Simulation Analysis and Experimental Evaluation of Improved Field-Oriented Controlled Induction Motors Incorporating Intelligent Controllers

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ABSTRACT This work discusses the simulation and experimental demonstration of a genetic algorithm hybrid fuzzy-fuzzy controller (GA-HFFC) system to achieve speed control of a variable-speed induction motor (IM) drive based on a space vector pulse width modulation (SVPWM) technique by means of an eZd-spF28335 digital signal processing (DSP) experiment board. Two features of field-oriented control (FOC) were used to design the GA-HFFC, namely, the current and frequency. To overcome the limitations of the FOC technique, the principles of the GA-HFFC were introduced through the acceleration-deceleration stages to regulate the speed of the rotor with the help of a fuzzy frequency controller, while a fuzzy stator current amplitude controller was involved during the steady-state stage. The results revealed that the proposed control approach could deliver a practical control solution in the presence of diverse operating conditions.

INDEX TERMS Digital signal processing, genetic algorithm, hybrid fuzzy-fuzzy control, induction motor, reliable auxiliary circuits.

I. INTRODUCTION

In industrial applications, induction motors are well known for their reliability, minimal maintenance and low cost. At present, induction motors have extensive applications ranging from speed motion control systems to high-level control, including punching presses, compressors, elevators, centrifugal pumps and so forth [1], [2]. A high-performance modern electrical drive should exhibit the following features: small steady-state error, robustness to variations in the system parameters, direct and fail-safe control algorithms, a fast transient response, small overshoot, a wide operating range, minimal maintenance, and low-cost applications [3]. Several reports have been published on indirect and direct field-oriented controllers (IFOCs and DFOCs, respectively). For example, Herber *et al.* [4] introduced a fuzzy logic design

The associate editor coordinating the review of this manuscript and approving it for publication was Zijian Zhang.

approach that could meet the speed tracking requirements even when detuning occurs. In the effort to achieve a robust field-oriented control against load disturbance, [5] proposed a robust control with a neural-network load torque estimator and identification. In [6], Shi et al proposed a novel hybrid fuzzy-PI for IFOC based on FOC features. Other alternative techniques for high-performance electrical drives are the direct torque control (DTC) as mentioned in [7], and the sensor-less speed control as discussed in [8]. The DTC and sensor-less speed controllers are much simpler than the FOC due to the absence of coordinate transformation, no requirement for a pulse width modulator and a position encoder. However, the DTC and the sensor-less speed control techniques have the similar challenging issues as the FOC; they need to rely on flux and torque estimator, which make the control strategy difficult.

To change the gains of a PI controller, many research methodologies have been used, such as fuzzy logic

controllers (FLCs), particle swarm optimization (PSO), and genetic algorithms [9]–[11]. The benefit schedule, also known as artificial intelligence, is utilized to provide a better solution under certain operating situations [12]–[16].

Modern high-performance electrical drives are characterized by small steady-state errors, resilience to system parameter fluctuations, direct and fail-safe control algorithms, quick transient response, small overshoots, wide operating ranges, low maintenance, and low-cost applications [17]. Due to their low cost and durable design, induction motors are the backbone of the industry. However, induction motor control is complicated by the existence of severe nonlinearity [18]. Expert systems (ESs), fuzzy logic (FL), artificial neural networks (ANNs), and genetic algorithms (GAs) are examples of existing artificial intelligence (AI) algorithms. Artificial neural networks (ANNs) are one of the most extensively used AI approaches for controlling the speed of induction motors, although such controllers take a long time to train [19]. In their paper, Lftisi and Rahman [20] proposed fuzzy logic controllers (FLCs) and finite element controller maps (FECMs) as artificial intelligence alternatives; however, these methods require some tweaking. An example of a method known as hybrid fuzzy controller consisted of PI-type Fuzzy controller and conventional PI controller for improving the controllers' performances can be found in [21]–[23]. In other cases, for example [24], [25], hybrid fuzzy-PID controller method has been used in which the proposed method was simulated for 3-Phase induction motor system. In their paper, [26] reported an implementation of the adaptive fuzzy control and conventional PI controller on a PV grid connected inverters. In addition, several successful work on neural networks and fuzzy logic have been reported in [27]–[29]. Another example of an artificial intelligence alternative is the report of designing of a fuzzy sliding mode controller by genetic algorithms for induction machine speed control, [30].

Global optimization strategies have attracted the interest of various researchers in the field of controller parameter optimization. Genetic algorithms (GAs) have been used to regulate the speed of induction motors [31]–[37] and have been successful in obtaining optimal or near-optimal solutions for optimization problems [38]. In a control engineering application, a GA's typical goal is to identify the optimal values for a given set of free parameters that describe either a process model or a control law [39]. GAs have been effectively implemented in the industrial electronics areas of parameter and system identification, control robotics, and classifier systems. Because the population is valuable for preserving diversity, GAs are more robust and resilient than other local search algorithms [40]. GAs are also less expensive and easier to implement than other methods and seek only a single goal to evaluate; hence, GAs have been successful in obtaining the best solutions to optimization problems. Genetic algorithms may be used to optimize hybrid fuzzy controllers in either simulation or hardware experiments. Genetic algorithms may be used to optimize hybrid fuzzy controllers in either through

simulation or hardware experiments. In [9], the authors did an optimal fuzzy gain scheduling of PI controller to the speed control of induction motor. The parameters of PI controller are scheduled by FLC where firstly the parameters of the FLC are optimized by genetic algorithm. The performance result is reported to be better as compared to FLC when optimized by human operator. In a related paper, [41] reported an optimization design of fuzzy controller parameters based on GA. The GA techniques are recognized as being useful in solving fuzzy-related optimization problems. For example, there are quite a number of research carried out that utilize GA to optimize fuzzy controller in applications such as in deep-sea mining, wellhead back pressure, urban traffic flow, energy flow management, solar photovoltaic, shape optimization and earth pressure balance have been reported in [42]–[48]. Examples of the work to find solution for DC and AC motor drives FLC system optimized using genetic algorithm have been reported in [49]–[52].

When compared to FLCs optimized by a human operator, the GA-optimized performance is superior. In contrast, an artificial bee colony algorithm was proposed in [53], [54] to address the long convergence time in the speed control of DC and AC drives. As another alternative, the ant colony optimization (ACO) algorithm, which is used to regulate the speed of a switching reluctance motor, was described for the first time in [55]; however, the primary disadvantage of this method is that it requires a sophisticated theoretical analysis. One research project [56] evaluated the firefly algorithm (FFA), which was employed to control the speed of a DC series motor powered by a solar system. Swarming tactics in fish schooling have also been used for the speed management of a DC permanent magnet motor and an induction motor in particle swarm optimization (PSO) [57]–[63]. Nonetheless, because of partial optimism, PSO does not have much precise control over its speed and direction [64]. As a result, the bacterial foraging (BF) scheme, a relatively new evolutionary computational methodology, was proposed in [65]–[69], but this method works on the basis of random search directions, which adds to the time it takes to find the global solution. The imperialist competitive algorithm (ICA) and the bat search algorithm (BSA) were both explored in [70]–[75]. Although the ICA can be used to find the optimal controller settings, it also has the abovementioned drawbacks in optimization approaches.

Although the FOC method has been widely applied to achieve high performance in variable-speed induction motor drives, it also has some disadvantages. The first drawback when applying the FOC method is its sensitivity to variations in parameters. Consequently, errors accumulate during the assessment of definite integrals; for example, in the event of an extended control time, the transient responses are affected and the steady-state performance degrades due to drift in the parameter values and an excessive accumulation of errors. Other drawbacks involve the requirement of continuous control with an initial state and the involvement of complicated calculations [8].

This study investigates the resilience of induction motor control drive systems that use GA-HFFC three-phase squirrel-cage induction motor (SCIM) drives to overcome the shortcomings of vector control. To do so, this investigation evaluates the drive system's performance in terms of speed tracking and external load rejection and its performance as a function of variations in the parameters. The motivation for this project stems from the possibility of expanding and scaling up research on AC motor drives using the techniques described in the following sections.

The objective of this research is to demonstrate a practical implementation of the proposed GA-HFFC system to control an induction motor (IM) based on the space vector pulse width modulation (SVPWM) technique in digital signal processing (DSP). To fulfill this objective, an incremental encoder was joined to the motor shaft, and Hall effect current sensors were used to identify the direct currents to the motor with the designed auxiliary circuits. The main purpose was to apply a powerful control action to the load disturbance and employ abrupt fluctuations in the reference speed and to compare the results with those of an HFFC, a hybrid fuzzy-PI controller (HFPIC) and an IFOC [2]. The dynamic responses of the speed and reference phase 'a' stator current were investigated with several reference speeds and load disturbances. The results of this study substantiate some of the predominant behaviors in most of the scenarios. This paper introduces a new method in light of the aforementioned disadvantages of the vector control method. The GA-HFFC system is shown to overcome those disadvantages and is effectively applied and compared with classic controllers. The results of simulations and experiments verify the proposed method when compared to the traditional methods.

The remainder of this research paper outlines the simulation and experimental demonstration of the proposed GA-HFFC system and is organized as follows: In Section II, the mathematical model of the IM hybrid fuzzy-fuzzy controller is defined, including a fuzzy frequency controller and a fuzzy current amplitude controller. Section III describes the implementation of a GA optimization method for hybrid fuzzy-fuzzy rules. The hardware setup is described in Section IV. Sections V, VI and VII describe and discuss the simulation and comparative study based on different speeds, experimental results and performance indices for simulation studies, respectively. Finally, a comparison between the simulation and real-time implementation results is described in Section VIII.

II. HYBRID FUZZY-FUZZY CONTROL OF AN IM

The relationship between the input and output in an IM can be written as

$$\omega_m = IM\,(i_s, \omega, T_l) \tag{1}$$

In this research study, two features of FOC are considered. First, FOC is not able to directly control the frequency because the supply frequency varies throughout the acceleration-deceleration period; however, the slip frequency

remains the same. Second, the magnitude of the supply current remains stable when a torque command is present [5]. Table 1 explains this relationship implemented in the HFFC. The first feature can be confirmed by the relationship of (2) among the supply frequency ω, the slip frequency ω_{sl} and the rotor angular speed ω_m:

$$\omega = \left(\omega_{sl} + \frac{P}{2}\omega_m\right) \tag{2}$$

where the slip frequency is

$$\omega_{sl} = \left(\frac{3r_r T^*}{P\lambda_{dr}^{e*2}}\right) \tag{3}$$

From (3), it can be observed that if T^* is kept constant throughout an acceleration stage, then ω_{sl} is also constant, and as ω_m fluctuates throughout the acceleration-deceleration stage, ω also differs. Thus, (2) satisfies the first feature. On the other hand, the second feature can be confirmed from (4), as given below:

$$\mid i_s \mid = \left(\frac{2}{3}\sqrt{i_{ds}^2 + i_{qs}^2}\right) \tag{4}$$

where

$$i_{ds} = \left(\frac{\lambda_{dr}^{e*}}{L_M}\right) = constant \tag{5}$$

and

$$i_{qs} = \left(\frac{3L_r T^*}{PL_M \lambda_{dr}^{e*}}\right) \tag{6}$$

The second feature is satisfied by the fact that (4) remains constant if the torque command T^* is kept constant.

A. FUZZY FREQUENCY CONTROLLER

A fuzzy frequency controller is described in this section with the help of the frequency aspect of the field orientation principle. During the acceleration-deceleration stages, the torque command shows a high value; however, a small value is depicted in the steady-state stage. The rotor speed and reference speed represent these values. The normal range of speed for an IM is from -1350 rpm to 1350 rpm, for which the range of the speed error is from -2700 rpm to 2700 rpm. The proposed fuzzy frequency controller solves this issue when the supply frequency rises too fast and the torque produces oscillations and is designed using the FOC equations.

TABLE 1. HFFC relationship.

	Supply frequency	Current amplitude	Rotor speed	Control objective
Acceleration	Change	Constant	Change	Speed change
Steady-state	Constant	Change	Constant	Reduce oscillation

The relationships given below show the steady-state slip frequency:

$$\omega_{sl} = \begin{cases} \left(\dfrac{3r_r}{P\lambda_{dr}^{e*2}}\right) T_{acceleration}, & \text{when, } \Delta\omega_m \neq 0 \\ \left(\dfrac{3r_r}{P\lambda_{dr}^{e*2}}\right)\left(\dfrac{T_{rated}}{\omega_{mrated}}\right)\omega_m^*, & \text{when, } \Delta\omega_m = 0 \end{cases} \quad (7)$$

where $\Delta\omega_m = \omega_m^* - \omega_m$ and the relationship among the slip frequency, rotor speed and reference rotor speed can be written as $\omega_{sl} = f(\omega_m^*, \Delta\omega_m)$. This relationship demonstrates that $\Delta\omega_m$ and ω_m^* can be employed as the inputs of the fuzzy frequency controller. The nine sets that are formed by classifying the fuzzy sets are "Z:zero", "PB:positive big", "NB:negative big", "PS:positive small", "NS:negative small", "PBB:positive big big", "PM:positive medium", "NM:negative medium" and "NBB:negative big big". In this study, the centroid method is implemented to execute the defuzzification operation. The membership functions of the input and output for the fuzzy frequency controller are presented in Fig. 1 (a), (b) and (c). Furthermore, the control rule matrix is depicted in Table 2. Using (7), the samples of the slip frequency of the two stages can be calculated, and the results are given in Table 3. On the other hand, the IM parameters are given in Table 4.

TABLE 2. Rule matrix for the fuzzy amplitude/slip controller.

Speed Error	Reference speed						
	NB	NM	NS	Z	PS	PM	PB
NB	NBB	NBB	NBB	NBB	NBB	NBB	NBB
Z	NB	NM	NS	Z	PS	PM	PB
PB	PBB	PBB	PBB	PBB	PBB	PBB	PBB

TABLE 3. Speed, current amplitude, slip frequency and fuzzy linguistic values.

Stage	ω_m^*	A	ω_{sl}	$f_A, f_{\omega_{sl}}$
Deceleration	–	−1.566	−61.997	NBB
Steady − state	−1350	−0.7735	−43.557	NB
–	−900	−0.5533	−29.038	NM
–	−450	−0.3618	−14.519	NS
–	0	0	0	Z
–	450	0.3618	14.519	PS
–	900	0.5533	29.038	PM
–	1350	0.7735	43.557	PB
Acceleration	–	1.566	61.997	PBB

B. FUZZY CURRENT AMPLITUDE CONTROLLER

The stator current magnitude was regulated during the acceleration-deceleration stages, as the system was driven by the maximum permissible values of the inverter. Nevertheless, the speed of a rotor is controlled by regulating the magnitude of the stator current during the final steady-state period, although the supply frequency is kept constant. The values of the current amplitude are represented as follows:

$$|i_s| = \begin{cases} 1.5, & |i_s| \geq 1.5A \quad \text{when, } \Delta\omega_m \neq 0 \\ |i_s|, & |i_s| < 1.5A \quad \text{when, } \Delta\omega_m = 0 \end{cases} \quad (8)$$
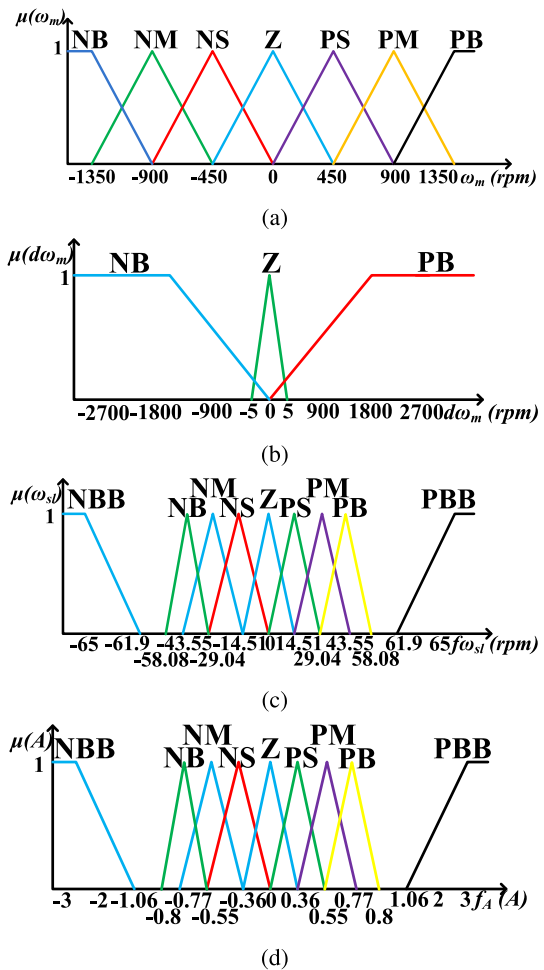

FIGURE 1. Membership functions of the (a) reference speed, (b) speed error, (c) slip frequency, and (d) current amplitude.

$$|i_s| = \begin{cases} \left(\dfrac{2}{3}\sqrt{\left(\dfrac{\lambda_{dr}^{e*}}{L_M}\right)^2 + \left(\left(\dfrac{3L_r T^*}{PL_M\lambda_{dr}^{e*}}\right)T_{acceleration}\right)^2}\right) \\ \left(\dfrac{2}{3}\sqrt{\left(\dfrac{\lambda_{dr}^{e*}}{L_M}\right)^2 + \left(\left(\dfrac{3L_r T^*}{PL_M\lambda_{dr}^{e*}}\right)\left(\dfrac{T_{rated}}{\omega_{mrated}}\right)\omega_m^*\right)^2}\right) \end{cases} \quad (9)$$

where $\Delta\omega_m = \omega_m^* - \omega_m$ and the current amplitude can be written as $i_s = f(\omega_m^*, \Delta\omega_m)$, which shows that $\Delta\omega_m$ and ω_m^* can be used as the inputs to the fuzzy current amplitude controller. For the HFFC, the samples of the current amplitude can be calculated from (9), and the results are shown in Table 3. For the "175 w" Lab-Volt IM, "$T_{acceleration} = 1.3\ Nm$", "$\lambda_{dr}^{e*} = 0.9\ wb$", "$T_{rated} = 1.23796\ Nm$", "$\omega_{mrated} = 1350\ rpm$", and "$\mu = 0.000917\ Nm/rpm$". The membership functions of the input and output are illustrated in Fig. 1 (a), (b) and (d) by applying rules similar to those given in Table 2. Fig. 2 displays the structure of the proposed GA-HFFC.
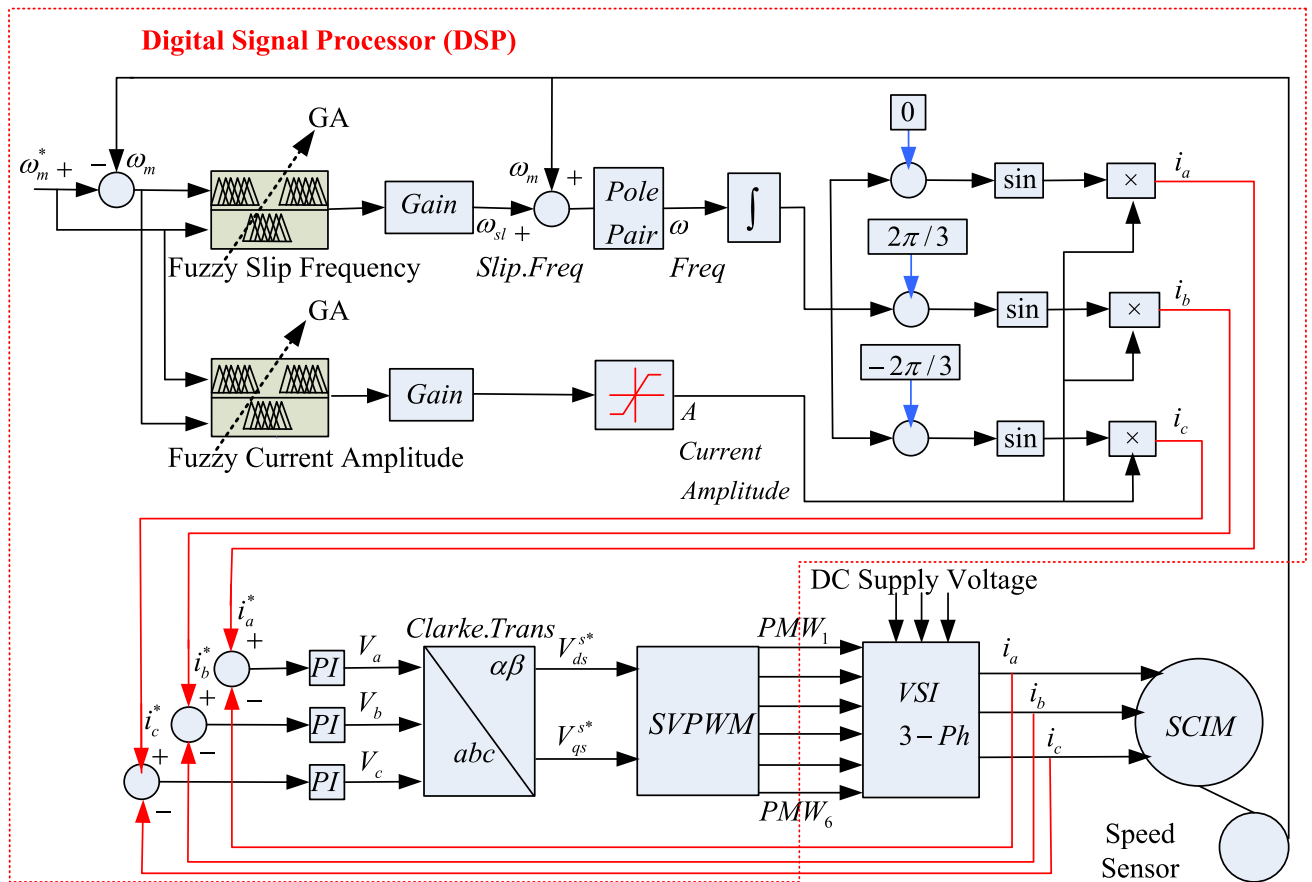
FIGURE 2. Structure of the proposed GA-HFFC.

TABLE 4. Characteristics of the Lab-Volt IM model $8221 - 0X$.

Name	Symbol	Value
Resistance of stator	r_s	$45\ \Omega/ph$
Resistance of rotor	r_r	$38\ \Omega/ph$
Self-inductance of stator	L_s	$2.34912\ H/ph$
Self-inductance of rotor	L_r	$2.34912\ H/ph$
Magnetizing inductance	L_M	$2.228\ H/ph$
Rotor inertia	J	$0.001\ kgm^2$
Damping constant	$B or f$	$0.00021\ kgm^2$
Number of pairs of poles	P	2

III. GA OPTIMIZATION OF HYBRID FUZZY-FUZZY RULES

The performance of the proposed hybrid fuzzy-fuzzy controller (HFFC) in a variable-speed induction motor (IM) driving system is discussed in this section. To determine the fuzzy controller's rule base, a basic genetic algorithm (GA) is applied to address the issue of optimizing an objective function, such as the integral of absolute error (IAE) criterion. A simulation reveals that for IM speed control, the HFFC with GA optimization is a superior technique to both an HFFC without GA and a conventional hybrid fuzzy-PI controller (HFPIC).

Many scientists have reported a variety of clever strategies to fine-tune fuzzy systems [76]–[81]. To showcase this point of view, a neural network was coupled with an evolutionary optimization algorithm while advancing the membership rules or functions that change into a pattern while developing a fuzzy logic system. The advantages of the GA strategy include a lower cost: the GA requires only a specified goal for which the survey is being conducted and a straightforward execution technique. Fig. 3 depicts a generic GA configuration for a fuzzy control system that includes an inference engine, a defuzzifier, and a fuzzifier.

The usage of a GA is critical in this study to improve the fuzzy inference system's rules. The essential objective is to monitor the execution of a fuzzy controller based on heuristics and to establish a controller using an optimization technique. As a consequence, the best mix of fuzzy input and output variables should improve the inference rules of a fuzzy controller designed for a specific purpose of fuzzy logic control [82], [83].

GAs are computing techniques that use administrators to understand the heuristic pursuit process within a search space with the expectation that a perfect solution to the optimization problem can be found. The standard integral of absolute error (IAE), which is specified in (10), is the proposed objective function in this optimization problem [84]:

$$IAE = \left(\int_0^T e(t)\, dt \right) \qquad (10)$$
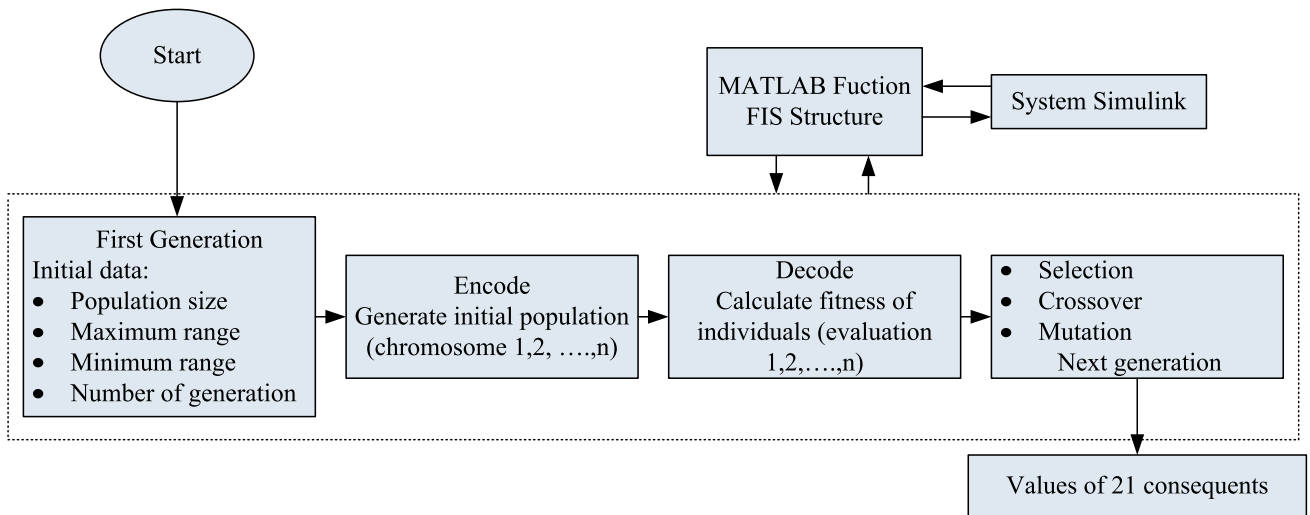
Equation 10 specifies an objective function that is reduced during the optimization process and reflects a reasonable response to set point changes. The objective function was considered in addition to other highly important foci, such as the steady-state error, settling time, overshoot, rot percentage, and time increase [85]. In this investigation, only the rule base was achieved in all circumstances using an optimization technique.

The GA is linked to the end goal of achieving the finest rules encircling a certain fuzzy controller. The antecedents were gathered in a group as part of a MATLAB algorithm that adapted to linguistic input variables [82], [83]. The GA made use of this algorithm when it obtained the contentions, that is, the results of the controller among the appraisals. The assessment was carried out for every single member in the population across all predetermined generations. Similarly, the binary code was actualized to make it effortless to implement. The following are the attributes:

$$[NBB \quad NB \quad NM \quad NS \quad Z \quad PS \quad PM \quad PB \quad PBB] \quad (11)$$

The yield language variables were then coded in the following order:

$$[0001 \quad 0010 \quad 0011 \quad 0100 \quad 0101 \quad 0110 \quad 0111 \quad 1000 \quad 1001] \quad (12)$$

Table 2 shows a possible chromosome, which might be systematized as follows:

$$[0001 \quad 0010 \quad 1001 \quad 0001 \quad 0100 \quad 1001 \quad 0001 \quad 0101 \quad 1001$$
$$\cdots \quad 1000 \quad 1001] \quad (13)$$

The hereditary technique was initiated with each individual having the 21 outcomes of a fuzzy controller with the establishment of an arbitrarily generated population of individuals. Because 21 consequences may be employed inside the MATLAB function to construct the rules, it is critical to systematically generate the population as a binary chain. This procedure was applied to generate numbers ranging from 1 to 9:

$$[NBB = 1, \quad NB = 2, \quad NM = 3, \quad NS = 4, \quad Z = 5,$$
$$PS = 6, \quad PM = 7, \quad PB = 8, \quad PBB = 9] \quad (14)$$

These complete values were then used to identify the antecedents' linguistic principles, as shown below:

$$[NB = 1, \quad NM = 2, \quad NS = 3, \quad Z = 4, \quad PS = 5,$$
$$PM = 6, \quad PB = 7] \quad (15)$$

For the purpose of framing the rule base of a fuzzy controller, it is important to perceive the estimations of the precedents, the fuzzy operators present within the rule base weights, and the fuzzy rules; in this case, antecedents 1 and 2 and the other qualities placed inside a matrix in the MATLAB function can be viewed in the matrix, as shown below [82], [83]:

$$\begin{bmatrix} Ant_1 Ant_2 Con_1 R_w R_c & \cdots & Ant_7 Ant_7 Con_7 R_w R_c \\ \vdots & \ddots & \vdots \\ Ant_1 Ant_3 Con_3 R_w R_c & \cdots & Ant_{21} Ant_{21} Con_{21} R_w R_c \end{bmatrix} \quad (16)$$

where Ant_n denotes antecedent n, Con_n denotes the subsequent n, R_w denotes a rule weight, and R_c denotes a rule connection. Finally, a similar MATLAB function was used to store the ranges of the input and output variables and the information from the membership function. This function's output is known as the MATLAB fuzzy inference system (FIS), which was identified with the help of a structure that combines the framework's fuzzy inference data and was used as a fuzzy controller in the SIMULINK library's feedback plan. A flowchart of the proposed technique is depicted in Fig. 4.

The following values for the GA parameters were kept:
IAE is a performance indicator.
Crossover probability: 0.8
30 people were in the initial population.
Probability of mutation: 0.09
30 generations is the maximum number of generations that may be created.

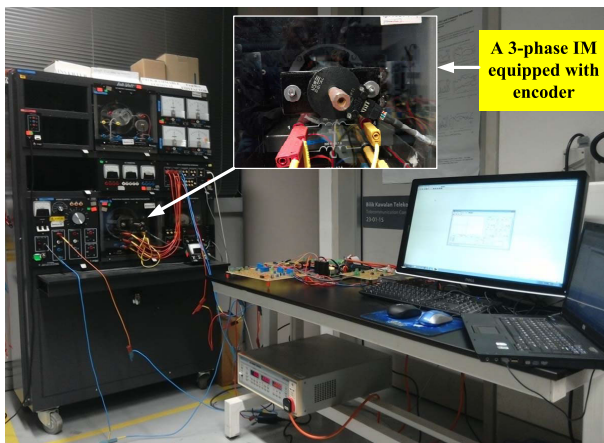**FIGURE 4.** Flowchart of the proposed approach.
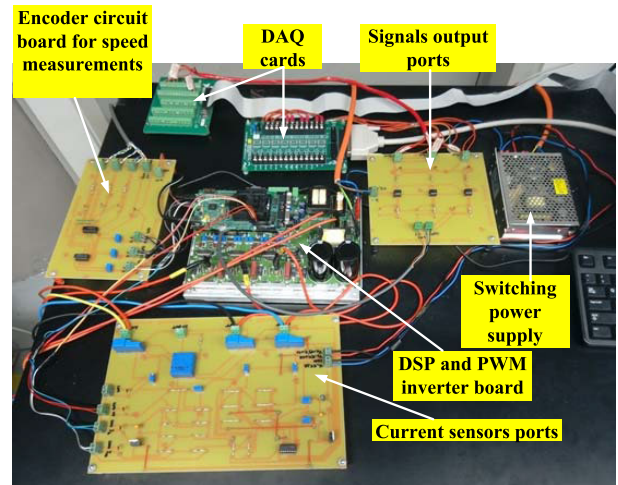

FIGURE 5. Complete experimental system.

FIGURE 6. Close-up view of the circuit connection.

The execution file from the feedback method was examined and provided back to the genetic algorithm to establish consistency in the hereditary method.

Finally, the rule base was established as follows:

$$\begin{bmatrix} 1 & 2 & 2 & 2 & 1 & 1 & 3 \\ 1 & 2 & 2 & 4 & 8 & 8 & 8 \\ 9 & 9 & 7 & 9 & 7 & 9 & 8 \end{bmatrix} \quad (17)$$

IV. HARDWARE SETUP

Figs. 5 and 6 present the experimental setup of the drive system and a detailed view of the circuit connection. Firstly, the GAs is evaluated offline to improve the fuzzy inference system's rules based on the objective function defined for the speed control, and secondly, to use the improved rules and parameters during the experiments for evaluation of the performances. The control system and drive board comprise a DMC1500 digital motor control (delivered by Spectrum Digital, Inc.), an interface for the encoder input

board, an eZdspF28335 development board (delivered by Spectrum Digital, Inc.), a signal output board, and auxiliary circuits (including a board of Hall effect current sensors) (Fig. 7 (a,b,c)). Moreover, a switching power supply for the auxiliary circuits (HF55W-Q-C), a data acquisition (DAQ) card with supported software and a data acquisition PC were used. The host PC supported the debugging process of the program and was connected to the DSP board via a USB connection. Code Composer Studio (CCS) version 4.5 was implemented to translate the controllers in C/C++ or assembly language code for the DSP controller. With the help of the SVPWM technique for the six power switching devices in the inverter, the DSP controller generated six PWM signals. Three input currents of the induction motor, namely, i_a, i_b, and i_c, were measured using a current sensor (LEM, HY10-P). An E3-500-500-IE-H-T-B encoder (delivered by US Digital, Inc.) was used to monitor the rotor speed. Subsequently, the
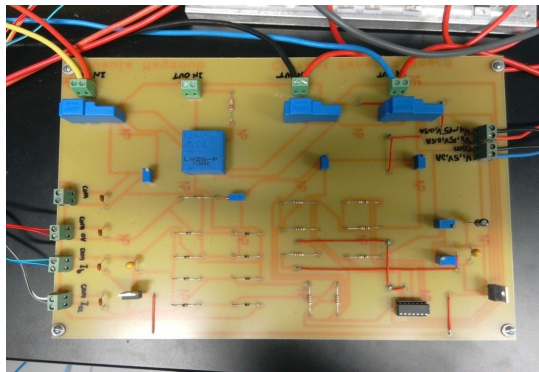
(a)
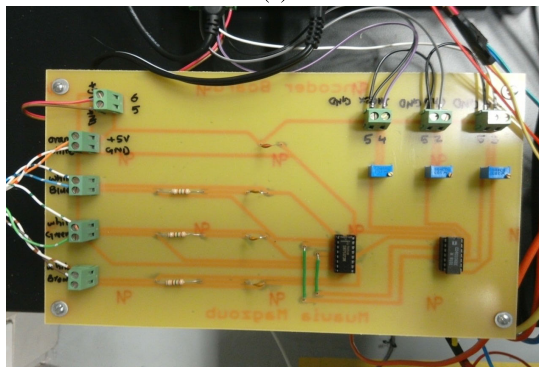
(b)
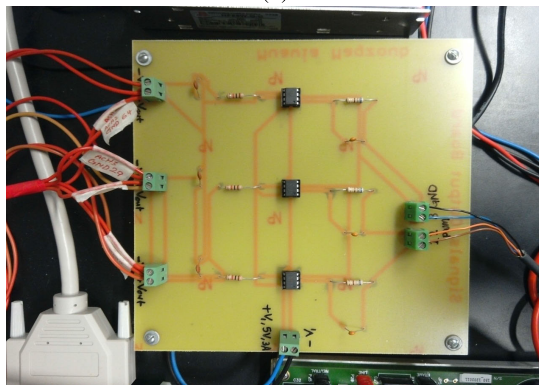
(c)

FIGURE 7. Auxiliary circuits (from left to right): (a) current sensor, (b) encoder interface and (c) output signals.

data were directed to the DSP board via analog-to-digital converters. For the purpose of this experiment, a 3-phase IM (240/415 V, 50 Hz, 175 W, and 1350 rpm, delivered by Lab-Volt, Inc.) was used as the IM. The reference stator phase 'a' current was limited to 1.5 A. The encoder type was an incremental optical encoder with 500 pulses per revolution. The load was provided using a dynamometer (delivered by Lab-Volt, Inc.). The maximum voltage that could be achieved by the DMC1500 was 380 V, so the DC voltage was restricted to that limit. It is important to note that the use of a higher DC voltage results in a higher rate of change in the torque. The voltage source inverter switching frequency was kept constant at $f_s = 20$ kHz.

V. SIMULATION AND COMPARATIVE STUDY BASED ON DIFFERENT SPEEDS

The fuzzy frequency controller and fuzzy current amplitude controller were combined to form an HFFC. This controller provides a supply frequency similar to that of a field-oriented controller and is robust to noise and load disturbances, which are the advantages of this controller. A model of the HFFC for an induction motor was produced by using MATLAB/SIMULINK software.

The HFFC was produced by combining the fuzzy frequency controller and the fuzzy current amplitude controller. Throughout the final steady-state stage, the fuzzy frequency controller outputs the frequency related to the speed command. During the acceleration-deceleration stages, the fuzzy current amplitude controller outputs the maximum permitted current. The model of the HFFC for the induction motor was built using MATLAB/SIMULINK, as presented in Fig. 8.

To study the performance of the induction motor drive with the proposed GA-HFFC, the HFFC model is connected to the 3-phase induction motor model and a 3/2 transformation block with the SVPWM technique. Then, both models are connected to simulate the GA-HFFC, as shown in Fig. 8.

A specific test case was investigated to examine the response from standstill to the rated step speed command, followed by the application of the rated torque and subsequent step reduction of the reference speed to approximately half the rated speed. All the speed controllers were initially tuned to yield essentially an identical speed response to the application of the rated step speed command (900 rpm) under no load conditions. It is believed that such an approach allows a fair comparison to be made. The first part of the comparison was to run the motor from standstill to its rated speed (900 rpm) and then to 500 rpm, an approximately 50% reduction from the rated speed. The transient behavior of the system was compared in terms of the overshoot, rise time in terms of the speed tracking performance, and load torque. Then, at the rated speed, the robustness of the drive was tested by employing external load disturbances at a half-rated load of 1 Nm and a rated load of 2 Nm. The load was applied by adding a constant step command to the input load of the motor model. The behaviors of the IFOC, HFFC, HFPIC, and GA-HFFC were compared in terms of the settling time and undershoot of the speed. The behaviors with load disturbances are shown in Fig 9.

Regarding the simulation results, Fig. 9 shows the resulting speed responses of the IFOC, HFFC, HFPIC, and GA-HFFC under no load conditions. The speed responses of the GA-HFFC and HFFC yield approximately equal rise times. From this figure, good tracking responses were obtained for all four controllers under both transient and steady-state conditions.

The second series of tests was performed by reducing the reference speed from the rated speed of 900 rpm to approximately one-half of the rated speed (500 rpm). The simulation results shown in Fig. 9 demonstrate that the responses
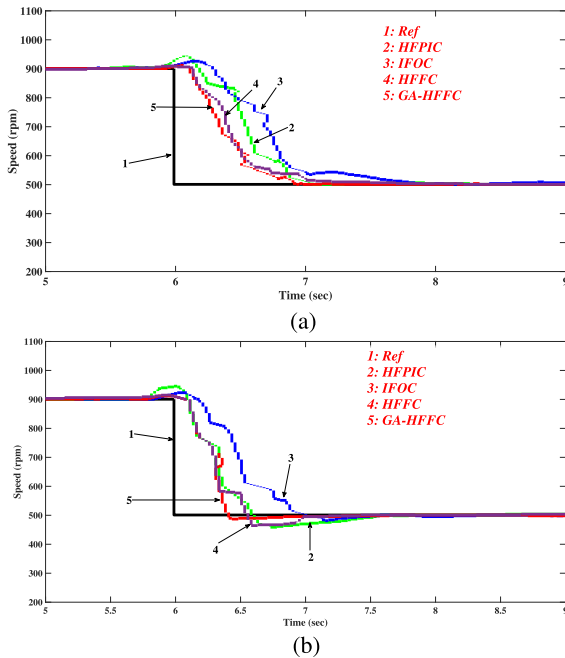
FIGURE 8. Model diagram of the proposed GA-HFFC.

FIGURE 9. Speed responses during the speed reduction from 900 rpm to 500 rpm.

obtained from the controllers were nearly similar in terms of the undershoot and settling time.

VI. EXPERIMENTAL RESULTS

In the first experiment, the motor was run from standstill. A reference speed was implemented, i.e., 500 rpm. The responses at the reference speed with no load and 1 Nm load are depicted in Fig. 10 (a and b), indicating that good tracking performance was achieved for the GA-HFFC, as the rotor speed tracked the reference speed with a smaller overshoot and shorter settling time than the HFFC, HFPIC and IFOC. Under no load conditions (Fig. 10 (a)), the acceleration was enormously fast.

The same experimental procedure was repeated with an induction motor coupled to a dynamometer with a load of 1 Nm. The responses of the four controllers are depicted in Fig. 10 (b). A fast rise time was achieved with the GA-HFFC compared with the other controllers. The IFOC exhibited a small overshoot for the step command, and the controller required an excessively long time to reach the speed command as the speed decreased. Although the GA-HFFC displayed a fast rise time, it demonstrated a sluggish performance to achieve a steady state as the speed was reduced.

(a)

(b)

FIGURE 10. Speed responses in the experiment at 500 rpm for the HFPIC, IFOC, HFFC and GA-HFFC with (a) no load and (b) a load of 1 Nm.

A second experiment was conducted to observe the performance of the controllers after the speed was reduced from the initial 900 rpm to 500 rpm with no load (Fig. 11 (a)). An overshoot occurred when the speed decreased. Nonetheless, compared to the HFFC, HFPIC and IFOC, the GA-HFFC system was able to rapidly catch up with the speed demand.

The same experimental procedure was repeated; however, in this test, the motor was coupled to a dynamometer. The current produced a load of 1 Nm on the motor. This load was applied during the motor at standstill. The experimental results are depicted in Fig. 11 (b). Although the GA-HFFC achieved a shorter settling time than the HFFC, HFPIC and IFOC, it is obvious that the performances of the GA-HFFC,

FIGURE 11. Speed responses in the experiment with a step reduction from 900 rpm to 500 rpm for the HFPIC, IFOC, HFFC and GA-HFFC with (a) no load and (b) a load of 1 Nm.
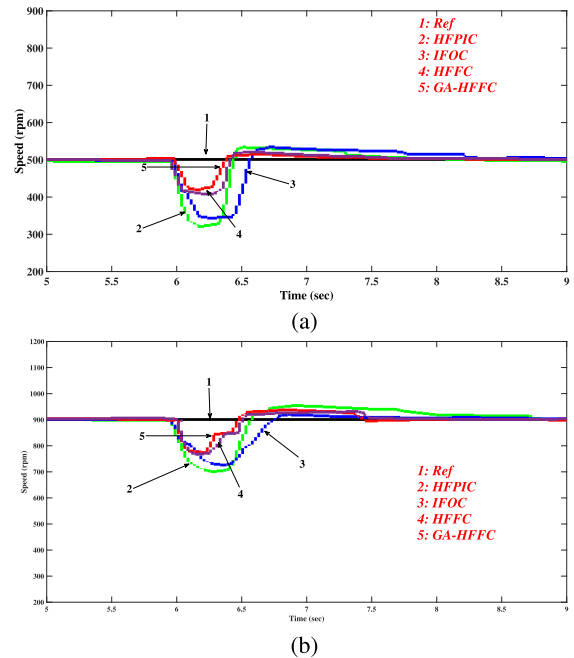

FIGURE 12. Speed responses in the experiment results for the HFPIC, IFOC, HFFC and GA-HFFC when a load of 1 Nm was applied at (a) 500 rpm and (b) 900 rpm.
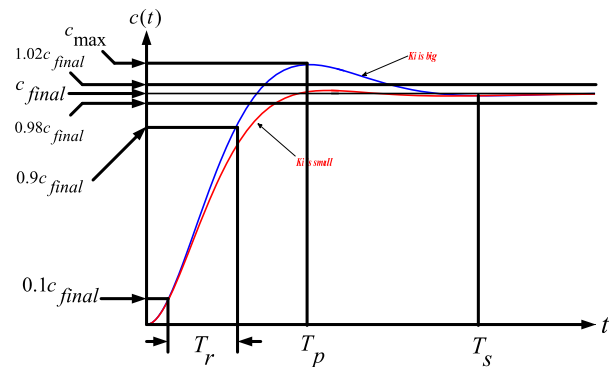
HFFC and HFPIC were influenced by some oscillation of the speed response.

Finally, a third experiment was implemented to examine the load rejection behavior when the load was applied to the motor during steady-state operation and to test the robustness of the controller. During steady-state operation, the performance of the speed responses at 500 rpm and 900 rpm after the application of a 1 Nm load to the motor is presented in Fig. 12 (a and b). A slight oscillation was observed after the application of the load, and with the GA-HFFC, the motor was able to recover the speed rapidly as compared to the HFFC, HFPIC and IFOC.

VII. PERFORMANCE INDICES FOR THE SIMULATION

The performance indices for characterizing the transient response are shown in Fig. 13. The performance indices for the transient response are defined as follows [148]:

a) Rise time, t_r. The time required for the waveform to go from 0.1 of the final value to 0.9 of the final value.

b) Peak time, t_p. The time required to reach the first, or maximum, peak.

c) Percent overshoot, %OS. The amount that the waveform overshoots the steady state or final value at the peak time, expressed as a percentage of the steady-state value.

d) Settling time, t_s. The time required for the transient damped oscillations to reach and become stable within either ±2% or ±5% of the steady-state value [149]. In this work, the settling time was considered to be reached when the response was within ±5% of the steady-state value.

The essential function of a feedback control system is to reduce the error e(t) between any variable and its demanded

FIGURE 13. Performance indices of the transient response.

value to zero as quickly as possible. Therefore, any criterion used to measure the quality of the system response must take into account the variation in the error (e) over the whole range of time. The smaller the value of the integral criterion is, the better the performance of the control loop. The integral error is generally accepted as a good measure of a system's performance. The following are some commonly used criteria based on the integral error for a step set point or disturbance response.

A. INTEGRAL OF ABSOLUTE ERROR (IAE)

The IAE integrates the absolute error over time. It does not add a weight to any error in the system response. Simply integrating the absolute error may be quite conveniently handled computationally. The integral criterion is given in 10 [13].
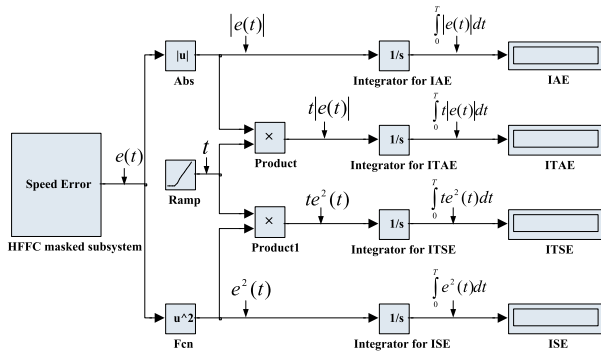
FIGURE 14. SIMULINK model for calculating the performance indices.

B. INTEGRAL OF SQUARED ERROR (ISE)

The ISE integrates the square of the error over time and penalizes large errors more than smaller errors (since the square of a large error is much larger than the square of a small error). The ISE is the simplest performance index and is based on the following integral:

$$ISE = \left(\int_0^T e^2(t)\, dt \right) \qquad (18)$$

C. INTEGRAL OF TIME-MULTIPLIED ABSOLUTE ERROR (ITAE)

The ITAE is an improvement over the IAE. This index reduces the contributions of large initial errors to the value of the integral. The ITAE integrates the absolute error multiplied by time over time.

$$ITAE = \left(\int_0^T t \mid e(t) \mid \, dt \right) \qquad (19)$$

D. INTEGRAL OF TIME-MULTIPLIED SQUARED ERROR (ITSE)

This index has the advantage that large initial errors (e.g., after step inputs) do not greatly contribute to the ITSE value computed as

$$ITSE = \left(\int_0^T te^2(t)\, dt \right) \qquad (20)$$

The MATLAB/SIMULINK model used to calculate the performance indices is shown in Fig. 14. For the simulation in MATLAB/SIMULINK, the speed error is integrated based on equations (10), (11), (12) and (13). With regard to Fig. 9, a comparison of the viability of executing the GA-HFFC, HFFC, IFOC and HFPIC based on these performance indices is illustrated in Table 5.

It is worth noting that the HFFC enhanced with a GA achieved a better rise time under variable-speed control. Similarly, the responses of the HFFC, HFPIC and IFOC exhibited moderately extended rise times under variable-speed control. The response of the GA-HFFC system also did not display an overshoot, demonstrating the improved performance with the GA. The performance indices reflect that the performance of the GA-HFFC was better than that of the HFFC and HFPIC,

TABLE 5. Comparison of the performance indices of the framework.

No.	Performance Index	HFPIC	HFFC	IFOC	GA-HFFC
1	Overshoot (%)	0.000	0.000	0.000	0.000
2	Rise time (s)	0.4363	0.2803	0.3107	0.2648
3	Settling time (s)	0.27	0.25	0.2	0.18
4	Final SS value	120.0989	120.08483	120.0681	120.08391
5	IAE	289.3	194	193.23	186
6	ISE	3.409e+004	2.311e+004	2.23e+004	2.287e+004
7	ITAE	2544	1656	1657	1625
8	ITSE	2.691e+005	1.765e+005	1.81e+005	1.799e+005

as the GA-HFFC system demonstrated the smallest indices with an IAE of 186, ISE of 2.287E4, ITAE of 1625 and ITSE of 1.779E5. The HFPIC, a variable-speed controller, exhibited an IAE of 289.3, ISE of 3.409E4, ITAE of 2544 and ITSE of 2.691E5.

The important discoveries of this study are as follows:

- The performance of an HFFC can be enhanced by optimizing the I/O scales and membership functions.
- The minimum rise time was achieved by the GA-HFFC without an overshoot and returned to the steady-state level when variable-speed control was considered.
- The GA-HFFC was able to effectively coordinate the IFOC of the variable-speed drive.

VIII. COMPARISON BETWEEN THE SIMULATION AND REAL-TIME IMPLEMENTATION RESULTS

This subsection presents a comparison between the simulation and real-time implementation results. The pattern of real-time implementation results was almost the same as the simulation results. The resulting step responses of the HFPIC, IFOC, HFFC and GA-HFFC from the simulation and real-time implementation are shown in Fig. 15 and Fig. 16. A comparison of the settling times among the HFPIC, IFOC, HFFC and GA-HFFC is summarized in Table 6. The values of the settling time (i.e., the time elapsed to reach and remain within an error band ($\pm5\%$) of the speed command) from the simulation and real-time implementation are summarized as percentages with reference to the simulation results. In other words, the settling time provides information about how quickly the speed response reaches the set point and remains stable. The settling time value should be regarded only as an approximation.

As shown in Table 6, the maximum difference in the settling time at 0–900 rpm for the $\pm5\%$ tolerance band is 44%, while for the reduction from 900 to 500 rpm, it is 42%. The performance of the GA-HFFC slightly differs between the simulation and experiments. With reference to the simulation diagrams in Fig. 15, Fig. 16 and Table 6, the HFFC and GA-HFFC are modeled almost the same as the real-time implementation. Some noises from the current sensors and encoder in the experimental setup might produce the differences. In addition, as shown in Table 6, the percentage differences in the settling time for the four controllers (IFOC, HFPIC, HFFC, and GA-HFFC) at 900–500 rpm are slightly higher than those in the speed at 0–900 rpm; these differences might be due to the fuzziness, ranges of the membership functions and the selected rule base, and more spread among
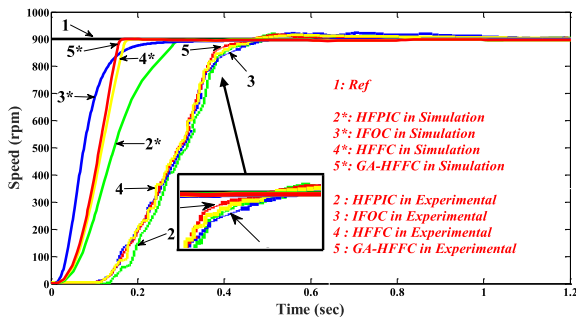
FIGURE 15. Magnified view of the overlapping speed responses from the simulation and experimental results for the HFPIC, IFOC, HFFC and GA-HFFC.
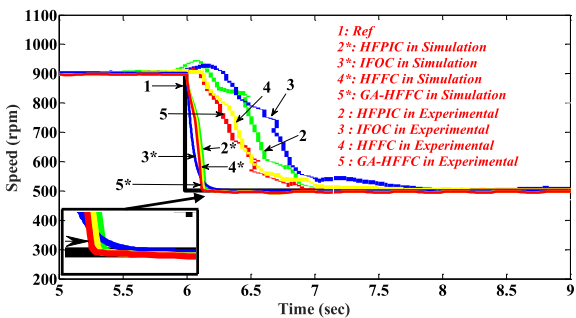

FIGURE 16. Magnified view of the overlapping speed responses from the simulation and experimental results with a step reduction from 900 rpm to 500 rpm for the HFPIC, IFOC, HFFC and GA-HFFC.

TABLE 6. Comparison between the simulation and real-time implementation results.

Data	Reference step speed (rpm)	Settling time (sec)				Figure No
		IFOC	HFPIC	HFFC	GA-HFFC	
Simulation	0–900	0.27	0.25	0.2	0.18	15
Implementation	0–900	0.39	0.3	0.24	0.2	15
Simulation	900–500	0.35	0.3	0.29	0.27	16
Implementation	900–500	0.5	0.4	0.37	0.34	16

the controllers may mean that all of these factors affect the settling time of the controller when using fuzzy principles. In Table 6, the difference in the settling time among the four controllers (GA-HFFC, HFFC, IFOC, and HFPIC) reveals that the proposed GA-HFFC can achieve a very efficient speed response with a smaller difference between the simulation and real-time implementation.

IX. CONCLUSION

This research work represents the development of a GA-HFFC that can be effectively integrated with the SVPWM technique to control a 3-phase IM. The findings show that a drive equipped with the GA-HFFC can be easily operated with high performance by using different speed commands and load disturbances compared with an HFFC, HFPIC and IFOC. The model established in this study could be utilized to further enhance advanced control techniques, which could also be a good source for future research studies to enhance the IM variable-speed drive performance. To validate the simulation results, a hardware implementation was carried out to support an experimental study. The hardware

implementation relied on an efficient digital signal processor from Texas Instruments supported by specially built auxiliary circuits. The test rig was developed for experimentation and to evaluate the proposed control method with general and modular building blocks while taking practical situations into account. Several tests were conducted to perform the analysis and to evaluate and improve the control strategies of the FOC on a single 3-phase IM. The critical parts of the rig components were equipped with reliable auxiliary circuits that support PWM drivers, and the software and hardware were satisfactorily integrated.

In this paper, by adopting an intelligent control viewpoint, a control algorithm referred to as an GA-HFFC is proposed. The purpose of this GA-HFFC is to overcome the drawbacks of vector control and improve the variable-speed control performance of three-phase induction motors to reduce the overshoot, settling time, IAE, ISE, ITAE, and ITSE and eliminate the steady-state error. The GA-HFFC also has good tracking performance and good external load rejection behavior in the presence of diverse operating conditions. The proposed algorithm can be an alternative controller to supplement the conventional methods used for variable-speed drive control using a field-oriented controller.

The contribution of this paper shall pave ways for promising future research directions from the fact that where in by integrating the GA-HFFC with the SVPWM technique has demonstrated to be an effective means of controlling a 3-phase IM system. The GA-HFFC has produced satisfactory results with regards to its current features and can be expanded to develop the torque traces and a speed control method that is resilient to system parameter fluctuations, and then validate against the state-of-the-art meta-heuristic or other artificial intelligence control methods to assess viability of the controller.

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