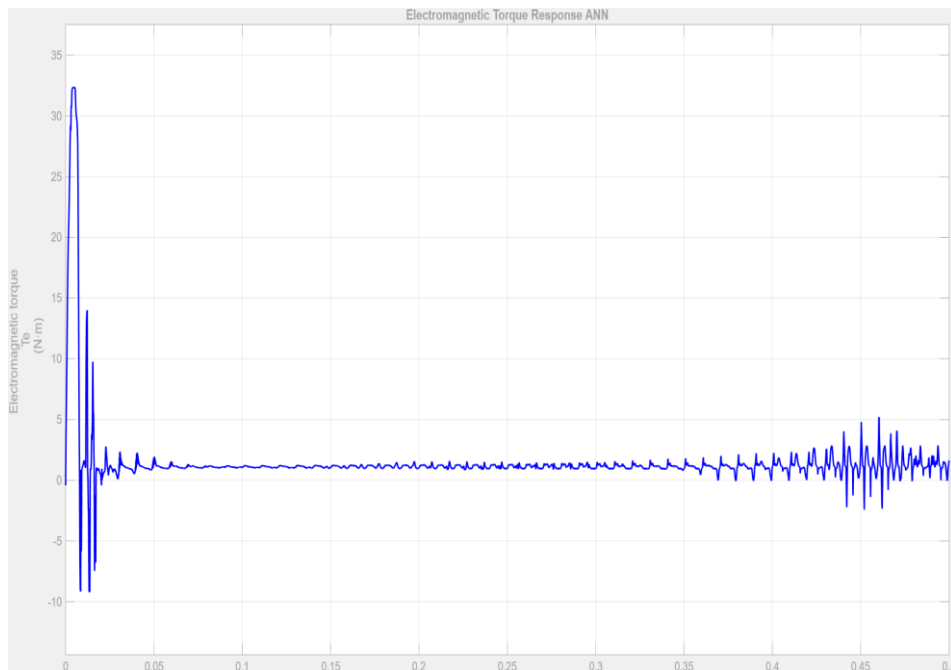


Fig. 3. Electromagnetic Torque Response of FOC- ANN

Results show a significant improvement in the newly designed controllers with the existing PI controller the following table depicts the same observation,

Table 2. Results Comparison

Performance Parameter	PI Controller	PI-ANN Controller
Pre-shoot (%)	2.9736	4.5238
Overshoot (%)	0.8065	0.6667
Undershoot (%)	1.9826	1.9926
Settling Time (s)	18.4681	16.0881

5. Conclusion

The results show that adding the network to the controller makes the system better. This is because the PI response is set in the PI-ANN method, which makes the response speed much faster. This has no impact on the stability of the system in any way. The normal result shows that response speed affects stability. In other words, if a system reacts quickly, it will start to oscillate. But in the new control strategy, damping stays the same. Less overshoot. There was a small rise in pre-shoot, but it can be seen that the new method is a strong solution. The PI-ANN did show a little more before the shoot, but overall, it shows that we can get a faster response without losing stability. This means that the hybrid strategy is the best choice. By adopting different- different hybridized techniques we can fix the problems with the systems as we encounter.

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