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An Intelligent Method Based on Model Predictive Torque Control and Optimized ANFIS for Induction Motor Speed Control

Reza Zamani Shourabi*, Mohammad Reza Moradian

Islamic Azad University, Najafabad Branch, Faculty of Electrical Engineering, Najafabad, Iran

Keywords

ANFIS,
aABC,
MPTC,
DTC,
Induction motor.

Abstract

A large number of motors are being used for general purposes in our surroundings from house-hold equipment to machine tools in industrial facilities. The electric motor is now a necessary and indispensable source of power in many industries. Three-phase induction motors are widely used as industrial drives because they are self-starting, reliable and economical. In this paper, an intelligent method based on Model Predictive Torque Control (MPTC) and optimized Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed for a three-phase induction motor speed control. The proposed method includes the inverter model in control design and doesn't use any modulation block. The optimal selection of inverter switching states minimizes the error between references and the predicted values of control variables by the optimization of a cost function. Consequently, it reduces ripples and solves DTC drawbacks. Furthermore, this paper proposes an improvement in the external speed loop for MPTC scheme. An ANFIS controller replaces the traditional Proportional-Integrator (PI) controller to ensure more accurate speed tracking and increase the robustness against disturbance and uncertainties. In the proposed method, an adaptive and hybrid artificial bee colony (aABC) algorithm is used to train the ANFIS. aABC algorithm is one of the most powerful and accurate optimization algorithms which is introduced recently. The proposed method is compared with conventional DTC and other methods by computer simulation through the MATLAB/SIMULINK software. The obtained results show the superior performance of the proposed method in comparison with other methods.

1. Introduction

An electric motor converts electrical energy into a mechanical energy which is then supplied to different types of loads. A.c. motors operate on an a.c. supply, and they are classified into synchronous, single phase and 3 phase induction, and special purpose motors. Out of all types, 3 phase induction motors are most widely used for industrial applications mainly because they do not require a starting device. Three phase induction motors have been widely used in industry applications such as hybrid vehicles, paper and textile mills, robotics, and wind generation systems because of their several inherent advantages such as their simple construction, robustness, reliability, low cost, and low maintenance needs. The benefits of three phase induction motors make it widely used through various industrial modern processes, with growing economical and performing demands [1, 2]. Without proper controlling, it is virtually impossible to achieve the desired task for any industrial application. To achieve optimal efficiency of induction motors, several control techniques have been developed to control the induction motor such as scalar control, vector or field oriented control (FOC) and direct torque control (DTC) [3, 4]. The acceptable performace of these methods has been proved by differnet studies [1- 4].

The DTC technique [5] is a popular and powerful control technique for three-phase induction motor in present. It has very quick dynamic response, robust control, and simple structure and easy to implement because coordinate transformations are not required and the torque and stator flux can be controlled directly [6]. The appropriate stator voltage to control motor can be selected from an optimum switching table in accordance with the sector that the stator flux is located, and the signs of torque and magnitude of stator flux errors that are the output of hysteresis comparators [7]. The use of the hysteresis comparators results in high torque ripple, stator flux ripple and variable switching frequency, which produce noises, vibrations and increased losses that are the main drawback of DTC [7]. In recent

* Corresponding Author:
E-mail address: reza.zamani.sh@gmail.com – Tel, (+98) 9137734865 – Fax, (+98) 3833532087

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years, several methods have been proposed by researchers to overcome these drawbacks.

Some methods have been introduced in the past decades to mitigate these problems such as DTC based on space vector modulation (DTC-SVM) [8, 9], duty ratio control method [10, 11] and multilevel converters [12]. DTC-SVM still maintains DTC transient merits while the steady-state performances are improved in the wide speed range. Two PI controllers and SVM technique are used instead of hysteresis comparators and optimum switching table in order to compensate the torque and magnitude of stator flux errors and generate the optimal stator voltage reference vector for motor, respectively. As a result, the torque and stator flux ripples are reduced and the switching frequency is kept constant. To improve DTC-SVM, the over modulation technique [13] and DTC-SVM incorporate with sliding mode control [14- 16] have been presented. However, DTC-SVM operates in rotating reference frame that requires more complicated computation than DTC.

In duty ratio control, a selected active voltage vector is applied for a part of the sampling period and a zero voltage vector is applied for the rest in one switching cycle. In Ref. [17], the optimal weighting factor based on torque ripple and the control interval divided into two parts are suggested to obtain the stator current and torque ripple reduction for duty ratio control method. In Ref. [18], the similar technique was presented. The duration of the active voltage vector is calculated by using the principle of torque ripple minimization with fixed weighting factor. Although the steady-state performance is improved in both methods, the increase of processing leads to relative poor low speed performance [18], higher hardware requirements and more computational complexity. The duty ratio control technique can significantly mitigate the torque and stator flux fluctuations but it increases the complexity of the DTC algorithm and stimulates some problems such as the demagnetization phenomenon of the stator flux, especially in the low speed region. The robust control of three phase incuction motor speed in low speeds is a critical issue in many industrial applications [19].

In this paper, a model predictive torque control (MPTC) is proposed for the goal of torque and flux ripple reduction. In the proposed method, the optimal switching table in DTC is replaced by online optimization process. The best stator voltage vector is selected as the stator voltage vector that minimizes the cost function, which defines relating to torque and stator flux errors. The torque and stator flux are kept more accurately within their boundaries than DTC. In addition, an adaptive neuro-fuzzy inference system (ANFIS) controller is associated in the external loop for speed regulation. In the proposed method, we used aABC algorithm to train the ANFIS.

The rest of the paper is organized as follows. Section two explains the induction machine structure and voltage inverter models. Section three presents the basic direct torque control. Section four presents the proposed method with details and flowchart. Section five shows some simulation results and compare its performance with other methods. Finally section six concludes the paper.

2. Induction Machine and Voltage Inverter Models

2.1. Three Phase Induction Motor Model

The dynamic equation's model of the induction machine (IM) can be expressed by the following complex form in the stator reference frame, (1) and (2) present voltage, flux and electromagnetic equations respectively:

$$\bar{v_s} = R_s\bar{\imath_s} + \frac{d\overline{\psi_s}}{dt} \tag{1}$$

$$0 = R_r\bar{\imath_r} + \frac{d\overline{\psi_r}}{dt} - j\omega_r\bar{\psi_r} \tag{2}$$

$$\bar{\psi_s} = L_s\bar{\imath_s} + M_{sr}\bar{\imath_r} \tag{3}$$

$$\bar{\psi_r} = M_{sr}\bar{\imath_r} + L_r\bar{\imath_r} \tag{4}$$

$$T_e = p.Im\{\bar{\psi_s}.\bar{\imath_s}\} \tag{5}$$

where $\bar{v_s}$ is the stator voltage vector, $\bar{\psi_s}$ and $\bar{\psi_r}$ are the stator flux and rotor flux, $\bar{\imath_s}$ and $\bar{\imath_r}$ are the stator and rotor currents, L_s, L_r and M_{sr} are stator, rotor and mutual inductance, R_s and R_r are the stator and rotor resistances. Also ω_r is the electrical velocity and p is the number of pole pairs.

2.2. Two-Level Voltage Source Inverter Model

In this work, a two-level voltage source inverter (VSI) fed the controlled three phase induction motor. The voltage vector is generated by the following expression:

$$V_s = \sqrt{\frac{2}{3}V_{dc}}\left[S_a + S_b e^{j\frac{2\pi}{3}} + S_c e^{j\frac{4\pi}{3}}\right] \tag{6}$$

where V_{dc} is the DC link voltage.

The inverter's control bases on the logic values S_i, where:

$S_i = 1,\ T_i\ is\ ON\ and\ \bar{T}_i\ is\ OFF$

$S_i = 0,\ T_i\ is\ OFF\ and\ \bar{T}_i\ is\ ON$

with: i= a, b, c.

There are eight possible positions from the combinations of switching states. Six are active vectors (V1, V2 … V6) and two are zero vectors (V0, V7). These eight switching states are shown as space vectors in Figure 1.

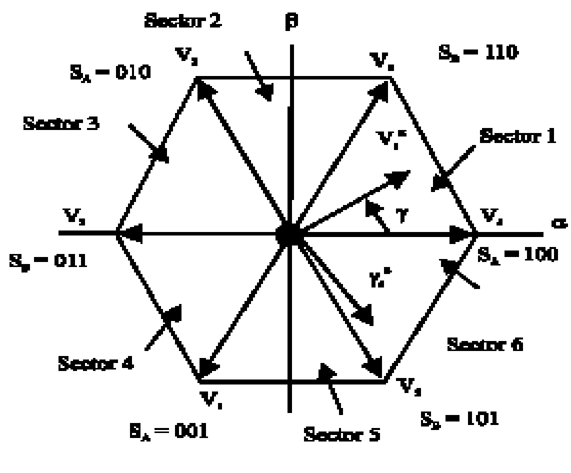

Figure 1. Two-level VSI voltage vectors in the complex plane

3. Model Predictive Torque Control

3.1. DTC

Direct torque control achieves a decoupled control of the stator flux and the electromagnetic torque in the stationary frame. The selection of the switching states is made by restricting the flux and torque magnitudes within two hysteresis bands. The outputs of hysteresis comparators with the aid of lookup switching table determine an appropriate voltage vector for each commutation period. The main diagram of DTC is shown in Figure 2.

3.2. MPTC

MPTC algorithm includes three main steps, the flux and torque estimation is first step. The second step is the prediction of the next-instant of current $\bar{\imath}_s(k+1)$, flux $\bar{\psi}_s(k+1)$, and torque $T_e(\mathrm{k}+1)$. The cost function optimization design is done finally [13].

$$\frac{d\overline{\psi_s}}{dt} = \bar{v}_s - R_s\bar{\imath}_s \tag{7}$$

$$\bar{\imath}_s = -\frac{1}{R_\sigma}\left(L_\sigma\frac{d\bar{\imath}_s}{dt} - k_r\left(\frac{1}{T_r} - j\omega\right)\overline{\psi_r}\right)\bar{v}_s \tag{8}$$

where $k_r = \frac{M_{sr}}{L_r}, R_\sigma = R_s + k_r^2.R_r, L_\sigma = \sigma L_s$.

To predict the required signals (currents, flux and torque) into the next step, the Euler forward discretization equation is used:

$$\frac{dx}{dt} \approx \frac{x(k+1) - x(k)}{T_z} \tag{9}$$

After discretization with the sampling time T_z, the stator flux prediction can be obtained as Eq .(10)

$$\overline{\psi_s}(k+1) = \overline{\psi_s}(k) + T_z\bar{v}_s(k) - R_sT_z\bar{\imath}_s(k) \tag{10}$$

The stator flux prediction can be obtained as Eq. (11)

$$\bar{\imath}_s(k+1) = \left(1 - \frac{T_z}{T_\sigma}\right)\bar{\imath}_s(k) + \frac{T_z}{T_\sigma}.\frac{1}{R_\sigma}$$
$$\left(k_r.\left(\frac{1}{T_r} - j\omega(k)\right)\overline{\psi_r}(k) + \bar{v}_s(k)\right) \tag{11}$$

With $T_\sigma = \frac{\sigma L_s}{R_\sigma}$.

By the predictions of the stator flux and current, the electromagnetic torque can be predicted as following:

$$\hat{T}_e(k+1) = p.Im\{\overline{\psi_s}(k+1).\bar{\imath}_s(k+1)\} \tag{12}$$

The cost function in the MPTC strategy compares the predicted and reference values. The classical cost function for the MPTC method is:

$$g = \left|T_e^* - \hat{T}_e(k+1)\right| + \lambda\left|\overline{\psi_s}^* - \overline{\psi_s}(k+1)\right| \tag{13}$$

where T_e^* is the reference torque and $\hat{T}_e(k+1)$ is the predicted torque for a given switching state, $\overline{\psi_s}^*$ is the reference stator flux and $\overline{\psi_s}(k+1)$ is the predicted stator flux, and λ is the weighting factor which defines a trade-off between the torque and flux tracking.

Various approaches have been presented for solving weighting factor choosing problem. In this work, a modified cost function is considered. This method modifies the expression (13) into the following equation:

$$g = \frac{1}{T_{en}^2}\left|T_e^* - \hat{T}_e(k+1)\right| + \frac{\lambda}{\psi_{sn}^2}\left|\overline{\psi_s}^* - \overline{\psi_s}(k+1)\right| \tag{13}$$

T_{en} and ψ_{sn} are the rated values for the torque and flux, respectively.

In MPTC, the cost function can be extended by adding other control objectives and system constraints. For example, current limitation term I_m is added in order to protect over current through the stator. This term is designed according to the maximum supportable current by the machine as Eq. (14)

$$I_m = \begin{cases} \infty, & if\ |\bar{\imath}_s(k+1)| > i_{max} \\ 0, & if\ |\bar{\imath}_s(k+1)| \le i_{max} \end{cases} \tag{14}$$

i_{max} is the maximum current rating of the IM. Thus, the complete cost function g for the controller is:

$$g = \frac{1}{T_{en}^2}\left|T_e^* - \hat{T}_e(k+1)\right| + \frac{\lambda}{\psi_{sn}^2}\left|\overline{\psi_s}^* - \overline{\psi_s}(k+1)\right| + I_m \tag{15}$$

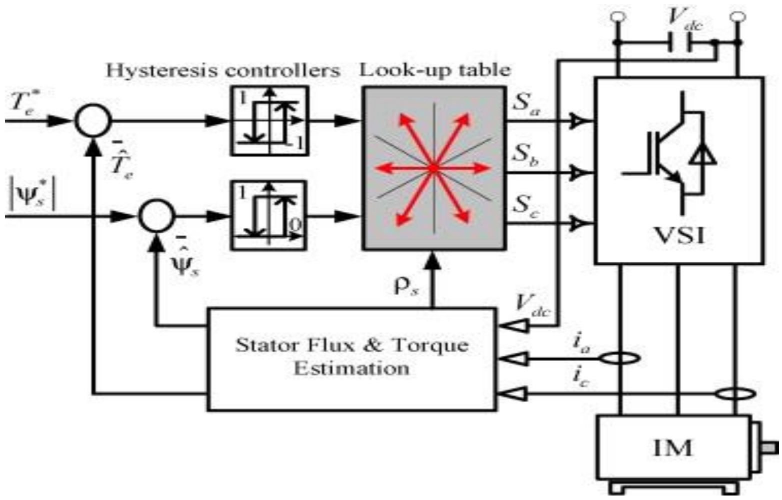

Figure 2. Diagram of DTC

In simulation, the speed and stator current measurements are taken at the discrete instant k, and at the same time the optimum voltage vector $\bar{v}_s(k)$ is applied to the machine. However, in experimental, the processor needs time to execute the algorithm. Hence, to implement a delay time compensation, the predicted stator flux, current and torque at instant $k+2$ are obtained by:

$$\overline{\psi_s}(k+2) = \overline{\psi_s}(k+1) + T_z\bar{v}_s(k+1) - R_sT_z\bar{\iota}_s(k+1) \tag{16}$$

$$\bar{\iota}_s(k+2) = \left(1-\frac{T_z}{T_\sigma}\right)\bar{\iota}_s(k+1) + \frac{T_z}{T_\sigma}\frac{1}{R_\sigma}\left(k_r.\left(\frac{1}{T_r} - j\omega(k)\right)\overline{\psi_r}(k+1) + \bar{v}_s(k+1)\right) \tag{17}$$

$$\hat{T}_e(k+2) = p.Im\{\overline{\psi_s}(k+2).\bar{\iota}_s(k+2)\} \tag{18}$$

By considering the calculation delay in real time implementation, the cost function become:

$$g = \frac{1}{T_{en}^2}\left|T_e^* - \hat{T}_e(k+2)\right| + \frac{\lambda}{\psi_{sn}^2}\left|\overline{\psi_s}^* - \overline{\psi_s}(k+2)\right| + I_m \tag{19}$$

4. The Proposed Method

In this paper, an intelligent method based on MPTC and optimized ANFIS is proposed for induction motor speed control. In the proposed method, an ANFIS based controller is designed to replace the PI controller and generate the reference's torque. The ANFIS is featured that it does not require an exact modeling or identification. The tracking error and its time derivative are considered as the input variables. The rotor speed error is defined by Eq. (20)

$$e_{\omega_r} = \omega_r^* - \omega_r \tag{20}$$

Figure 3 show the global diagram of predictive direct torque control associated to fuzzy logic speed controller. The speed control based on ANFIS basically consists of two phases: training and testing. In the training stage, parameters are calculated according to the chosen learning algorithm. The issue of the learning algorithm and its speed is very important for the ANFIS model. ANFIS is trained by using the existing input-output data pairs for the solution of available problems. Thus, IF-THEN rules in ANFIS are obtained. In [20] a new learning algorithm based on adaptive and hybrid artificial bee colony (aABC) is proposed for ANFIS training. The excellent performance of this method is proved by several numerical experiment. Therefore in this paper we propose the application of this new learning algorithm to train the ANFIS in the field of three phase induction motor speed control. More details regarding ANFIS and new training algorithm can be found [20].

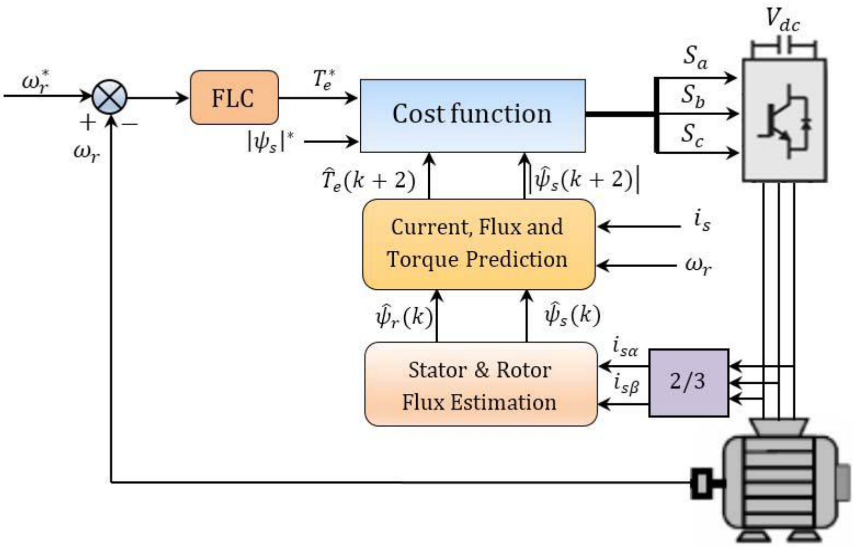

Figure 3. The main structure of the proposed system

In training of ANFIS, antecedent and conclusion parameters found in layer 1 and 4 are optimized. In this study, the mentioned parameters are optimized by using aABC algorithm. The parameters which belong to ANFIS structure used in training are shown in Fig. 4. Number of parameters found in structure of ANFIS and to be used in training is equal to the total of number of antecedent and conclusion parameters [21]. In aABC algorithm, the position of a food source represents a possible solution for the addressed problem. Therefore, a set of antecedent and conclusion parameters of ANFIS correspond to a food source in aABC algorithm. Thus, aABC algorithm operates for finding the best food source around the hive or the best antecedent and conclusion parameter set in the search space. The aABC algorithm should find the best parameters of ANFIS to enhance the accuracy of control system.

5. Simulation Results

5.1. Motor Parameters

In this section we evaluate the performance of the proposed method. The proposed method is applied on 1.1 KW three phase induction motor. The main parameters of test motor are listed in Table 1.

Table 1. Motor parameters

Parameter	Value
Power (W)	1.1
Rated voltage (V)	460
Rated speed (rpm)	1785
Synchronous speed	1800
R_s	14.85×10^{-3}
X_s	0.3027×10^{-3}
R_r	9.29×10^{-3}
X_r	0.3027×10^{-3}
Pole	2

In this section, several experiments have been done for evaluating of the proposed method. The computational experiments for this section were done on Intel core i7 with 16 GB RAM using ASUS computer. The computer program was performed on MATLAB (version 8.5.0.197613 [R2015a], Massachusetts, USA) environment.

5.2. Performance of the Proposed Method

In this experiment, the performance of the proposed method has been investigated. As mentioned, aABC algorithm is used to find the optimal values of antecedent and conclusion parameters of ANFIS. The control parameters of aABC algorithm have viyal role on its performance. The value of these parameters are listed in Table 2. This parameters are selected based on extensive simulations and the best obtained result. These parameters have led to best accuract, fast convergence and the best local and global search in different runs.

Table 2. Control parameters of aABC algorithm

Number of bees	30
γ	0.75
α	0.25
Maximum number of iterations	100

Based on the best obtained results, Gaussian membership functions have been chosen to model the input variables. In the designed fuzzy system, 4 rules are composed by using 3 membership functions for each input. Each Gaussian membership function has two parameters including center and spread. We have 2 inputs and each input have been defined using 4 Gaussian membership function. Therefore there are $2 \times 4 \times 2 = 16$ antecedent parameters. The number of conclusion parameters of each rule is one more than the number of inputs. In the structure of designed ANFIS using proposed method, with 2 inputs, the number of conclusion parameters of each rule is 3. Therefore there are $4 \times 3 = 12$ antecedent parameters. Therefore $16 + 12 = 28$ parameters in total are optimized. Membership functions with optimal parameters determined by aABC algorithm are plotted in Figures 4 and 5.

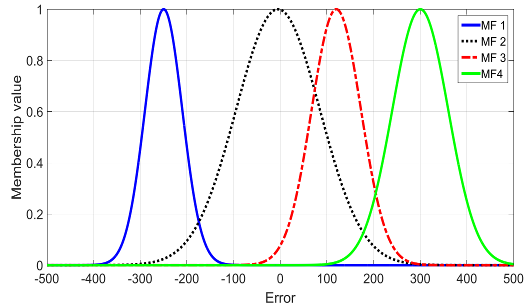

Figure 4. Membership functions for the first input in the proposed method

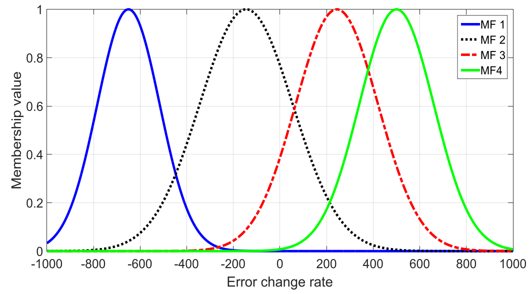

Figure 4. Membership functions for the second input in the proposed method

The reference speed is shown in Figure 6. In this experiment, the reference speed has been started from 0 rpm and is increased to 1500 rpm. Then in $t = 1\,sec$ the reference speed is decreased to 1000 rpm. Also for further investigation, in $t = 0.5\,sec$ and $t = 1.5\,sec$ the load torque has been changed. The proposed method should control the motor speed in different conditions. The obtained results using the proposed method and DTC is shown in Figure 7. In this figure, the horizontal axis shows the time and the vertical axis shows the speed. It can be seen that both methods has good settling time and steady state error. For further investigation with more details, the performance of the proposed method and DTC is shown in Figures 8 to 10 in small time range. Figures 8 and 9 show the speed of motor at load torque variation condition. Form this figure it can be seen that the proposed method has lower variation rather than DTC. Figure 10 shows the motor's speed at steady state condition. It can be seen that the proposed method has lower error rather than DTC.

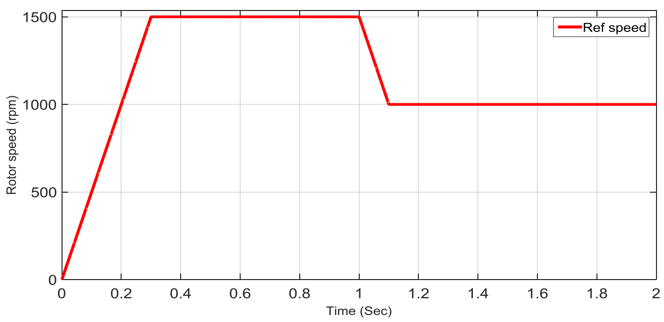

Figure 6. The reference speed

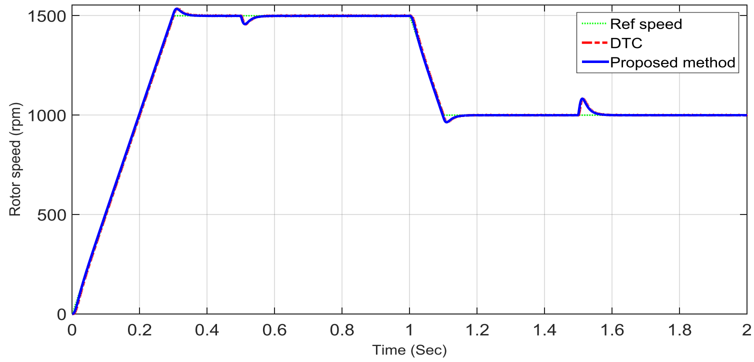

Figure 7. The obtained results using the proposed method and conventional DTC

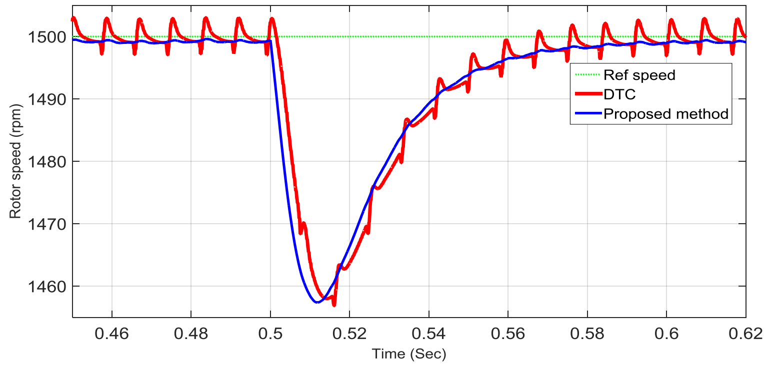

Figure 8. Comparison of the proposed method and DTC with more details at first load torque variation condition

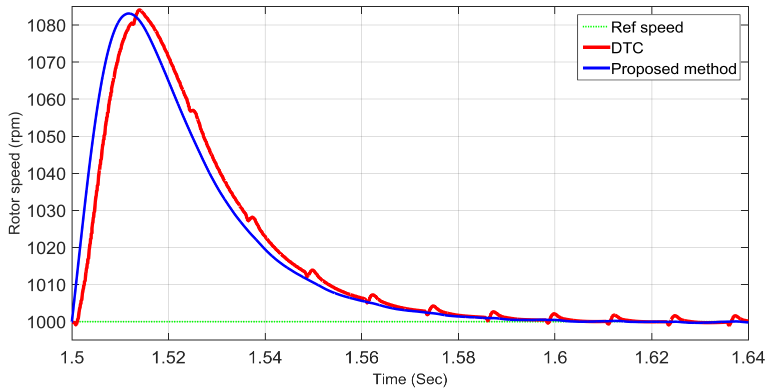

Figure 9. Comparison of the proposed method and DTC with more details at second load torque variation condition

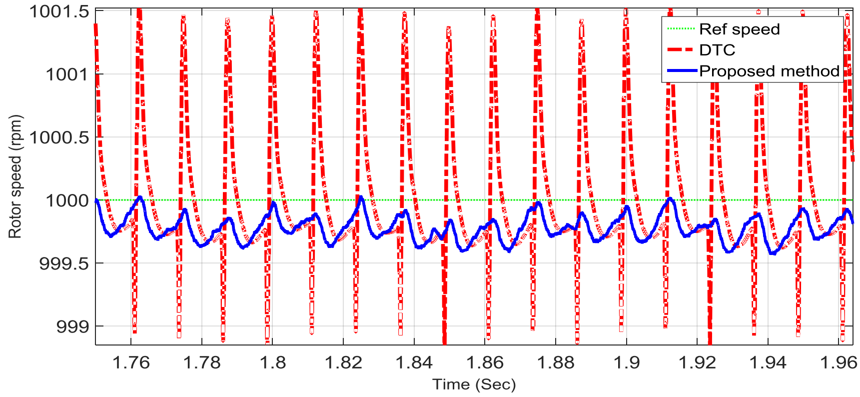

Figure 10. Comparison of the proposed method and DTC with more details at steady state condition

6. Conclusion

Induction motors are the most widely used ac machines due to the advantageous merits of cost, reliability, and performances. Among many control methods of induction machines, one of the most important method is the Direct Torque Control (DTC). The DTC suffers from high torque and flux ripples due to the use of hysteresis comparators. In this paper, an intelligent method based on Model Predictive Torque Control (MPTC) and optimized Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed for induction motor speed control. Model predictive direct torque control has been investigated as an alternative for conventional motor control methods, i.e., direct torque control and field-oriented control. Predictive control may result in faster dynamic response and precise steady-state response as well. In this paper, an intelligent method based on model predictive torque control and optimized ANFIS is proposed for induction motor speed control. Here, to show the superiority of the proposed method over other alternative techniques available in the literature, several experiments have been done. The obtained results showed that the proposed method has much better performance rather than conventional DTC.

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