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Intelligent Speed Control of an Induction Motor Drive Using an Online TLBO-Based Fuzzy PI Tuning Strategy

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ABSTRACT

This paper proposes an intelligent speed control strategy for a three-phase induction motor drive based on indirect field-oriented control (IFOC), fuzzy logic, and the Teaching–Learning-Based Optimization (TLBO) algorithm. The proposed approach is developed to improve the dynamic performance of the motor drive by optimally tuning the proportional–integral (PI) controller parameters in response to variations in the speed error. In the proposed strategy, fuzzy logic is employed to adapt the controller parameters according to the instantaneous control error and its variation, while the TLBO algorithm is utilized to determine suitable controller parameters and enhance the overall tuning process. The complete control scheme is implemented and evaluated in the MATLAB/Simulink environment under different operating conditions. The performance of the proposed controller is assessed in terms of speed tracking, transient response, overshoot, settling time, and disturbance rejection. The obtained results are compared with those of a conventional PI controller tuned using the Ziegler–Nichols method. The simulation results demonstrate that the proposed online TLBO-based fuzzy tuning strategy provides improved speed-tracking performance and enhanced dynamic behavior compared with the conventional tuning approach. These findings indicate that the integration of fuzzy adaptation with TLBO optimization can provide an effective and flexible control solution for induction motor drive applications.

1. INTRODUCTION

In recent years, significant advances in power electronics have led to substantial developments in the control of AC electrical machines. Induction machines are widely used because of their simple construction, flexibility, high efficiency, low cost, compact size, and economical operation at constant speed. Consequently, the development of new methods for achieving accurate speed control and efficient operation of induction machines while minimizing undesirable effects on the output variables has continuously attracted considerable attention.

Recent developments in speed-control drives have enabled induction machines to be operated at variable speeds over a wide operating range. Although induction machines offer several advantages over DC machines in terms of size, weight, motor inertia, efficiency, maximum speed, reliability, cost, and other characteristics, their highly

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nonlinear dynamic structure requires a considerably more complex control scheme than that of DC drives. The application of three-phase AC machines under various operating conditions is continuously increasing. However, these applications are associated with several limitations, including harmonic generation, excessive reactive power consumption, and difficulties in speed control compared with DC drives. Therefore, a thorough investigation and analysis of the behavior and performance of these AC machines under different operating conditions are essential. Three-phase induction machines are standard in industrial electrical drives because of their cost, reliability, robustness, and maintenance-free operation [1].

The main difficulty in controlling three-phase induction motors arises from the fact that the current components responsible for torque production and flux production are inherently coupled. This problem can be effectively addressed through advanced control techniques such as vector control. The fundamental principle of vector control is to decouple the relevant current components and subsequently control each component independently. Therefore, a drive system with a desirable dynamic response can be developed to effectively respond to changes in the load or reference speed.

In conventional speed-controller designs, particularly Rotor Field-Oriented Control (ROFC) [2], a PI controller is commonly employed to regulate the speed of the induction motor drive. However, the use of a conventional PI controller can lead to several undesirable effects, such as excessive overshoot, speed and torque oscillations resulting from sudden load changes, and external disturbances. Its limited ability to attenuate the effects of system uncertainties, parameter variations, and external disturbances is another important drawback of the PI controller. Such behavior can adversely affect the overall performance of the drive system. Conventional control methods are highly dependent on the accuracy of the mathematical model developed for the system [2]. Moreover, motor performance may deteriorate in the presence of load disturbances, magnetic saturation, and thermal variations. Classical linear control generally provides satisfactory motor performance only around a specific operating point or speed. Under such conditions, selecting appropriate controller gains in the presence of parameter variations becomes a particularly challenging task.

Advanced control methods based on artificial intelligence techniques are generally referred to as intelligent control. Intelligent control can provide greater adaptability than conventional control approaches such as PI control. Fuzzy logic is a methodology that incorporates human-like reasoning into control systems [3–5]. Fuzzy logic control is particularly useful and suitable for induction motor speed drives because it does not require an exact mathematical model of the motor. In this paper, a TLBO-based fuzzy logic controller is proposed for the speed control of a three-phase induction motor.

2. RESEARCH BACKGROUND

Induction motors are among the most widely used electrical machines in industrial systems because of their simple construction, mechanical robustness, relatively low cost, high reliability, and low maintenance requirements. Despite these advantages, accurate control of induction motor speed and torque remains a challenging issue because of the nonlinear nature of the dynamic model, coupling between flux and torque, variations in motor parameters, and the effects of load disturbances. The development of vector-control and direct-torque-control techniques has provided an effective basis for achieving desirable dynamic performance in induction motor drives. In this context, Bose [6] investigated the role of power electronic control and advanced AC machine control techniques in improving the performance of electrical drives and demonstrated that advanced control methods can significantly improve the speed and torque responses of drive systems.

In conventional vector-control methods, the primary objective is to make the dynamic behavior of an induction motor resemble that of a separately excited DC motor, such that flux and torque can be controlled approximately independently. Vas [7] presented the mathematical foundations and various structures of vector-control systems for AC machines and demonstrated that field-oriented control can provide desirable dynamic performance for induction motors. Nevertheless, the performance of these methods is dependent on motor parameters, particularly the stator and rotor resistances, as well as temperature variations, load changes, and modeling errors. These factors constitute important limitations of conventional controllers.

Another important approach for induction motor drives is Direct Torque Control (DTC). Takahashi and Noguchi [8] proposed a novel method for rapid torque and flux control of induction motors, in which torque and flux are directly regulated without relying on the conventional vector-control structure. Owing to its fast dynamic response and relatively simple structure, this method has attracted considerable attention in the field of induction motor drives. However, torque and flux ripples, together with variable switching frequency, remain among the major issues that must be considered in the practical implementation of DTC.

With the subsequent development of intelligent control techniques, the application of fuzzy logic emerged as an effective approach for controlling nonlinear systems. Fuzzy logic, whose foundations were established by Zadeh [9], enables the incorporation of experiential knowledge and linguistic rules into the controller design. Consequently, it has been extensively applied to systems whose exact mathematical models are complex or dependent on varying parameters. In induction motor drive systems, fuzzy controllers can convert variables such as speed error and its rate of change into appropriate control signals without requiring an exact and fully linearized motor model.

Bose [10] investigated the application of artificial intelligence techniques to electric motor drives, including fuzzy logic, neural networks, and other intelligent methods, for enhancing the adaptability of control systems. The results of these studies indicate that intelligent controllers can provide greater flexibility than some conventional controllers when system parameters vary or when the system is subjected to disturbances.

Despite the advantages of fuzzy control, one of the major challenges in designing a fuzzy controller is the appropriate selection and tuning of the parameters of the membership functions and controller gains. Manual selection of these parameters is generally dependent on the designer's experience and may not result in optimal performance under all operating conditions of the motor. Therefore, the use of metaheuristic optimization algorithms for the automatic determination of fuzzy-controller parameters has attracted considerable research attention.

In this context, evolutionary and population-based optimization algorithms, including the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and algorithms inspired by social behavior, have been employed to tune the parameters of intelligent controllers. These algorithms can optimize a predefined objective function, such as minimizing speed error, settling time, overshoot, or a combination of these performance criteria. The use of such methods can reduce the dependence of controller design on manual parameter tuning.

One of the relatively recent metaheuristic optimization algorithms is the Teaching–Learning-Based Optimization (TLBO) algorithm, which was introduced by Rao, Savsani, and Vakharia [11]. This algorithm is inspired by the teaching–learning process within a classroom and consists of two principal phases: the Teacher Phase and the Learner Phase. One of the major advantages of TLBO is that, unlike many metaheuristic algorithms, it does not require a large number of algorithm-specific control parameters. This characteristic has contributed to its widespread application in various engineering optimization problems.

Rao et al. [12] investigated the capability of the TLBO algorithm for solving engineering optimization problems and demonstrated that the algorithm can provide competitive solutions compared with several conventional metaheuristic approaches. Similarly, Rao and Patel [13] investigated the application of TLBO to engineering optimization problems and demonstrated its capability to efficiently explore the solution space and obtain high-quality solutions.

Considering the characteristics of induction motors and the nonlinear nature of drive systems, the combination of fuzzy control and the TLBO algorithm can provide an effective approach for designing an intelligent controller. In such a structure, TLBO can be employed either offline or online to tune the parameters of the fuzzy controller. In the offline approach, the controller parameters are optimized before system operation and for predefined operating conditions. In contrast, in the online approach, the controller parameters can be updated according to changes in operating conditions, load variations, and speed-error behavior. This capability can enhance the adaptability of the drive system.

Furthermore, the application of optimization algorithms to electric motor control requires the definition of an appropriate objective function. In induction motor speed control, criteria such as steady-state speed error, overshoot, settling time, rise time, and torque oscillations can be incorporated into the objective function. Therefore, the design of a multi-objective or composite objective function and the use of TLBO to tune the parameters of the fuzzy controller can provide an appropriate trade-off among response speed, tracking accuracy, and system stability.

Overall, previous studies demonstrate that vector control and DTC provide effective capabilities for the dynamic control of induction motors. However, their sensitivity to motor parameters and operating conditions has motivated the development of intelligent control strategies. Fuzzy control, on the other hand, can reduce the dependence of the system on an accurate motor model, although its performance strongly depends on the proper tuning of fuzzy-controller parameters. The TLBO algorithm, owing to its relatively simple structure and effective search capability, can be employed to optimize these parameters. Accordingly, the integration of fuzzy control with TLBO and the incorporation of an online tuning mechanism can be considered a promising approach for improving the adaptability of induction motor drive systems to variations in reference speed, load, and motor parameters. This concept constitutes the main foundation of the present study.

3. INTRODUCTION TO THE TLBO ALGORITHM

The Teaching–Learning-Based Optimization (TLBO) algorithm was introduced by Rao et al. in 2012 [12]. Since its introduction, the algorithm has gained considerable popularity and has become a powerful optimization technique that has been applied to a wide range of engineering disciplines. TLBO is capable of providing high-quality solutions within a relatively short computational time while exhibiting favorable and stable convergence characteristics. The TLBO procedure consists of two main phases: (1) the Teaching Phase and (2) the Learning Phase. The main steps of the TLBO algorithm are described below [12].

3.1. Initialization

In this step, the initial population with a size of **[NP × D]** is randomly generated, where **NP** denotes the population size (i.e., the number of learners) and **D** represents the dimensionality of the optimization problem.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} \;\cdots & x_{1,D} \\ x_{2,1} & x_{2,2} \;\cdots & x_{2,D} \\ \vdots & \vdots & \vdots \\ x_{NP,1} & x_{NP,2} & x_{NP,D} \end{bmatrix} \tag{1}$$

3.2. Teaching Phase

In this phase, the best individual in the population is selected as the "teacher" and aims to move the population mean toward their own position. This process directly mirrors the real-world role of a teacher, who strives to raise the average knowledge level of a class toward their own expertise.

For instance, the optimal solution (X_{best}) is identified and assigned as the teacher. The mean value of each variable (e.g., the average score achieved by different students in a specific subject) is then calculated across all subjects and problem variables.

$$M_d = [m_1, m_2, \dots\dots, m_D] \tag{2}$$

The difference between the mean value in a specific subject and the corresponding teacher's results is given as follows:

$$M_{diff} = rand(0,1)[X_{best} - T_F M_d] \tag{3}$$

Where T_F is the teaching factor, rand (0,1) is a random number generated between 0 and 1, and the value of T_F is chosen randomly as either 1 or 2, calculated using the following formula:

$$T_F = round\ [1 + rand(0,1)] \tag{4}$$

The current population is updated using the following equation:

$$X_{new} = X + M_{diff} \tag{5}$$

The updated value X_{new} is accepted if it yields a better objective function value $f(X_{new}) < f(X)$; otherwise, the previous value X is retained.

3.3. Learner Phase

In this phase, the population members (who are considered classmates) enhance their knowledge through mutual interaction. This mirrors the real-world learning process that occurs among peers and classmates. A learner (student) is selected randomly and strives to improve their knowledge with the assistance of other students. The learning process in this phase is structured as follows:

Random selection of two decision variables (solutions), X_i and X_j, such that $i \neq j$.

$$X_{new} = X_i + rand(0,1)\left(X_i - X_j\right), \text{ if } f(X_i) < f(X_j) \tag{6}$$

Otherwise:

$$X_{new} = X_i + rand(0,1)\left(X_j - X_i\right) \tag{7}$$

If X_{new} performs better, it is accepted.

One of the most prominent features of this algorithm is its parameter less nature. Since it requires the minimum number of parameters, it offers a distinct advantage in optimization problems.

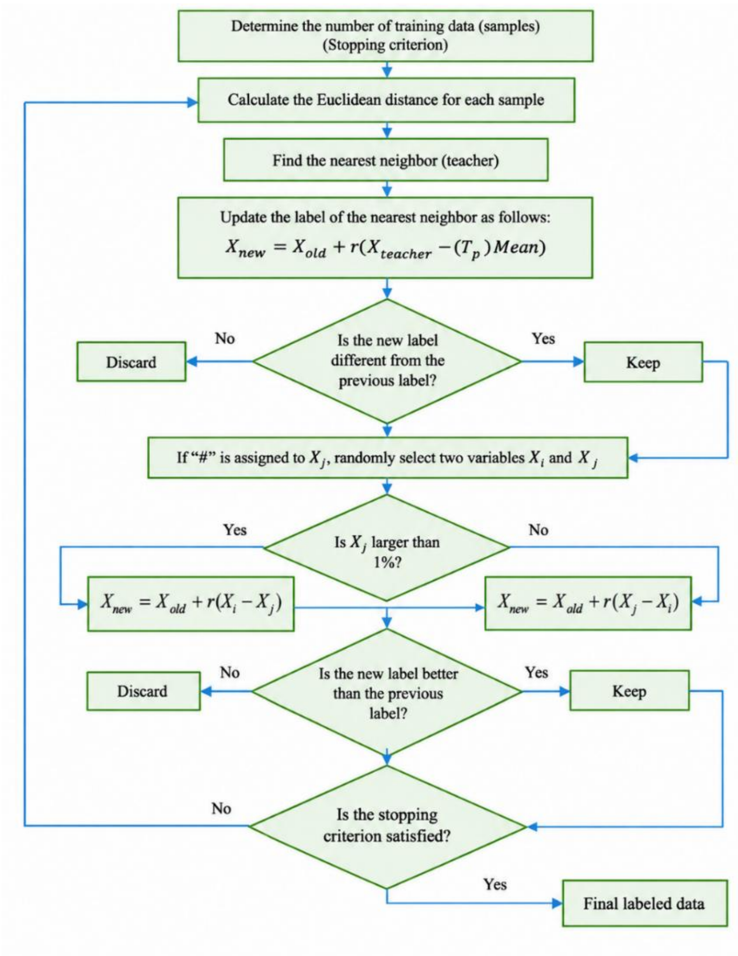

Fig. 1. Flowchart of the TLBO algorithm

3.4. Rotor Flux Orientation in Induction Motors

Field orientation is established based on the rotor flux vector. The magnitude of the rotor flux is obtained using a flux observer; however, the rotor field frequency is neither calculated nor estimated, as it depends directly on the load torque value. The mathematical model of the induction motor is expressed as follows [1, 5, 14, 15]:

$$\theta_e = \int \omega_e = \int (\omega_r + \omega_{sl}) = \theta_r + \theta_{sl} \tag{8}$$

The rotor circuit equations of the induction motor in the d-q reference frame are given as follows:

$$\frac{d\psi_{dr}}{dt} + \frac{R_r}{L_r}\psi_{dr} - \frac{L_m}{L_r}R_r.i_{ds} - \omega_{sl}.\psi_{qr} = 0 \tag{9}$$

$$\frac{d\psi_{qr}}{dt} + \frac{R_r}{L_r}\psi_{qr} - \frac{L_m}{L_r}R_r.i_{qs} - \omega_{sl}\psi_{dr} = 0 \tag{10}$$

For decoupled control, the flux component of the stator current (i_{ds}) must be aligned with the d-axis, and the torque component of the stator current (i_{qs}) must be aligned with the q-axis, which leads to $\omega_{dr} = \omega_q, \omega_{qr} = 0$. Consequently:

$$\frac{L_r}{R_r}.\frac{d\psi_r}{dt} + \psi_r = L_m.i_{ds} \tag{11}$$

The slip frequency is calculated as follows:

$$\omega_{sl} = \frac{L_m.R_r}{\psi_r L_r} i_{qs} \tag{12}$$

If the above angular slip frequency is utilized for field orientation, this decoupling can be achieved. By substituting the control of rotor flux $\frac{d\omega_r}{dt} = 0$ and ω_r into Equation (4), the rotor flux is regulated as follows:

$$\psi_r = L_m.i_{ds} \tag{13}$$

The developed electromagnetic torque in the motor is expressed as follows:

$$T_e = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r}(i_{qs}.\psi_{dr}) \tag{14}$$

However, $\omega_{dr} = L_m.i_{ds}$. Instead:

Here, i_{qs} represents the torque-producing component of the stator current, and i_{ds} represents the flux-producing component of the stator current. Furthermore, the flux linkage remains unaffected by changes in i_{qs}, demonstrating complete dynamic decoupling.

4. DESIGN OF TLBO-BASED FUZZY LOGIC CONTROLLER

The control framework proposed for the application of the TLBO-based fuzzy logic system as an intelligent unit designed for the precise tuning of conventional PI controllers is illustrated in Figure 2. The TLBO-based fuzzy PI controller consists of two levels: a conventional PI controller and a fuzzy system unit whose membership functions are optimized via the TLBO algorithm. As shown in Figure 2, the intelligent fuzzy system unit utilizes the speed error signal and its time derivative as fuzzy input variables to adaptively tune the PI control parameters. To implement fuzzy logic for tuning the PI controller, a set of fuzzy rules (comprising 18 rules) is employed to map the input variables (e and Δe) to the output variables (Kp, proportional gain, and Ki, integral gain).

The implemented fuzzy rules are presented in Table 1. The membership functions for the input and output variables are categorized as Negative Large (NL), Negative Medium (NM), Negative Small (NS), Positive Small (PS), Positive Medium (PM), and Positive Large (PL). These rules are structured using triangular membership functions, which are the most widely used. The antecedents of each rule are formulated using the AND operator (interpreted as minimum). Additionally, the Mamdani fuzzy inference system is utilized in this architecture.

Table 1. Fuzzy Rule Base

ΔF / ΔP_L	NL	NM	NS	PS	PM	PL
S	NL	NM	NS	PS	PS	**PM**
M	NL	NL	NM	PS	PM	**PM**
L	**NL**	**NL**	**NL**	**PM**	**PM**	**PM**

Although the fuzzy PI controller demonstrates superior performance compared to conventional methods, its effectiveness depends heavily on the proper choice of membership functions. Without accurate prior knowledge of the system dynamics, selecting optimal membership functions is challenging, preventing the fuzzy PI controller from achieving peak performance across a wide range of operating conditions. To address this limitation, a complementary algorithm is employed to perform online tuning of the membership functions.

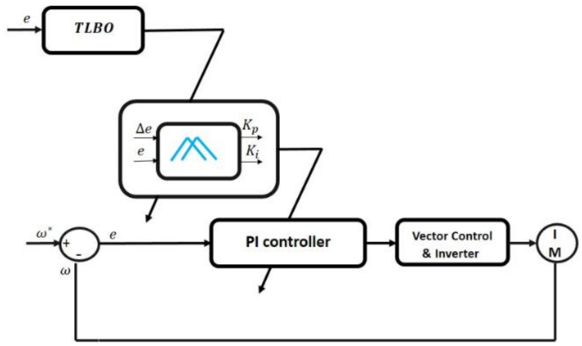

Fig. 2. Structure of the TLBO-Based Fuzzy Logic Controller

Here, e (error) denotes the tracking error between the desired reference input and the actual system output.

5. SIMULATION RESULTS AND DISCUSSION

Indirect vector control of a three-phase induction motor drive system was simulated using Matlab/Simulink. To evaluate the effectiveness and validity of the proposed method for tuning the speed controller parameters, the simulation results of the indirect vector-controlled induction motor using conventionally tuned parameters were compared against those obtained using the TLBO-based fuzzy logic tuning technique. The induction motor parameters utilized in the simulation are presented in Table 3.

Table 2. Induction Motor Parameters

HP	10	Rotor Resistance, Rr(ohm)	0.451
Supply Voltage, Line-to-Line, Vs	460	Rotor Leakage Inductance, Llr (H)	**42e-4**
NO .of Poles , P	4	Mutual Inductance, Lm (H)	**149e-3**
Frequency, F	60	Inertia (Kg.m2)	**0.05**
Stator Resistance, Rs(ohm)	0.684	Friction Factor (NmS)	**81e-4**
Stator Leakage Inductance, Lls (H)	42e-4	RPM	**1760**

Figure 3 illustrates the simulation results comparing the conventional PI controller with the TLBO-tuned fuzzy controller for a reference speed of 120 rad/s under no-load conditions.

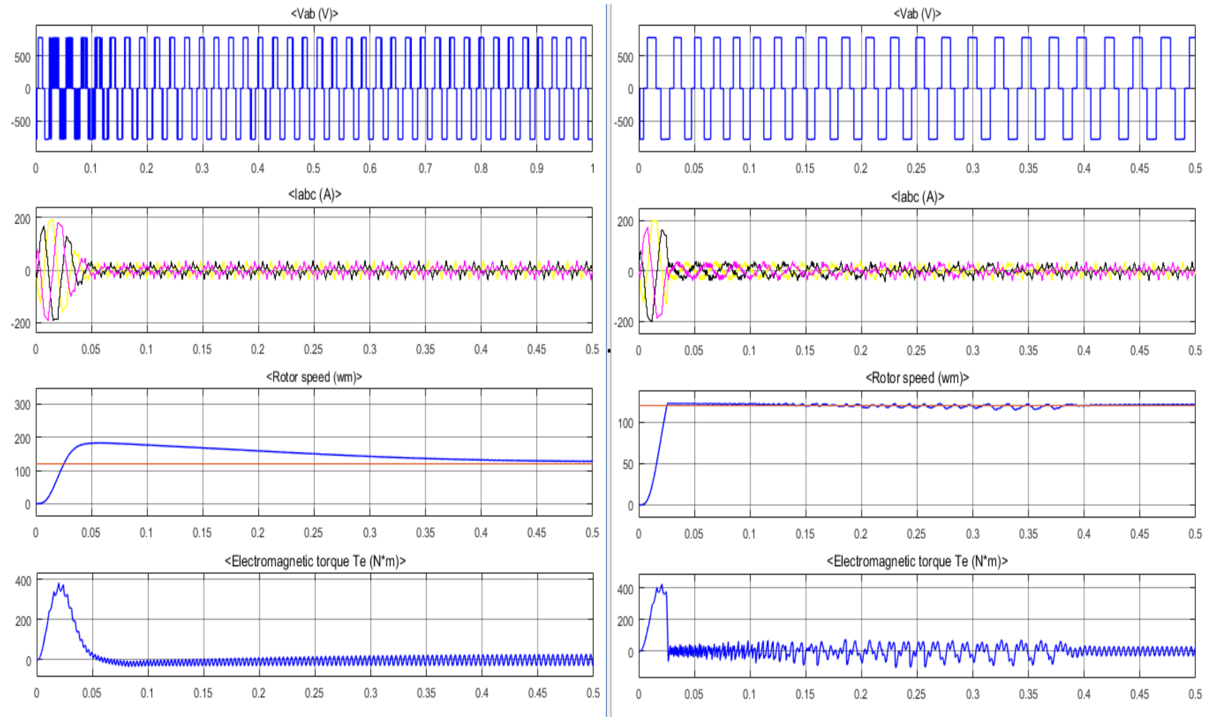

Fig. 3. (a) Response with conventional PI controller; (b) Response with TLBO-tuned fuzzy controller.

Figure 4 illustrates the rotor speed response for both controllers at a reference speed of 120 rad/s. As observed, the dynamic response time is significantly improved with the TLBO-tuned fuzzy controller compared to the conventional PI controller. Considering that the conventional PI controller inherently introduces drawbacks such as high overshoot, speed oscillations, and torque ripples in response to sudden load changes and external disturbances the implementation of this intelligent controller offers substantial performance advantages.

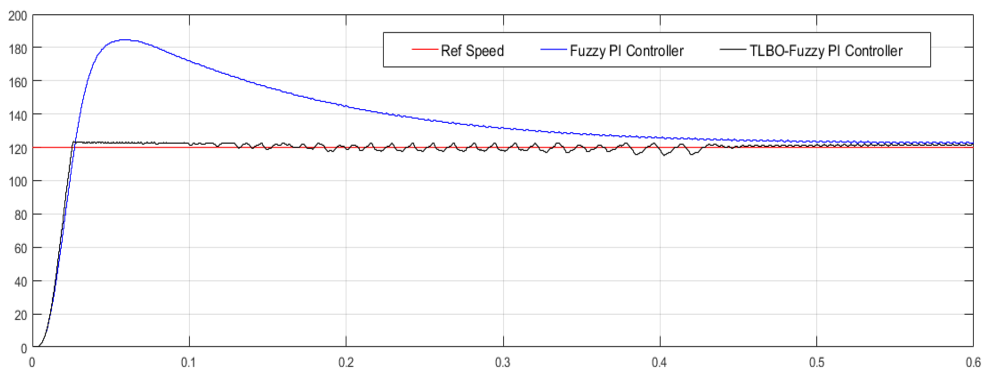

Fig. 4. Motor speed responses for the conventional PI controller and the TLBO-tuned fuzzy controller.

6. CONCLUSION

A primary challenge in utilizing conventional PI controllers lies in determining their optimal gains. Numerous techniques have been reported in the literature for gain selection, with pole placement and the Ziegler–Nichols tuning method being among the most widely applied. In this study, a TLBO-based fuzzy tuning technique was proposed to identify the optimal gains for the PI controller. This work addresses the rapidly growing industrial application of asynchronous motor drives and the ongoing demand for advanced control strategies. Indirect vector control serves as an effective methodology to meet these performance requirements. However, this cost-effective, vector-based control approach relies critically on the precise tuning of the PI controller parameters. The implementation of the proposed TLBO-based fuzzy tuning scheme successfully accomplishes this optimization, yielding enhanced system performance. Simulation results demonstrate that this approach delivers superior speed regulation for induction motor drives.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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