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Optimization techniques to enhance the performance of induction motor drives: A review

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ABSTRACT

Induction motor (IM) drives, specifically the three-phase IMs, are a nonlinear system that are difficult to explain theoretically because of their sudden changes in load or speed conditions. Thus, an advanced controller is needed to enhance IM performance. Among numerous control techniques, fuzzy logic controller (FLC) has increasing popularity in designing complex IM control system due to their simplicity and adaptability. However, the performance of FLCs depends on rules and membership functions (MFs), which are determined by a trial-and-error procedure. The main objective of this paper is to present a critical review on the control and optimization techniques for solving the problems and enhancing the performance of IM drives. A detailed study on the control of variable speed drive, such as scalar and vector, is investigated. The scalar control functions of speed and V/f control are explained in an open- and closed-loop IM drive. The operation, advantages, and limitations of the direct and indirect field-oriented controls of vector control are also demonstrated in controlling the IM drive. A comprehensive review of the different types of optimization techniques for IM drive applications is highlighted. The rigorous review indicates that existing optimization algorithms in conventional controller and FLC can be used for IM drive. However, some problems still exist in achieving the best MF and suitable parameters for IM drive control. The objective of this review also highlights several factors, challenges, and problems of the conventional controller and FLC of the IM drive. Accordingly, the review provides some suggestions on the optimized control for the research and development of future IM drives. All the highlighted insights and recommendations of this review will hopefully lead to increasing efforts toward the development of advanced IM drive controllers for future applications.

1. Introduction

Induction motors (IMs) are widely used in numerous applications and account for approximately 60% of the total industrial electricity consumption (including factories, industrial sectors, air compressors, fans, railway tractions, pumps, blowers, cranes, textile mills, electric home appliances, vehicles, modes of transportation, and wind generation systems) because they are dependent on the conversion of electrical to mechanical energy [1–3]. Moreover, IMs are easy to maintain due to their simple structure, reliability, high efficiency, and low cost [4–7]. The distinction of IM has led to its global increase in sales of up to 85% in electrical motors [7].

In the past, speed controls used in the DC motors drive because of their simple design in controlling flux and torque. However, DC motors are difficult to maintain, and they corrode and spark [3,8–10]. Then, AC motors have been used to replace DC motors; semiconductor devices, such as insulated gate bipolar transistor metal oxide semiconductor field-effect transistor, have been developed and improved [8–11]. In addition, the designs of AC motors use digital signal processor (DSP), microcontroller, and field programmable gate array to solve difficult and fundamental challenges [3,10–12]. However, the torque, flux, and speed controls of these IMs are difficult to control because of their complex design and nonlinear model [9,10,13,14]. Therefore, two main methods, namely scalar and vector control, have been developed to control the IM [1,3,4,7,13].

The scalar control method has been used in several studies because of its simple structure, low cost, easy design, and low steady-state error [1,3,4,13,15]. Moreover, it has the advantage of stability in controlling middle to high speed and does not require the parameters of an IM [16]. This method has been used by many researchers in controlling IMs (using DSP) [1,4,17–21], single- [22] and five-phase IMs [27], and permanent magnet synchronous motors (PMSMs; using DSP) [23–26].

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Conversely, the vector control method is the most commonly used control scheme in previous research because of its high performance in controlling IMs [9,10,13,28,29]. Its control principle is based on the magnitude of obtained amplitudes and frequency voltages in controlling IMs. Thus, the vector control is used in controlling the position of the flux, voltage, and current vectors [3,13,24]. However, it has the disadvantage of coupling between the electromagnetic torque and flux that leads to difficulty and complexity of the IM controller [3,10], and it is also affected by the sensitivity of IM parameters [3,28,30]. This first problem can be solved through field-oriented control (FOC) and direct torque control (DTC) [26,28,29,31]. FOC consists of two control techniques, namely direct FOC (DFOC), which was proposed by Blaschke in 1972 [32], and indirect FOC (IFOC), which was proposed by Hasse in 1968 [33]. FOC has been used in several studies because of the high performance of controller in IM drives. DFOC and IFOC aim to obtain torque and flux decoupling even with their complex mathematical equations for IM. These methods have been used by numerous researchers in several applications [3,7,10,14,15,30,31,34–38].

Many control schemes are used to control the IM drive system. Among such schemes are the conventional controllers, namely, proportional–integral–derivative (PID) control, proportional–integral (PI) control, and proportional–derivative control. These conventional controllers were proposed by Taylor Instrument Company in 1936 [39]. PID is considered a good control technique because of its easy to use design, low cost, and simple structure; thus, it is utilized in numerous applications along with scalar and vector techniques [38,40,41]. PID controller is also used in regulating main variables, such as voltages, currents, speed, torque, and rotor flux in IMs [42]. However, the parameters for PID controller, namely proportional gain (kp), integral gain (ki), and derivational gain (kd), are difficult to obtain. These parameters play an important role in model control in terms of sensitivity and stability [16,30,38,43,44]. Therefore, PID control parameters should be suitable with sudden changes in speed or mechanical load [16]. The coefficient of PID controller can be identified using several methods, such as Ziegler–Nichols (Ziegler and Nichols, 1940) [45], Cohen–Coon (1953), Lambda tuning method (Dahlin, 1968) [46], and visual loop tuning method. These methods, however, experience process upset, undergo trials and errors, and require several calculations and mathematical models [47–49].

The fuzzy logic controller (FLC) was proposed by Zadeh in 1965 [50]. Recently, it has been used due to its adjusted online control according to adaptive modeling with sudden event changes in systems [14,51]. Moreover, FLC does not require an exact mathematical model; it can handle both linear and non-linear systems; and it is based on linguistic rules, which is the basis of human logic [30,44,52–55]. Therefore, FLC has become increasingly popular in designing the control systems of several models, such as in Refs. [1,16,56–59]; it was used to improve the control for the scalar speed control of IMs. In Refs. [14,30,36,52,60–63], FLC was used to develop the vector control for IM. In Refs. [60,64,65], FLC was used to control the variable speed of wind turbine based on dual star induction generator. FLC was also used in Ref. [66] to provide optimal control for the voltage and frequency of an AC microgrid. In Refs. [67,68], FLC was used to improve the sensorless stator FOC on an IM. FLC was also used to control a five-phase IM [69].

Pulse width modulation (PWM) techniques for driving three-phase voltage source inverter (VSI) play an important role in controlling IMs by dominating the switching devices [49,58,70–72]. Therefore, the main principle of VSI is to regulate the AC output voltage and frequency from a constant DC supply voltage. Moreover, PWM techniques develop the output waves of the inverter for high efficiency, low distortion, minimized harmonics, less switching loss, easy implementation, and less computation time [54,55]. Sinusoidal PWM (SPWM) is a PWM method in which the reference modulation wave is compared with a triangular carrier wave, and the intersections define the switching instants. Within every carrier cycle, the average value of the output voltage becomes equal to the reference value; SPWM is also a simple and easy structure [73,74]. Space vector PWM (SVPWM) is one of the most popular PWM technique that has recently gained interest among researchers. Meanwhile, the hysteresis band PWM (HBPWM) and random PWM (RPWM) reduce switching losses and harmonics, respectively [19,27,49,71,73,75]. In Ref. [76], Piao and Hung reported a unified SVPWM technique for a multilevel inverter that requires complex nonlinear calculation involving modulation implicit functions of SVPWM. In general, most of the SVPWM requires complex online computation which leads to difficulty in real time implementation. Thus, the conventional SVPWM requires additional memory that limits the choices of switching frequency and thereby reducing the accuracy of SVPWM [77,78]. To solve this problem genetic algorithm (GA) based SVPWM is utilized [79], but the GAs requires much iteration to find the best results, which is time consuming. An artificial neural network (ANN) is also used in SVPWM [77,78] for efficient inverter operation. In Refs. [80–82], the adaptive neural fuzzy inference system (ANFIS) based SVPWM is used for the two-level inverters. Moreover, optimized hybrid modulation strategies based on multiple divisions of active vector time and control are utilized to improve the harmonic elimination performance, reduce switching losses and current ripples of the IM drive [83,84]. However, the above-mentioned methods encountered problems because of their huge data requirement, long training, and learning times of linear and nonlinear functions that consume huge memory for real-time implementation. In Ref. [85], a random forest (RF) regression based implementation of space vector pulse width modulation (SVPWM) for two-level inverter is utilized using BSA optimization to improve the performance of the IM drive over conventional schemes in terms of damping capability, settling time, steady-state error, and transient response under different operating conditions.

Computational intelligence optimization algorithms are nature-inspired computational methodologies that address complex real-world problems. These algorithms can be divided into swarm intelligence methods and evolutionary algorithms (EAs). Swarm intelligence optimization algorithms generally use reduced mathematical models of the complex social behavior of insects or animals. The most popular swarm intelligence methods are particle swarm optimization (PSO) [86], artificial bee colony (ABC) [87], and ant colony optimization (ACO) [88]. The PSO mimics the movements of bird flocking or fish schooling [89]. The ABC method is inspired by the food-searching mechanism of honeybees and uses the foraging behavior of these insects [87]. Meanwhile, ACO was developed based on the behavior of ants when searching for the optimal path between their colony and food source [88]. EAs derive their working principles from natural genetic evolution. At each generation, the best individuals of the current population survive and produce offspring that resembles them; hence, the population gradually comprises enhanced individuals. Operations, such as recombination, crossover, mutation, selection, and adaptation, are involved in the EA process [90]. Popular EA paradigms are the genetic algorithm (GA) [91], evolutionary programming, differential evolution [92], evolutionary strategy, and genetic programming. These algorithms are based on the principles of Darwinian theory and other evolution theories of living beings. Recently, a numbers of researches have been developed on multi-objective IM parameter estimation to minimize the error between the estimated and the manufacturer data using sparse grid optimization algorithm [93,94], BSA [55], explicit model predictive control via quadratic programming [95].

Many real-world optimization problems involve nonlinearities and complex interactions among problem variables, and therefore nature-inspired optimization techniques are applied to solve such problems. The problem-solving capacity of these techniques is generally achieved by modifying existing algorithms, hybridizing algorithms, and developing new algorithms. Several nature-inspired optimization techniques have been proposed to overcome the limitations of their predecessors. The following descriptions highlight the recent nature-inspired optimization techniques published in scientific literature.

Recently, optimization techniques have been used in several studies to improve the performance of control systems; for instance, FLC design optimization techniques use differential search algorithm optimization to develop FLC and control photovoltaic (PV) inverters [53]. Optimization techniques that are based on conventional controller improve the control system in IM drives [96–98]. In Ref. [99], particle swarm optimization (PSO) is was adopted to enhance FLC for maximum power point tracking (MPPT) in a grid-connected PV inverter. In Refs. [57,100], GA was used in selecting PID coefficients to control the speed of an IM. PSO improved the PID controller of an AVR in Ref. [101]. In Ref. [102], a GA was utilized to enhance the fuzzy-phase plane controller for the optimal position/speed tracking control of an IM. The GA–PSO algorithm was applied to improve indirect vector control for the loss minimization operation and optimal torque control of an IM in Ref. [103]. In Ref. [104], PSO was utilized as a model-parameter identification method for permanent magnet synchronous motors. An advanced predictive torque control has been reported to control IM drives allowing high performance and fast dynamics using multi-objective fuzzy decision making [105], Kalman filter covariance technique [106] and finite-control set model predictive control [107]. In Refs. [55], backtracking search algorithm (BSA) optimization technique was used to enhance the performance of the fuzzy logic speed controller for IMs. However, optimization techniques generally have limitations on global minimum, trial-and-error procedure, local minima, and optima trapping; they also have a weakness in diversifying the algorithms and computational time to achieve best optimization performances. To solve the above optimization problems, a novel quantum lightning search algorithm (QLSA) is applied to improve the FLC for controlling the speed response of the IM drive in terms of damping capability and transient response under different load and speed conditions over many others FLC based optimization techniques [108].

In thispaper, different control and optimization techniques are reviewed to create an advanced control scheme on conventional scalar and vector control to achieve high IM drive system performance. A tabular comparison of existing optimization algorithms in different controllers and platforms is analyzed for further development of the IM drive control. Issues and challenges of the existing IM drive controller are also highlighted toward providing suggestions. Thus, this paper highlights the existing challenges and provides recommendations for the improvement of future advanced optimized IM drive controller.

2. Variable frequency drives (VFDs)

The overall IM control system generally comprises four main parts: IM, control system, three-phase inverter, and load, as shown in Fig. 1.

Several studies have focused on IM control methods. In an IM control development survey in 1946, Weygandt and Charp used an analog computer to investigate the performance of a transient IM [109,110]. In 1956, Bell Laboratories invented a silicon-controlled rectifier or thyristor for motor control [111]. In 1959, Kovacs and Racz performed a new analysis to study the transient IM of rotating reference frames [110]. At the beginning of the semiconductor revolution in the 1960s, power electronic devices were developed to assist in designing several power electronic converters, such as rectifiers, inverters, and DC–DC converters. Switching techniques were used to control the IM drive. Accordingly, VFD methods were designed and developed in many bodies of research for control purposes. IMs were investigated in terms of improving speed control, implementing a motor control strategy, and reducing energy losses. In IM control for nonlinear dynamical systems, rotor flux and currents are difficult to measure, and the heating of rotor resistance results in changes in resistance value. These challenging issues should be addressed. VFDs can be categorized into two main methods, namely scalar and vector control methods (Fig. 2), according to IM speed, voltage, current, flux and torque control [3,7].

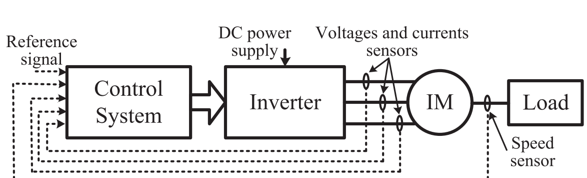

Fig. 1. Architecture of the IM control system.

2.1. Scalar control

Scalar control, in which the V/f control is based on the open- and closed-loop control system of the IM speed, was introduced in 1960 for IM control [111]. Speed response accuracy is not required in open-loop speed controls, such as in ventilation, air conditioning, fan, and blower applications [112].

The variable voltage and frequency of an IM in a closed-loop control system are always employed to control the speed and torque of IM drives [113]. The V/f control strategy is applied to IM drives to develop the performance and dynamic response of the IM. This method offers several advantages, including a simple structure, low cost, easy design, and low steady-state error. Moreover, the initial current requirement is low. The acceleration and deceleration can also be controlled by controlling the change of supply frequency. The main advantage of V/f control is that parameters are not required for IM implementation [1,3]. V/f control is applied to control the supply voltage magnitude of IMs, and it is one of the best choices for variable speed and torque applications. Therefore, this research adopts V/f control for IM speed drive controller implementation [27]. The main principle of V/f control is to maintain the scalar voltage/frequency ratio constant, thereby maintaining the magnetic flux in the maximum air gap. No explicit relationship exists between voltage and frequency; however, the flow of electromagnetic flux produces a relationship between voltage and frequency, as shown as follows [3]:

$$\psi_m \cong \frac{V_p}{f} \cong K_v \tag{1}$$

where ψ_m is the maximum air gap flux, V_p is the maximum phase voltage, and K_v is the ratio of V_p to f.

The block diagram of the V/f control method and the slip speed (ω_{sl}) in Fig. 3 are the variable speed calculated on the basis of IM characteristics. This slip speed control is added with ω_{rm} to generate ω_{sm}. The synchronous speed is then converted to a synchronous frequency to generate the peak voltage using V/f control. The main limitation of this control is its low performance in low-speed operations [1,3,7].

Many researchers have applied V/f control for controlling IM speed [1,57–59,114–116]. The open-loop V/f control was used to adjust IM speed response [4]. In Ref. [27], a five-phase IM was controlled with an open-loop V/f constant control. V/f control was also utilized to control the scheme of single- to three-phase PWM converters for low-power IM drives [18]. The open-loop V/f control was used to control the SVPWM of a three-level inverter [19,117]. V/f control was adjusted for the motor operations of a stand-alone squirrel cage IM [20]. In Ref. [21], the space vector–modulated current source inverter (CSI) with V/f control was used to control an IM. In Ref. [22], a single-phase IM was controlled with V/f, which was used for high-speed PMSM drives [23,24,118,119] and PMSM for micro-gas turbine generation system [25]. In Ref. [120], the V/f Control of an IM for a DC grid power-leveling system was implemented. In Ref. [121], the V/f control of an IM was fed by a SVPWM Z-source inverter and was applied to control a

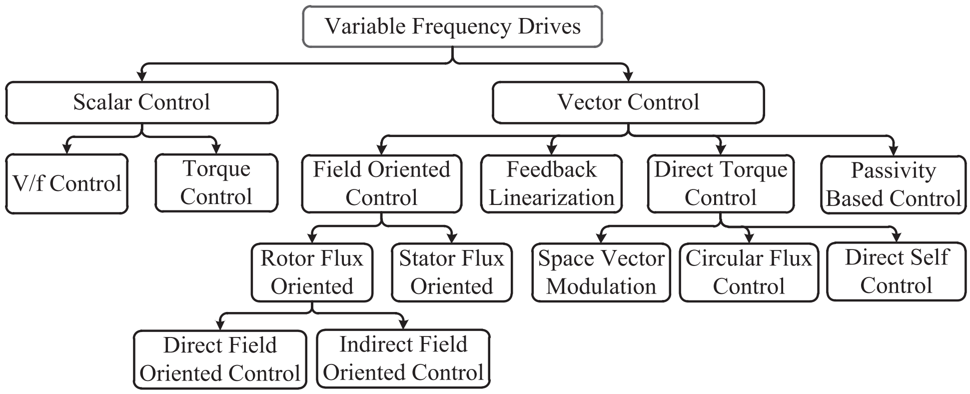

Fig. 2. Categorization of variable frequency drive methods.

doubly fed induction generator [122].

2.2. Vector control

Vector control is the most commonly used method in many IM applications because of its high performance for IM control. The principle of vector control is based on obtaining the magnitude and phase of voltages or currents to control IMs. Thus, vector control is based on controlling the position of the flux, voltage, and current vectors of the IM. This control is performed depending on the Clarke and Park transformations, which are responsible for generating torque and flux, respectively. An IM operates similar to a separately excited DC motor drive, in which the torque and flux are controlled by two independent orthogonal variables, namely, the armature and field currents, respectively [10,13,28,123]. This characteristic results in disadvantageous coupling between electromagnetic torque and flux, which leads to the difficulty and complexity of using IM controllers [3,10,13,124]. This problem can be solved by using FOC.

2.2.1. Field oriented control (FOC)

In 1968–1971, Hasse and Blaschke from the Darmstadt University of Technology in Germany proposed FOC [125]. FOC is classified into two main methods, namely, DFOC and IFOC. DFOC uses two Hall effect sensors that are mounted in air gap to estimate rotor flux on the basis of air gap measurements. The block diagram of the DFOC for an IM drive is shown in Fig. 4 [3,7]. Given that installing flux sensors in the motor air gap is undesirable, IFOC is applied to solve the problem. The main advantage of the IFOC is that it estimates rotor flux from measured currents and speed without flux-measuring sensors. IFOC has been used by many researchers because of its optimization capability and the performance of the IM drive controller. IFOC aims to achieve torque and flux decoupling despite the complexity of mathematical equations for IMs. FOC has several disadvantages, such as coordinate transformation, sensitivity to IM parameters, and numerous sensor requirements [7,126]. The block diagram of IFOC for IM drives is shown in Fig. 5.

Many researchers have integrated FOC into controlling systems; for example, IFOC has been used in many IM drive applications to control speed, current, and flux [10,13,14,35,38,67,127]. IFOC has also been applied to control a double-star IM [30,128]. Speed estimation based on a model reference adaptive system in IFOC was adopted for controlling IM model [129]. A single-phase IM was controlled by IFOC [130,131]. According to Ref. [132], a fault occurred in the IFOC feedback sensors of IM. FOC was controlled on a synchronous motor [133]. A wind generation system used IFOC to control speed variation [134]. A PV system was supplied to IM by using the FOC method [135]. In Ref. [136], IFOC was used to control the speed of a five-phase IM. Torque and flux controls were generated by FOC for high-performance IM drives [36]. IFOC was improved using regulation algorithms for IM [137]. IFOC enhanced a controller by replacing its speed control with position control for IM [138,139]. IFOC also controlled a seven-level diode-clamped inverter for IM [140].

2.2.2. Direct torque control (DTC)

Another control method known as DTC was proposed by Takahashi in 1986 [141]. The principle of this control method is based on torque reference magnitudes and stator flux reference subtracted from the corresponding estimated values of feedback signals. The result is an error signal, and the errors are processed through hysteresis band controllers. The feedback signals of the torque and flux are calculated from motor terminal voltages and currents to compute the number of flux vectors. The torque and flux error generates changes in torque and

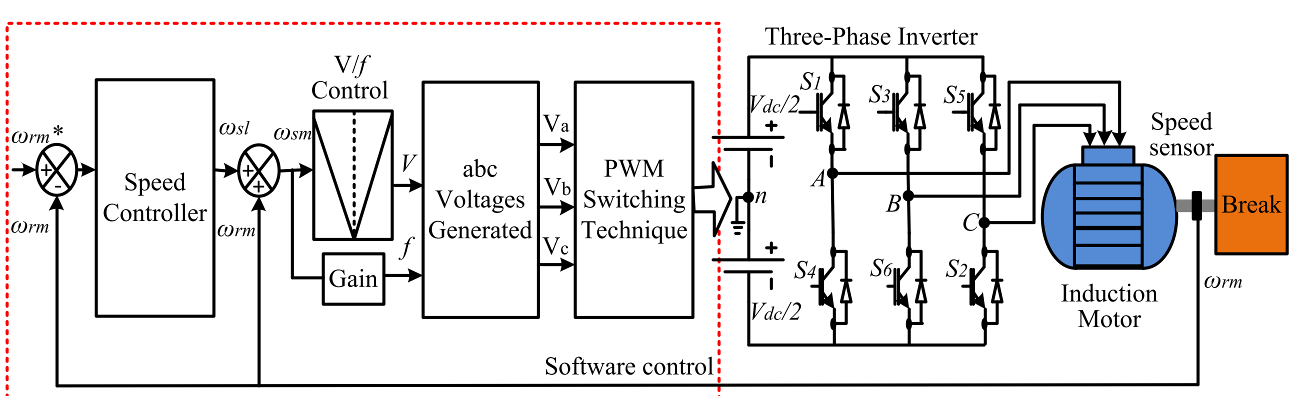

Fig. 3. Closed-loop of scalar control for IM drive.

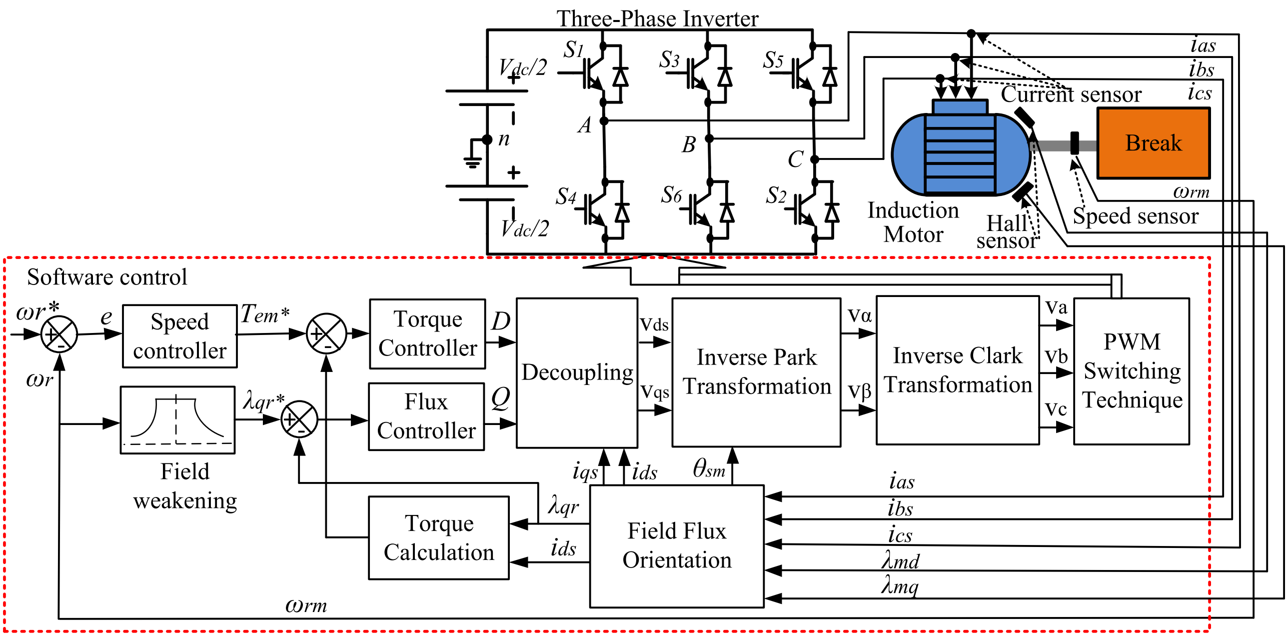

Fig. 4. Block diagram of DFOC for IM drive.

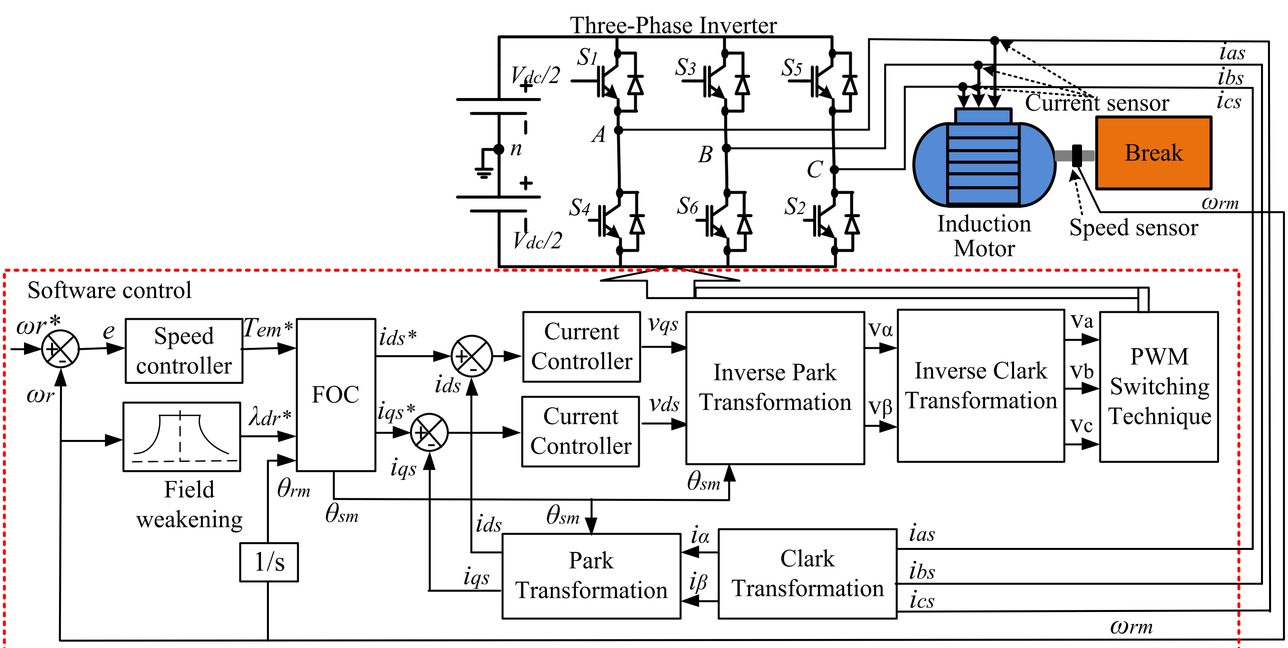

Fig. 5. Block diagram of IFOC for IM drive.

flux by using comparators. Thus, the voltage vector selector is subjected to torque and flux changes with the sector number of flux vector to generate a duty ratio and supply it to the IM, as shown in Fig. 6. DTC has many advantages over FOC, such as its simple implementation, not requiring speed sensor, less motor parameter dependence, and high dynamic torque response [3,29,141]. However, DTC also has many disadvantages, such as its requirements for measuring voltages, currents, and stator resistance. In addition, DTC presents current ripple, variable-switching frequency behavior, high noise, and difficult control, especially under low-speed conditions [126].

Several researchers have used DTC to improve different control system applications, such as IM [142,143]. In Ref. [144], torque ripple was minimized with constant switching frequency in the DTC of an IM drive. The current research is focused on the comparison between FOC and DTC to show their advantages and disadvantages [126]. VFD with DTC was used to improve IM control [145]. In Ref. [146], DTC was used to control PMSM [147], and a three-level inverter was utilized in feeding the IM drive to minimize current ripples [148]. Table 1 shows a comparison between the performance of scalar and vector control in IM.

3. Review of optimization algorithms

At the end of the last century, optimization algorithms are developed for many applications to solve several problems. These algorithms are classified according to the underlying principle of biology- and physics-based algorithms. The first category is the biology-based algorithm, which includes GA, harmony search algorithm, PSO, bacteria foraging optimization, cuckoo search algorithm, bee colony algorithm, ACO, firefly algorithm (FA), backtracking search algorithm

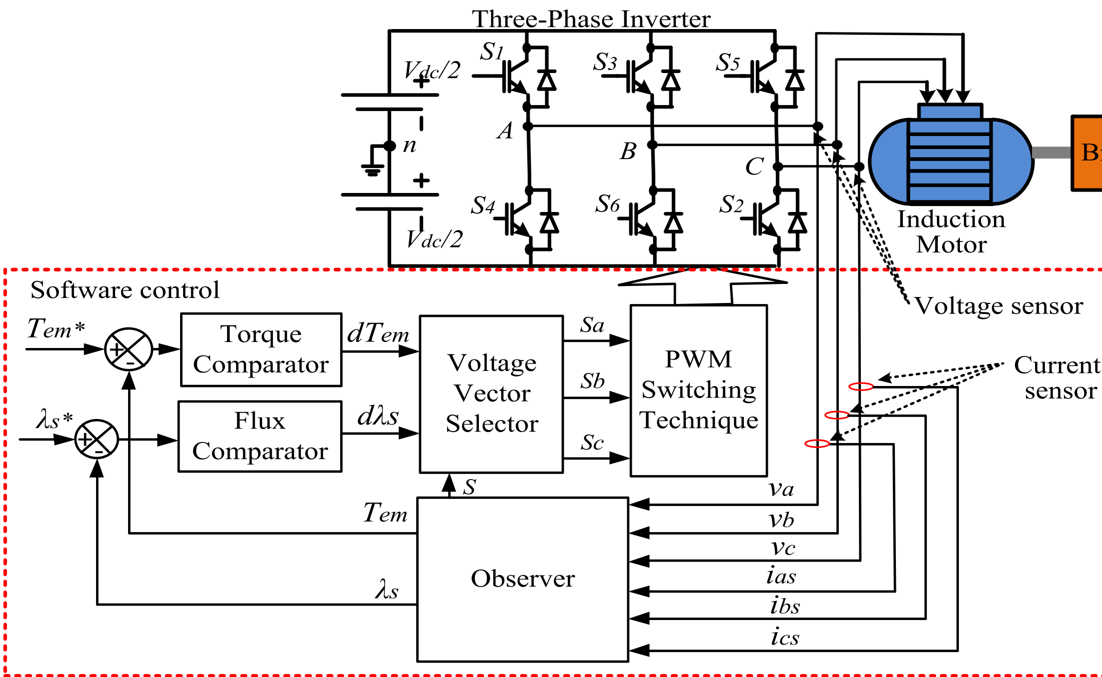

Fig. 6. Block diagram of DTC for IM drive.

(BSA), and lightning search algorithm (LSA). The second category is the physics-based algorithm, which includes simulated annealing, gravitational search algorithm (GSA), and chaotic optimization algorithm (COA) [51]. In this research, some of the popular optimization algorithms are explained in the succeeding sections.

3.1. Genetic algorithm (GA)

GA is a stochastic global adaptive search optimization technique based on the mechanisms of natural selection proposed by [91]. This algorithm is initialized to a population containing a number of chromosomes, in which each one represents a solution to the problem that is evaluated by an objective function [51,149]. GA is also integrated into modern applications [150] to find the best parameter values of rational functions. It is used in a control system on an electric distribution network [151]. GA is also applied for MPPT to improve the energy harvesting capability of a PV system [152]. It is also utilized to improve the reliability and power quality of distribution systems [153]. However, GA has limitations; it cannot guarantee the identification of global minimum; it also requires much time to achieve convergence and fine tune all parameters (such as mutation rate, elitism percentage, crossover parameters, and fitness normalization); and it is essentially a trial-and-error procedure [154].

3.2. Particle swarm optimization (PSO)

PSO is an evolutionary computation technique developed by Eberhart and Kennedy (1995); it is inspired by the social behavior of bird flocking. PSO has been applied by numerous researchers because of its verified robustness, ease of implementation, and global exploration capability in various applications [155]. The particles in the PSO algorithm search the space in two locations. The first location is the best point where the swarm finds the current iteration (local best); whereas the second location is the best point found through all previous iterations (global best). The principle of PSO algorithm depends on two factors, namely, velocity and position of particles. These factors can be updated using the following equations [156]:

$$V_i^d(t+1) = wV_i^d(t) + c_1 r_1 (P_i^d(t) - X_i^d(t)) + c_2 r_2 (P_t^d(t) - X_i^d(t)) \quad (2)$$

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \quad (3)$$

where c_1 and c_2 are the social and cognitive rates, respectively; $r_1$andr_2 denote the random in the interval (0, 1); V is the velocity factor of agent i at iteration d; t is the present iteration; w is the inertia factor; and X is the position factor.

The PSO algorithm is performed in many applications, such as in Ref. [157], to optimize the threshold parameters of the rule-based power management strategy for hybrid electric vehicles and solve the optimal power flow problem of power systems [158]. In Ref. [159],

Table 1
Comparison between scalar and vector control.

Scalar control	Vector control
1. Simple structure	1. Complex structure
2. Low cost and easy design in prototype implementation	2. High cost and difficult design in prototype implementation
3. Normal and low performance under low-speed conditions	3. High performance in FOC and low performance of DTC in a low-speed response
4. Does not require IM parameter identification	4. Requires and is sensitive to IM parameters
5. Requires one sensor, that is, speed sensor	5. Requires many sensors, such as six sensors in DFOC, four sensors in IFOC, and six sensors in DTC
6. Minimizes current ripple	6. High-current ripple in DTC
7. Does not require coordinate transformations	7. Requires a coordinate transformation in FOC

PSO algorithm was used in improving the MPPT method to adjust the rotor side converter of a wind turbine-fed induction generator [160]. PSO was also implemented to determine the optimal sizing of hybrid PV, wind, and battery system [161]. PSO has several advantages, including fast convergence and capability to solve complex optimization problems in different application domains. However, PSO has some limitations; it easily becomes trapped in local minima, and it improperly selects control parameters, resulting in poor solution [162].

3.3. Firefly algorithm (FA)

FA is a nature-inspired algorithm based on the flashing patterns and behavior of fireflies; it was proposed by Yang in 2007 at Cambridge University [163]. This algorithm is based on three basic rules. First, fireflies are attracted to one another regardless of their sex. Second, fireflies move through a dim firefly to a brighter one. If no brighter firefly exists, they move randomly. Third, the brightness of a firefly is selected by the landscape of the objective function. The attractiveness variation is calculated in terms of distance using the following equation [163,164]:

$$\delta = \delta_0 e^{-\gamma r^2} \tag{4}$$

where δ is the variation in attractiveness, r is the distance among fireflies, and δ_0 is the attractiveness at $r = 0$. The attractiveness movement among fireflies is calculated on the basis of the condition in which a dimmer firefly i moves toward a brighter firefly j, as shown as follows [163]:

$$x_i^{t+1} = x_i^t + \delta_0 e^{-\gamma r_{ij}^2}(x_j^t - x_i^t) + \sigma_t \epsilon_i^t \tag{5}$$

where x is the attraction, σ is the randomization parameter, and ϵ is a vector of random numbers drawn from a Gaussian distribution or uniform distribution at time t.

FA is implemented in numerous applications, such as in Ref. [165], for the optimal load frequency controller of a multi-area multi-source system. This algorithm was also applied in selecting the optimum switching angles for an 11-level cascaded H-bridge multi-level inverter to minimize the harmonics of an output waveform [166]. In Ref. [167], FA was used to solve the problem of wind turbine position, which involved the selection of the best position. FA offers certain advantages, such as easy implementation and automatic subdivision capability; it also deals with multimodality. However, FA also has some limitations, such as getting trapped into several local optima, performing local search, and incapability to memorize or remember any history of a good situation; thus, it may end up missing situations [168].

3.4. Gravitational search algorithm (GSA)

GSA, which was proposed by [169], is classified as physics-based algorithm that depends on the law of gravity and mass interactions. The operating principle of GSA is based on the laws of motion and Newtonian gravity, which states that "every particle in the universe attracts every other particle with a force that is directly proportional to their masses and inversely proportional to the square of the distance between them," as expressed as follows [169]:

$$F = G\frac{M_1 M_2}{R^2} \tag{6}$$

where F is the magnitude of the gravitational force; G is the gravitational constant; M_1 and M_2 are the mass of the first and second particles, respectively; and R is the distance between the two particles.

According to Newton's second law, acceleration a is directly proportional to force and inversely proportional to mass M, as expressed as follows:

$$a = \frac{F}{M} \tag{7}$$

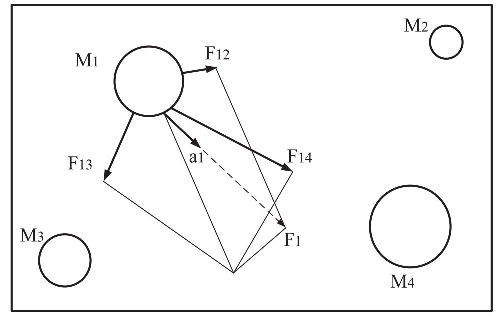

Fig. 7. Mass effects with other masses.

Gravitational constant $G(t)$ is calculated as the initial value of the gravitational constant $G(t_0)$ multiplied by the ratio between initial time t_0 and actual time t, as shown as follows:

$$G(t) = G(t_0) \times \left(\frac{t_0}{t}\right)^\beta, \beta < 1 \tag{8}$$

The effect of forces between the mass with other masses and the process of extracting the net force and acceleration is shown in Fig. 7.

The positions of the N number of the initialization agents are initialized (that is, the masses are randomly selected within the search interval provided), as shown as follows:

$$X_i = (X_i^1, \ldots, X_i^d, \ldots, X_i^n), fori = 1, 2, \ldots, N \tag{9}$$

where X_i^d is the position of ith agent in the dth dimension, and n is the space dimension. The computation aims to minimize problems and determine the masses of each agent, as shown as follows:

$$best(t) = \min_{j \in \{1,\ldots,N\}} fit_j(t) \tag{10}$$

$$Worst(t) = \max_{j \in \{1,\ldots,N\}} fit_j(t) \tag{11}$$

$$m_i(t) = \frac{fit_i(t) - Worst(t)}{best(t) - Worst(t)} \tag{12}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_i(t)} \tag{13}$$

The total force F computation in different directions in the ith agent, acceleration a, velocity computation V, position X, and gravitational constant G of the agents at the next iteration t are expressed as follows:

$$G(t) = G_0 e^{(-\alpha t/T)} \tag{14}$$

$$F_{ij}^d(t) = G(t)\frac{M_{pi} \times M_{aj}}{R_{ij} + \varepsilon}(X_j^d(t) - X_i^d(t)) \tag{15}$$

$$F_i^d(t) = \sum_{j \in Kbest, j \neq i} rand_j F_{ij}^d(t) \tag{16}$$

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{17}$$

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{18}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{19}$$

Many applications have been used for GSA optimization algorithm [170,171] to find the optimum solution for short-term hydrothermal scheduling problem and enhancing its performance. GSA is implemented to solve different single- and multi-objective optimal power flow problems [170] and improve control methodology for self-excited induction generator [172]. It is also used to enhance the load frequency control of multi-area power system and solve the identification problem for turbine regulation under load and no-load conditions [173,174]. GSA has the advantages of fast convergence for solution compared with other conventional optimization techniques that are dependent on the physical laws (Newtonian laws). However, it has some limitations, such as being easily trapped in local minima and weakness in strategy to diversify the population of the algorithm [172,175].

3.5. Backtracking search algorithm (BSA)

BSA optimization technique, which was proposed by Civicioglu [176], is an evolutionary computation technique for producing a trial population that includes two new crossovers and mutation operators. BSA dominates the value of the search on the best populations and in the space boundary to find remarkably sturdy exploration and exploitation capabilities. Thus, it has been proven in several studies as one of the most powerful optimization techniques. BSA structure consists of five parts: initialization, selection-I, mutation, crossover, and selection-II. The initialization process is the primitive configuration of population for the numerical values of population and is expressed in the following equation [176]:

$$X_{ij} = rand.\,(up_j - low_j) + low_j \tag{20}$$

where $i = 1,2,\ldots,N$, in which N is the population size; and $j = 1,2,\ldots,D$, in which D is the problem dimension. The historical population ($\mathrm{oldX_{ij}}$) to be used for calculating the search direction is constructed by

$$oldX_{ij} = rand.\,(up_j - low_j) + low_j \tag{21}$$

$oldX_{ij}$ remembers the population from a randomly chosen previous generation for creating the search-direction matrix, which considers the partial advantage of previous experiences to generate a new trial population. The comparison between two random values is shown as:

$$if a < b,\ then \mathrm{oldX_{ij}} := \mathrm{X_{ij}} \tag{22}$$

$$\mathrm{oldX_{ij}} = permuting\,(\mathrm{oldX_{ij}}) \tag{23}$$

Mutation is a process that produces new population of the initial and history population, as shown in Eq. (24), where F value controls the amplitude of the search-direction matrix.

$$Mutant = X_{ij} + F.\ randn.\,(oldX_{ij} - X_{ij}) \tag{24}$$

BSA generates a trial population and then takes a partial advantage of its experiences from previous generations. Crossover is generated by the trial population. The initial of the trial populations is taken from the mutation. The crossover consists of two parts. The first part generates the binary matrix called $\mathrm{map_{ij}}$. The second part is a process comparison between population $\mathrm{X_{ij}}$ and the trial population. Crossover is used to obtain $\mathrm{map_{ij}}$ updates. In addition, this part works on boundary control mechanism for the trial population. The last part is selection-II. In this part, optimization process runs to compare the population $\mathrm{X_{ij}}$ and trial population to obtain the best population, as well as the objective value.

BSA algorithm is applied many modern applications to solve problems, enhance the power flow of high-voltage DC power systems, and generate solutions to ascertain distributed generators [177,178]. BSA is implemented to solve economic dispatch problems and find the best position for distributed generators placement [179,180]. It is also used to design optimal analog circuits and operational amplifier circuits [181]. BSA has the advantages of being suitable for search exploration process and mutation and crossover strategies. However, its computation is time-consuming because of the use of the dual population algorithm, wherein only one parameter is used to control the amplitude of the search-direction matrix in the mutation phase; moreover, crossover is complex [176].

Fig. 8. Step leaders descending from a storm cloud.

Table 2
Summary of the optimization algorithms for improving controller techniques.

References	Optimization algorithms	Controller techniques	Platform
[102]	GA	FLC and PI	Interface card
[185]	GA	PI	Matlab/ Simulink
[47]	GA	FLC	DSP
[186]	GA	ANN	DSP
[188]	GA	PI	dSPACE
[189]	GA	Hybrid FLC–PI	dSPACE
[10]	GA	Sliding	Matlab/ Simulink
[57]	GA	PI	dSPACE
[104]	PSO	Intelligent model	Matlab/ Simulink
[99]	PSO	FLC	Matlab/ Simulink
[190]	PSO	FLC	Matlab/ Simulink
[191]	PSO	ANFIS	Matlab/ Simulink
[192]	PSO	FLC	Matlab/ Simulink
[182]	LSA	FLC	DSP
[108]	QLSA	FLC	DSP
[54]	GA and PSO	PID Hybrid FLC–PI	Matlab/ Simulink
[103]	Hybrid GA–PSO	PI	Matlab/ Simulink
[194]	BSA	PID	Matlab/ Simulink
[195]	BSA	PI and PID	Matlab/ Simulink

3.6. Lightning search algorithm (LSA)

LSA is a modern optimization method proposed by Shareef et al. [182]. LSA optimization allows the achievement of desired goals according to several modern optimization techniques. LSA optimization technique depends on the concept of a step leader propagation mechanism called “lightning,” as shown in Fig. 8. LSA considers the involvement of fast particles, known as projectiles, in the formation of the binary tree structure of the step leader in the concurrent formation of the two-leader tips at fork points, instead of a conventional step leader mechanism. LSA mechanism consists of three steps: projectile and step leader propagation, projectile properties, and projectile modeling and movement, which will be explained in detail in the succeeding sections.

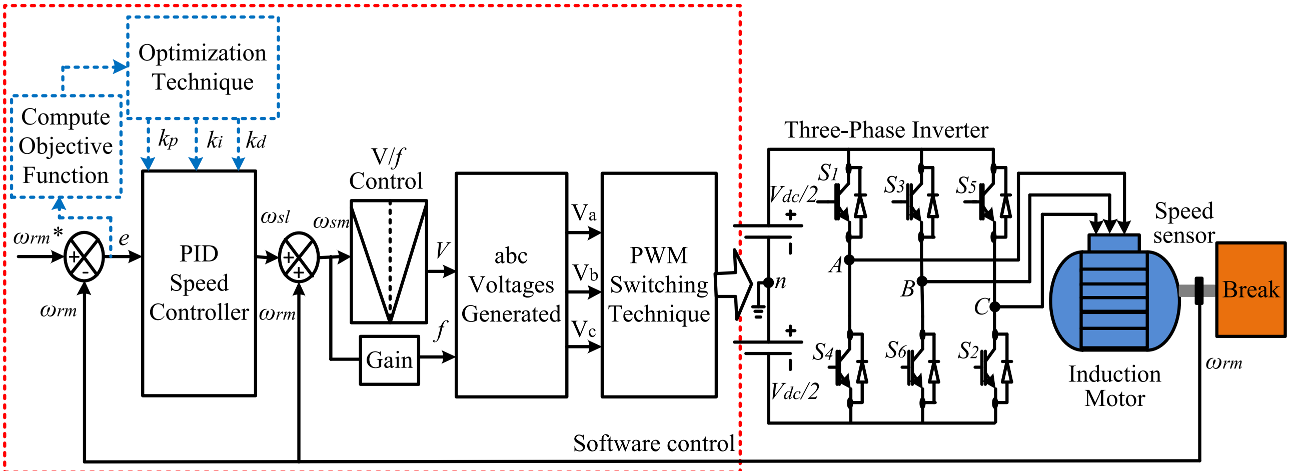

Fig. 9. Optimization technique based on PID speed controller for scalar control.

3.6.1. Projectile and step leader propagation

Many atoms are observed near thunderclouds in the form of hydrogen, nitrogen, and oxygen; moreover, the intensive freezing of water molecules forms ice at intense speeds, which results in the separation of hydrogen and oxygen atoms and is ejected in a random direction as projectiles. LSA techniques consider each projectile as the initial population size. The projectile term is similar to the particle and agent term in PSO and GSA techniques, respectively [182].

3.6.2. Projectile properties

Projectile moves in the atmosphere; however, it loses its kinetic energy during elastic collisions with molecules and atoms in the air. Projectile velocity is expressed as

$$v_p = \left[1 - \left(\frac{1}{\sqrt{1-(v_0/c)^2}} - \frac{sF_i}{mc^2}\right)^{-2}\right]^{-1/2} \tag{25}$$

where v_p is the current velocity of the projectile, v_0 is the initial velocity of the projectile, F_i is the constant ionization rate, c is the light speed; m is the mass of the projectile; and s is the length of the path traveled. The number of projectiles is increased by adding channels that are created during forking, which results in an increased population size. LSA technique creates forking by using two methods. The first method generates symmetrical channels, because the nuclei collision of the projectile is realized by using the opposite number, as shown as follows:

$$\overline{p_i} = a + b - p_i \tag{26}$$

where $\overline{p_i}$ is the opposite projectile in one dimension, a and b are boundary limits, and p_i is the original projectile in one dimension. The population may improve in some complex solutions. In the second type of forking, a channel is assumed to appear at a successful step leader tip because of the energy redistribution of the most unsuccessful leader after several propagation trials. The unsuccessful leader can be redistributed by defining the maximum allowable number of trials as channel time. In this case, the population size of step leaders does not increase.

3.6.3. Projectile modeling and movement

Three types of projectile are developed to represent the transition projectiles that generate the first-step leader population N. Transition projectile may be in a random direction through the transition formed by an ejected projectile from the thunder cell. Therefore, transition projectile can represent a random number by forming a random distribution in space. The probability density function $f(x^T)$ of the standard uniform distribution can be represented as

$$f(x^T) = \begin{cases} 1/(b-a) & for \quad a \le x^T \le b \\ 0 & for \quad x < a \text{ or } x^T > b \end{cases} \tag{27}$$

where x^T is a random value that represents the initial tip energy E_{sl_i} of the step leader sl_i; a is the lower bound of the solution space; b is the upper bound of the solution space; $SL = [sl_1, sl_2, sl_3, \ldots, sl_N]$ are the step leaders for the population of N; and $P^T = [P_1^T, P_2^T, P_3^T, \ldots, P_N^T]$ are the required solution dimensions for each population. The population of the leader moves to space, depending on the activity projectiles, and ionizes the section in the vicinity of the old leader tip in the next step. The new position of the projectile is formed by an exponential distribution with shaping parameter μ. The probability density function $f(x^s)$of an exponential distribution is

$$f(x^s) = \begin{cases} \frac{1}{\mu} e^{-\frac{x^s}{\mu}} & for \quad x^s \ge 0 \\ 0 & for \quad x^s \le 0 \end{cases} \tag{28}$$

where μ_i is the shaping parameter. In the LSA mechanism, μ_i is considered as the distance between the lead projectile p^L and the space projectile p_i^S under consideration. The new position is defined as

$$p_{i_{new}}^s = p_i^s \pm exprand(\mu_i) \tag{29}$$

where exprand is a random exponential number for μ_i. The new position $p_{i_{new}}^S$ may find a good solution by obtaining a new position $p_{i_{new}}^s$ and update to p_i^s. Otherwise, their positions will remain unchanged until the next step. When the step leaders access near the ground, the associated projectile has insufficient potential to ionize large sections in front of the leader tip. Therefore, the lead projectile can be represented as a random number generated by the standard normal distribution with the shape parameter $\mu$and the scale parameter σ. The normal probability density function $f(x^L)$ is expressed as

$$f(x^L) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x^L-\mu)^2}{2\sigma^2}} \tag{30}$$

In LSA technique, σ_L is the scalar parameter that exponentially decreases as it finds the best solution, $\mu_L$for the lead projectile p^L. The new position of p^L is represented as

$$p_{new}^L = p_i^L \pm normrand(\mu_L, \sigma_L), \tag{31}$$

where *normrand* is a random number generated by the normal distribution function. LSA has the advantages of fast convergence for solution compared with the other conventional optimization techniques, because it is inspired by natural phenomenon of lightning. Moreover, it does not require numerous setting algorithm parameters. However, it easily gets trapped in local minima and requires searching for the best new position of the step leader.

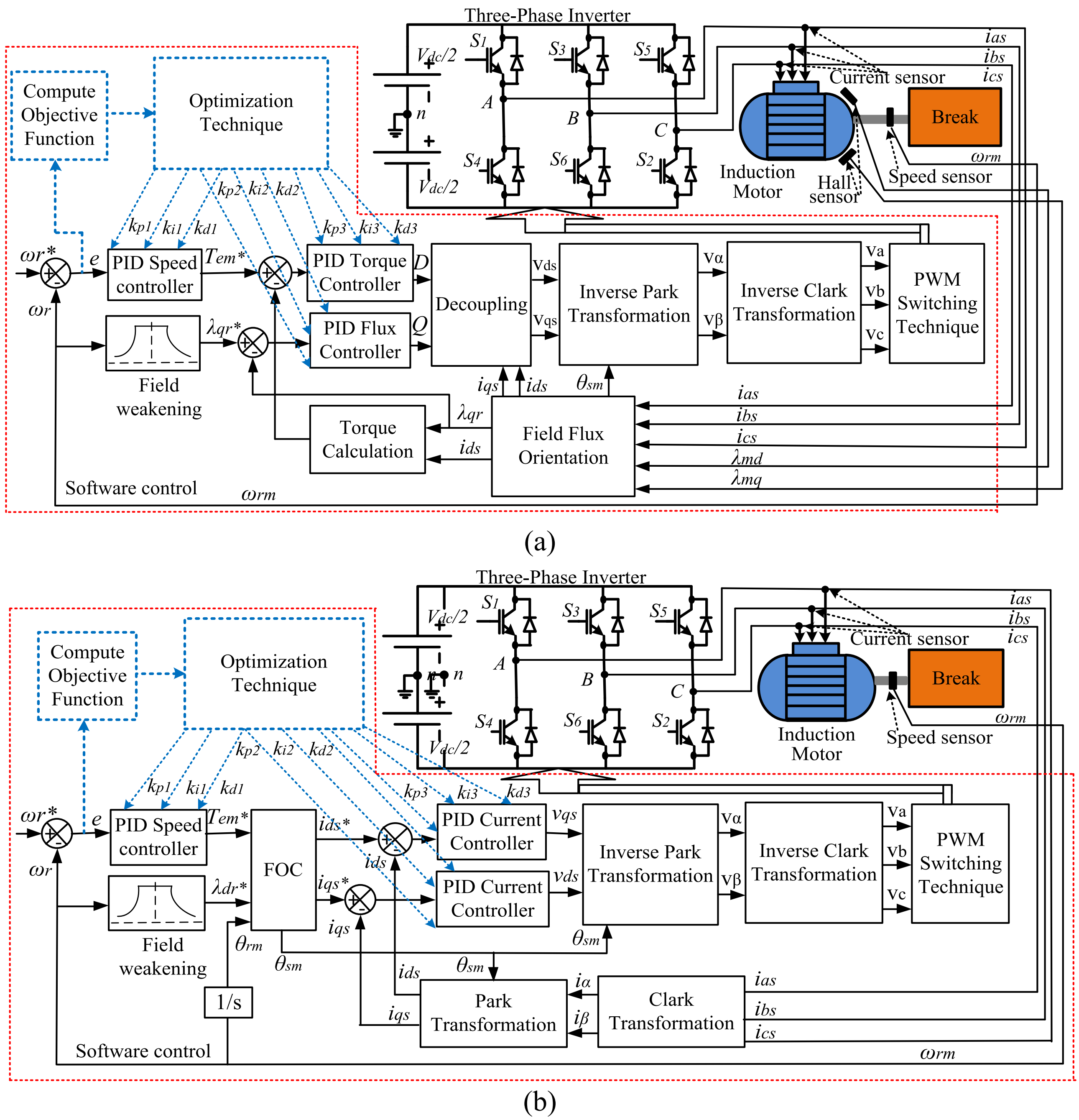

Fig. 10. Optimization technique based on PID controllers for (a) DFOC and (b) IFOC.

3.7. Quantum lightning search algorithm (QLSA)

The concept of quantum lightning search algorithm (QLSA) involves developing the original LSA [182] by searching for a new position for the population to obtain the best position for step leaders. At the beginning, QLSA is conducted to build memory according to the mean of the best positions of the step leaders, which are called global step leaders (Gsl_{ij}^{t}). Global step leaders represent the best step leaders that can obtain the minimum value of the evaluation. In QLSA, each step leader exhibits the quantum behavior with its quantum state formulated by a wave function (ψ_w). $|\psi_w|^2$ is the probability density function, which depends on the potential field where the step leader lies. QLSA achieves the attraction and convergence of each step leader with a global minimum and searches for the best position by relying on the stochastic attractor of step leaders p_j as represented in the following novel equation [108].

$$p_{ij}^{t} = \frac{a_{ij}^{t}.\ P_{ij,best}^{t} + b_{ij}^{t}.\ Gsl_{ij}^{t}}{c_{ij}^{t}.\ SF} \tag{32}$$

for $i = 1,2,\ldots,N$, $j = 1,2,\ldots,D$, and $t = 1,2,\ldots,T$, where N, D, and T are the population size, the problem dimension, and the maximum number of iteration, respectively; a, b, and c are three uniformly distributed random numbers on the range (0,1) for the jth dimension of step leaders; $P_{ij,best}^{t}$ is the best step leader for each population; and SF is the scale factor, which is suggested to set between 4 and 20.

QLSA has several distinctive properties when compared with the original LSA. First, QLSA explores new positions using an exponential distribution obtained through the global convergence between step

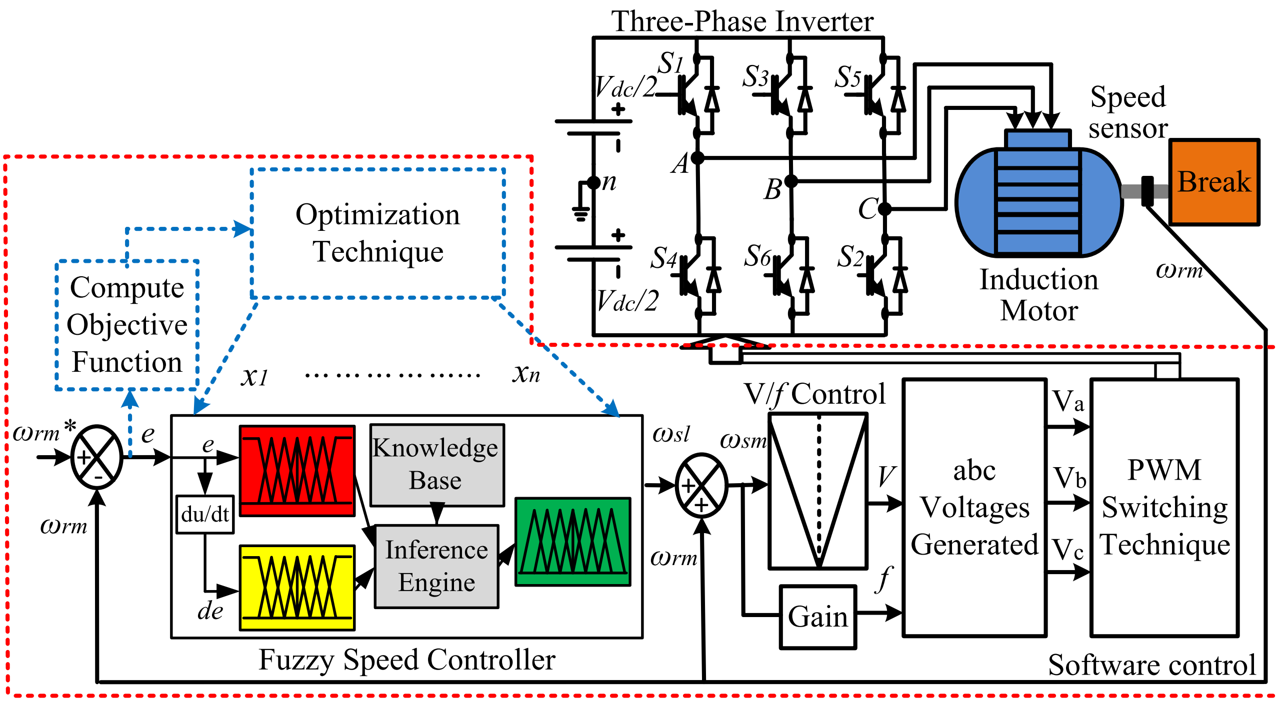

Fig. 11. Optimization technique based on fuzzy logic speed controller for scalar control.

leaders. Second, QLSA calculates the mean best position to enhance the original LSA. Moreover, each step leader in QLSA cannot approach the global best position without regarding other step leaders. The distance between step leaders and $MeanBest_j^t$ directs the new position distribution for each iteration as follows.

$$P_{ij}^{t+1} = p_{ij}^t \pm \beta|MeanBest_j^t - P_{ij}^t| ln(1/u_{ij}) \tag{33}$$

Suppose the global best position for a step leader is far from the other step leaders, the MeanBest_j^tmay be pulled toward the global best position. By contrast, in QLSA, the step leaders around the global best position may move in any direction to obtain the best new position. In particular, the QLSA algorithm is tested and validated through functional characteristics, such as dimensionality, separability, and modality [182–184]. The modality of a function refers to the number of vague peaks in the function surface. A function is multimodal if it has two or more vague peaks. An algorithm that encounters these peaks while searching may be trapped in one of the local minima. Separability indicates the difficulty level of various benchmark functions. In general, separable functions are easier to solve than non-separable functions because each variable of a function is independent of other variables. Moreover, the difficulty of a problem also increases along with function dimensionality. For highly non-linear problems, dimensionality may be a significant barrier for nearly all optimization algorithms.

4. Optimization algorithm-based controller techniques

Optimization algorithms are used in many applications to improve their performance and efficiency. This section explains some of the previous works on controller techniques based on optimization algorithms. For example, GA is used to improve FLC and PI controller for the optimal speed tracking control in the IFOC of an IM [102]; to design the fuzzy gain scheduling of a PI controller for speed control in the IFOC of an IM [185]; to optimize FLC by selecting a factor for the input of membership functions (MFs) [47]; to find the best PI speed controller parameters for the motor and prototype implementation of DSP; to determine the optimal weights between the membership and rule layers of a recurrent fuzzy neural network and implemented using DSP [186,187]; to enhance the PI speed controller parameters in the V/f control of an IM and implement using DSP [188]; to develop the performance of an IM and prototype implementation using dSPACE, which is based on a hybrid FLC–PI controller [189]; to optimize the sliding surface slope and thickness of the boundary layer implemented using DSP [10]; and to improve ANFIS speed controller in V/f control for IM by searching for the best PI parameter values and implemented using DSP [57]. PSO is used to identify optimal intelligent model parameters for high-power PMSM [104]; to optimize nine-rule FLC for MPPT in a grid-connected PV inverter [99]; to improve FLC by searching for the best values of the setting values of the input MFs in the MPPT algorithm for PV systems [190]; to improve the speed control of IM [191]; and to optimize FLC by searching for the best values for the scaling factor of the input and output FLC, thereby enhancing the speed control of a quasi-Z source DC/DC converter-fed drive [192,193]. In Ref. [54], PID and FLC–PI controllers were improved with the GA and PSO. The PID controller was enhanced through the optimization methods to find the best values for PID parameters. The FLC–PI controller was optimized with GA and PSO to find the best values of the scaling factor for its input and output. In Ref. [103], a hybrid GA–PSO was tuned for a PI-speed controller and PI-current controller in IFOC to minimize operation losses and the optimal torque control of IM. In Ref. [194], BSA was used to tune the PID parameters for DC torque motor systems. In Ref. [195], BSA was applied to tune the PI and PID controller parameters for DC torque motor systems. Table 2 summarizes the optimization algorithms for improving controller techniques.

5. Challenges and recommendations

The controller techniques play an important role in enhancing the performance of control systems. However, controller techniques encounter challenges and issues in implementing the control systems. In this paper, optimization techniques are recommended to solve and improve these issues, which are explained as follows.

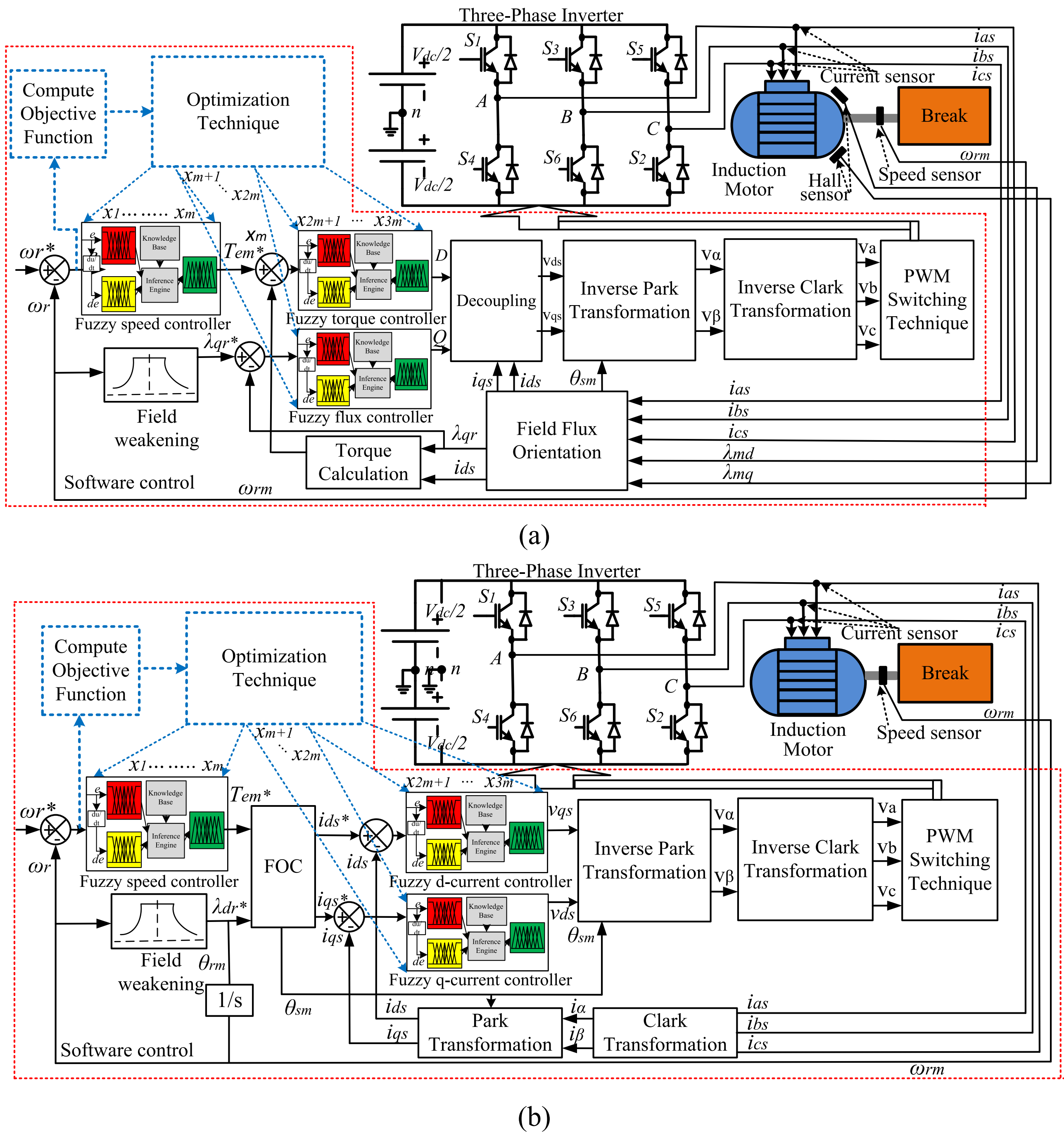

Fig. 12. Optimization technique based on FLC controllers for (a) DFOC and (b) IFOC.

5.1. Conventional controller challenges

Suitable parameters for IM control are difficult to obtain in a conventional controller. Also, the conventional controller requires mathematical modeling, which has high sensitivity on parameter variations, sudden change in reference speed, temperature variation, and load disturbances [16,30,38,43,44]. In this work, optimization techniques are suggested to solve these problems on scalar or vector control for IM drive, as discussed in the following sub-sections.

5.1.1. Optimization technique based on PID controller for scalar control

Speed controller-based optimization techniques can be used to improve the scalar IM drive control, as shown in Fig. 9. The recommended optimization technique receives rotor speed error and calculates objective functions, such as mean absolute error, root mean square error, and mean square error. This optimization technique aims to achieve good performance by minimizing the objective function under sudden speed change and mechanical load conditions. Then, the optimization technique searches for the best value of the conventional PID speed controller parameters.

5.1.2. Optimization technique based on PID controller for vector control

The optimization techniques based on speed, torque, and flux controllers can be used to improve the DFOC system for IM drive, as shown in Fig. 10(a). Fig. 10(b) shows the optimization technique based on speed and current controllers in improving the IFOC system for an IM drive. In both cases, these optimization techniques receive rotor speed errors and calculate the objective functions. Upon minimizing the objective functions under sudden speed change and mechanical load conditions, the optimization technique finds the suitable parameters for the conventional PID speed, torque, and flux controller for DFOC system, and PID speed and current controller for IFOC system.

5.2. FLC challenges

In the conventional FLC structure, the number and limits of each MFs should be selected in a suitable position, which is set by the designer using a trial-and-error procedure until the FLC provides a favorable result. However, this task is difficult to achieve because of its long computational time and effort to find the MF boundaries. Thus, an adaptive FLC design technique should be used to control the IM speed drive using an optimization technique, in which the exhaustive traditional trial-and-error procedure is avoided in obtaining the minimized or best MFs. The generated adaptive MFs are then implemented in the input and output of the fuzzy speed controller to solve the problems of the scalar or vector control.

5.2.1. Optimization technique based on FLC controller for scalar control

The optimization techniques based on fuzzy logic speed controller can be used to enhance the scalar control for an IM drive, as shown in Fig. 11. The recommended optimization technique receives rotor speed error and calculates objective functions. This optimization technique aims to achieve good performance by minimizing the objective functions under a sudden change of speed and mechanical load conditions. Then, the optimization technique searches for the best values for error, change of error, and MF boundaries for the input and output of the fuzzy speed controller to enhance the scalar control of the IM drive.

5.2.2. Optimization technique based on FLC controller for vector control

The optimization techniques based on fuzzy logic speed, torque, and flux controllers can be used to improve the DFOC system for an IM drive, as shown in Fig. 12(a). Fig. 12(b) shows the optimization technique based on fuzzy speed and fuzzy *dq* current controllers to improve the adaptive IFOC system for an IM drive. In both cases, the optimization technique receives rotor speed error and calculates objective functions. Upon minimizing the objective functions under sudden speed change and mechanical load conditions, the optimization technique searches for the best values for error, change of error, and MF boundaries for the input and output of the fuzzy logic speed, torque, and flux controller for the DFOC system, and fuzzy speed and fuzzy *dq* current controllers for the IFOC system.

6. Conclusion

IM drives significantly contribute either to the industrial electricity consumption or the energy conversion from electrical to mechanical or vice versa. Considerable amount of energy savings can be achieved if VFDs are used to replace the existing non-adjustable IM speed drives. Furthermore, an appropriate IM control can minimize loss and enhance the efficiency of a drive system. Numerous controller techniques and optimization algorithms are available for the IM drive, such as the conventional controller. Moreover, FLC controllers are investigated to address the issues of minimizing overshoot, settling time, and steady-state error of the IM drive. Various control system platforms explained the utilization of the optimization algorithms to improve the performance of the controller. To fulfill the objective, issues and challenges of controller techniques in the scalar and vector control for IM drive are highlighted for future research and development guidelines. Also some significant and selective suggestions for the further development of the IM drive controller have been produced in this review, such as:

i) Optimization technique based on conventional and FLC controller for scalar and vector IM drive control can reduce the MFs and find the best parameters for their controllers;
ii) A developed optimization technique can be applied in fuzzy type-2 controller, model free controller, or hybrid FLC–PI controller to enhance the control of a multi-IM drive system;
iii) A developed optimization technique can be applied in multi-DC motor drive or multi-PMSM drive to minimize the manufacturing cost of the control system;
iv) An optimization technique can be developed to find the best error and flux changes of the torque to minimize the current ripple, noise, and frequency variation of an IM drive system;
v) The optimization technique can achieve robustness, damping capability, enhanced transient responses, and significant speed reduction responses in terms of overshoot, steady-state error, and settling time to improve the overall performance of an IM drive system.

These suggestions would be remarkable contributions toward the maturity of IM drive control technologies. Thus, further development of optimized controller for IM drives should dominate the market in the future.

Acknowledgement

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