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A Comparative Performance Analysis for loss Minimization of Induction Motor Drive Based on Soft Computing Techniques

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Abstract
This paper presents a comparative performance assessment for loss minimization of vector controlled induction motor (IM) drive based on three different efficient optimization algorithms, namely Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Golden Search (GS). The present work deals with the recalculation of optimized flux component of current based on the mentioned techniques, for a better optimal efficiency operation of the IM drive. All the three algorithms based IM drive operation show improvement in efficiency by reduction in the core loss of the drive system. However, it is PSO based IM drive operation that has the advantages of fast response and high accuracy compared to other two schemes. The PSO based energy optimization scheme adaptively adjust the flux component of current to minimize the system loss Moreover, the three approaches have no effect on parameter variation and also need no additional hardware for hardware implementation. The simulation results for various speed patterns and operating conditions are presented here. Stability study of the whole drive system is also carried out utilizing the three optimizing schemes.

Keywords: Golden Search Algorithm, Genetic Algorithm, Particle Swarm Optimization, System Stability Analysis

INTRODUCTION

In practical applications, the energy optimization of induction motor (IM) drive in dynamic environment is vital, that involve the energy optimization algorithms to be capable of finding and tracking of changing optimum efficiency over a period of time [1]. IM drive have been widely used in industries, both in fixed and variable speed applications, due to the development of power semiconductor devices, microelectronics, and control techniques [2, 3]. These motors present as advantages the size, cost, weight, reliability, and easy maintenance [4, 5]. It is estimated that the induction motors consume two-third of the electricity produced in the United States, and in average, they operate at 60 percent of the rated load, because of oversized installations or under loaded conditions, and therefore have low efficiencies [6]. Since, a large number of IM drives are operational worldwide and every year there is definite positive increase in their numbers, thereby an improvement in efficiency by minimizing the losses will significantly have a good impact on energy saving [14]. Minimization of loss in the induction motor is directly related to choice of the flux level. But the extreme minimization causes a high copper loss [15]. For constant speed operation, provided torque is variable the flux has to vary, so as to improve the drive efficiency. A number of energy optimization strategies such as simple state control [16], search control [17], and loss model based control [18] for IM drive have been reported in the literature. The loss model based control consists of computing losses by using the machine model and selecting a flux level that can be used to minimize the losses. The second category is the power-measure-based approach, also known as search controllers (SCs), in which the flux is decreased until the electrical input power settles down to the lowest value for a given torque and speed [19], [20], & [12].

There are number of search optimization techniques such as GA, PSO, Ant Colony, Bee Colony etc. But, the PSO is found more popular due to its simplicity and accuracy. This algorithm is developed by Kennedy and Eberhart in 1990. The basic concepts regarding this are available in [7]. The application of this algorithm starts increasing in almost all the areas of engineering.

The particle swarm optimization (PSO) is characterized as simple in concept, easy to implement, and computationally efficient unlike the other heuristic techniques. PSO has a flexible and well balanced mechanism to enhance and adapt the global and local exploitation abilities [21].

The genetic algorithm (GA) based method mainly works on principle of optimization of a significant parameter (e.g., DC link power or DC-link current or stator current or drive losses) by trial and error method [22], [23]. Unlike other control strategies, the method does not depend upon the motor or converter parameters. They belong to the class of EAs, which are used to find solutions optimizing complex problems such as the optimization of closed-loop drive-fed motors. Indeed their uses to solve complex problems respond to the necessity to generate approximate solutions when the exact solution cannot be find with a classic optimization method (e.g. Newton-Raphson). However, the method suffers from the torque ripples and slow convergence rate. Nevertheless, the problem may be overcome using second order low-pass filter.

The golden search algorithm is generally used to minimize the IM drive loss. This also has a close relation to the Fibonacci search method [24]. However, the golden search technique has a definite edge over the Fibonacci search algorithm as the later needs to know a priori the number of evaluations in the minimum searching process, which is totally eliminated in the former one [25]. To achieve a minimal machine core loss, the golden search technique searches the optimal value of rotor flux reference using very fast convergence algorithm.

In the present work, the problem is formulated for efficiency optimization by minimizing losses using PSO, GA and GS based algorithms are used to minimize the loss in the IM drive. A comparative performance analysis of the 1.3 kW IM drive system is carried out for three (PSO, GA and GS) algorithms in different operating conditions together with conventional FOC method. The drive system consists of an energy optimization algorithm based on the power loss of drive and speed error signal to generate optimal value of and hence optimal rotor flux.

LOSS MINIMIZATION MECHANISM

The loss minimization algorithm is based on searching optimal value of the flux component of stator current , for which the input power of the system can be minimal. The input power is calculated as the product of the measured DC voltage and DC current as follow:

$$P_{in} = V_{dc} \bullet I_{dc} \tag{1}$$

The efficiency of machine is defined as the ratio of the mechanical output power to the electrical input power. Therefore, for increasing the efficiency of a machine, the electrical input power can be optimized to reduced value by minimizing the total losses. Thus, the loss minimization is accomplished by adjusting the flux level through the reference flux component current . The loss-model based approach [26], [27], [28], & [29] is utilized in this work for the generation of reference flux current. In this method, the loss is computed by using the machine model and selecting the flux level that minimizes the losses.

GOLDEN SEARCH ALGORITHM

In golden search based algorithm, the maximum value of the fluxcurrentequalstoitsratedvalue $\left(i_{ds\max} = i_{ds}\right)$ is defined andtheminimal value equals to $\alpha * i_{ds}$, where $\alpha = \sim 0.5$ depending on load levels. Thealgorithmcalculates the flux current in the interval between $(i_{ds\,min}, i_{ds\,max})$, which is fed to the control system to reduce the total input power of the drive. The input ower is calculated in eqn.1.

The new values of the reference flux current $(i_{ds})$are calculated using two golden search sections; F_1 and F_2 as below;

$$F_1 = \frac{\sqrt{5}-1}{2} = 0.618 \text{ and } F_2 = \frac{3-\sqrt{5}}{2} = 0.382 \tag{2}$$

The algorithm calculates two values of the reference flux currents $\left(i_{ds1}^*, i_{ds2}^*\right)$in interval $(i_{ds\,min}, i_{ds\,max})$ using the golden sections. The input power corresponding to these two current levels is calculated as as depicted in eqn. 1. The reference flux currents $\left(i_{ds1}^*, i_{ds2}^*\right)$ consequently are re-calculated and their corresponding values of input power are re-measured and re-evaluated. The search procedure repeats itself until the desired accuracy is achieved.

$$\left|i_{ds2}^* - i_{ds1}^*\right| < \varepsilon_i \tag{3}$$

where ε_i is the flux current tolerance. The final value of reference flux current is calculated by averaging the values of i_{ds1}^*, i_{ds2}^*

$$i_{ds}^* = \frac{i_{ds1}^* + i_{ds2}^*}{2} \tag{4}$$

The golden search algorithm is fast and immune for the motor parameters. The technique comprises of all the losses including the loss in inverter, since the power entering to the system is measured and used in the optimization algorithm.

GENETIC ALGORITHM

Genetic algorithm (GA) [Goldberg DE. Genetic Algorithms in Search], is inspired by Darwin's theory about evolution – "the Survival of the fittest". In GA, the optimization problem is resolved by imitating the practices through natural use i.e. selection, crossover, mutation and accepting [34]. In the most general sense, GA-based optimization is a stochastic search method that involves the random generation of potential design solutions and then systematically evaluates and refines the solutions until a stopping criterion is met. Sets of nonlinear equations are solved which are represented by objective functions based on some criterion

GAs is parallel, global search techniques which take the concepts from evolution theory and natural genetics. They emulate biological evolution by means of genetic operators such as reproduction, crossover and mutation etc. GAs work with a set of artificial creature (string) called population. In every generation, GAs generates a set of offsprings from old population according to a user-defined fitness function. The fitness function represents the performance of a problem. The higher the fitness value, the better the performance of a system. By exchanging the information between every individual, GAs keeps the better scheme, which may yield higher fitness, from generation to generation such that the performance can be improved [35], [36], [37], [38].

The GA is an adaptive heuristic search based on the evolutionary ideas of natural selection and genetics. It is intelligent exploitation of random search and exploits historical information to direct the search into the region of better performance within the search space [39], [40]. In GA method applied for optimization, the chromosomes are the solution for problems involved in optimization. Each chromosome in the process is assessed by blending it into the schedule with an objective function. In GA process, in the beginning stage, the chromosmes are produced randomly [41]. The mechanism of selection, crossover and mutation lead to birth of superior quantity offspring from the previous generation (parents). However, throughout the genetic evolution, only the stronger chromosomes survive. At the end stage of the evolutionary process, near-optimal or optimal solutions can be achieved.

Steps involved in GA optimization process are illustrated below:

Step 1: ***Generation of random population of 'popsize' chromosomes (i.e. suitable solution for the problem).***

The initial random population comprising of individuals whose characteristics is coded by the sequence of zeros and ones is achieved by the initialization generation. These individuals are genes in a chromosome. The size of the population is determined according to the complexity of the control problem.

Step 2: **Evaluation of the fitness function $f(i_{ds})$ of each chromosome 'i^*_{ds}' in the population ($f(i^*_{ds})$). Minimize ($f(i^*_{ds})$), where $i^*_{ds} = i^*_{ds1}, i^*_{ds2}, i^*_{ds3}, \ldots\ldots i^*_{dsn}$.**

The fitness function is the indication of GA performance in resolving the practicality of each chromosome. A fitness function is designed based on a suitable performance criterion. The fitness value for each chromosome inside the population is assessed then scaled.

Step 3: **Creation of a new population by iterating the selection, crossover, mutation and accepting process until the new population is complete.**

a. Selection: Selection is the process to select most of the better chromosomes in each generation to crossover and the rest or some of the rest to mutate. The tournament method is adopted in our GA. The reason is that in the tournament method the objective value of a chromosome can be used as the selection criterion.
b. Crossover: Crossover is the process during which two parents generate two offspring, such that the offspring inherit a set of building blocks from each parent. Assume the number of the chromosomes to be selected for crossover is *xsize*. Crossing the parents with crossover probability *Cr* = *xsize*/*popsize* to form new offspring and if no crossover is performed, offspring is the exact copy of the parents. often $Cr \in [0.5, 0.9]$.
c. Mutation: Mutation is the process during which some genes of a chromosome are changed and a new chromosome is generated. the number of the chromosomes to be selected for mutation is *msize,* and the ratio *Mr*=*msize*/*popsize* is termed mutation rate, often $Mr \in [0.1, 0.3]$.
d. Accepting: positioning new offspring in the new population.

Step 4: **Use of new generated population for further run of the algorithm.**

Reproduction is the operator carrying old strings through into a new population, depending on the fitness value. Individuals with higher fitness values will be more likely to be selected than those with lower fitness values. Moreover, the roulette wheel selection [42] method is adopted in this study for reproduction.

Step 5: **If the end condition is satisfied, stop and return the best solution in existing population.**

The GA is terminated when the search goal is completed or the required generation is attained. If this does happen, return to step 2 and repeat the steps again.

PARTICLE SWARM OPTIMIZATION

PSO, cited in reference [14], requires only primitive mathematical operators and computation requires small amount of memory PSO is stochastic, population-based, global optimization algorithm mainly dedicated to continuous problems (continuity of the search space). It was introduced in 1995 (Kennedy and Eberhart, 1995) [30] and is based on the observations of the social behavior of a population of animals (birds, fishes). This method has proven its efficiency in solving engineering problems and has received interest from optimization and engineering communities. In addition, it depends on few parameters to be set.

PSO is initially proposed to solve unconstrained problems. It is initialized with a set of particles, each one corresponds to a candidate solution. PSO finds the global optimum by moving each particle with randomly weighted velocities.

Particle swarm optimization (PSO) is an evolutionary computation technique developed by Kenney and Eberhart in 1995 [1]. The method has been developed through a simulation of simplified social models. PSO is based on swarms such as fish schooling and birdflocking.

According to the research results for bird flocking, birds are finding food by flocking (not by each individual). Like GA [31], [32]], PSO must also have a fitness evaluation function that takes the particle's position and assigns to it a fitness value. The position with the highest fitness value in the entire run is called the global best (P,). Each particle also keeps track of its highest fitness value. The location of this value is called its personal best (e) . The basic algorithm involves casting a population of particles over the search space, remembering the best (most fit) solution encountered. At each iteration, every particle adjusts its velocity vector, based on its momentum and the influence of both its best solution and the best solution of its neighbors, then computes a new point to examine. The studies shows that the PSO has more chance to "fly" into the better solution areas more quickly, so it can discover reasonable quality solution much faster than other evolutionary algorithms.

Inspired by the flocking and schooling patterns of birds and fish, Particle Swarm Optimization (PSO) was invented by Russell Eberhart and James Kennedy in 1995. PSO might sound complicated, but it's really a very simple algorithm. Over a number of iterations, a group of variables have their values adjusted closer to the member whose value is closest to the target at any given moment. Imagine a flock of birds circling over an area where they can smell a hidden source of food. The one who is closest to the food chirps the loudest and the other birds swing around in his direction. If any of the other circling birds comes closer to the target than the first, it chirps louder and the others veer over toward him. This tightening pattern continues until one of the birds happens upon the food. It's an algorithm that's simple and easy to implement.

The algorithm keeps track of three global variables:

- Target value or condition
- Global best (gBest) value indicating which particle's data is currently closest to the Target
- Stopping value indicating when the algorithm should stop if the Target isn't found.

Target value or conditio Global best (gBest) value indicating which particle's data is currently closest to the Targ Stopping value indicating when the algorithm should stop if the Target isn't found

Each particle consists of:

- Data representing a possible solution
- A velocity value indicating how much the data can be changed
- A personal best (pBest) value indicating the closest the particle's data has ever come to the target.

Data representing a possible solutio A velocity value indicating how much the data can be changed

A personal best (pBest) value indicating the closest the particle's data has ever come to the target.

The particles' data could be anything. In the flocking birds example above, the data would be the X, Y, Z coordinates of each bird. The individual coordinates of each bird would try to move closer to the coordinates of the bird which is closer to the food's coordinates (gBest). If the data is a pattern or sequence, then individual pieces of the data would be manipulated until the pattern matches the target pattern.

The velocity value is calculated according to how far an individual's data is from the target. The further it is, the larger the velocity value. In the birds example, the individuals furthest from the food would make an effort to keep up with the others by flying faster toward the gBest bird. If the data is a pattern or sequence, the velocity would describe how different the pattern is from the target, and thus, how much it needs to be changed to match the target.

Each particle's pBest value only indicates the closest the data has ever come to the target since the algorithm started.

The gBest value only changes when any particle's pBest value comes closer to the target than gBest. Through each iteration of the algorithm, gBest gradually moves closer and closer to the target until one of the particles reaches the target.

It's also common to see PSO algorithms using population topologies, or "neighborhoods", which can be smaller, localized subsets of the global best value. These neighborhoods can involve two or more particles which are predetermined to act together, or subsets of the search space that particles happen into during testing. The use of neighborhoods often help the algorithm to avoid getting stuck in local minima.

Algorithm for implement PSO.

1. Initialize a population array of particles with random positions and velocities on *D* dimensions in the search space.
2. Loop
3. For each particle, evaluate the desired optimization fitness function in *D* variables.
4. Compare particle's fitness evaluation with its *pbesti*. If current value is better than *pbesti*, then set *pbesti* equal to the current value, and *pi* equal to the current location
   xi in *D*-dimensional space.
5. Identify the particle in the neighborhood with the best success so far, and assign its index to the variable *g*.
6. Change the velocity and position of the particle according to the following equation (see notes below):

$$\begin{cases} \vec{v_i} \leftarrow \vec{v_i} + \vec{U}(0,\varphi_1) \otimes (\vec{p_i} - \vec{x_i}) + \vec{U}(0,\varphi_2) \otimes (\vec{p_g} - \vec{x_i}) \\ \vec{x_i} \leftarrow \vec{x_i} + \vec{v_i} \end{cases}$$

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7. If a criterion is met (usually a sufficiently good fitness or a maximum number of iterations), exit loop.
8. end loop

Notes: – $\vec{U}(0,\varphi_1)$ represents a vector of random numbers uniformly distributed in $[0,\varphi_1]$ which is randomly generated at each iteration and for each particle.

– ⊗ is component-wise multiplication.

– In the original version of PSO, each component of $\vec{v}_i$ is kept within the range [-*V*max,+*V*max].

The proposed technique is applied to a 3-hp induction machine [1] to identify fluxcomponent of current [33].

LOSS MODEL OF INDUCTION MOTOR

The IM drive model with iron loss (Figure 1) is given by following equations as [43], [44]:

$$v_{ds}^s = R_s i_{ds}^s + \sigma L_s p i_{ds}^s + L_m p i_{dm}^s - \omega_e \left(\sigma L_s i_{qs}^s + L_m i_{qm}^s\right) \quad (5)$$

$$v_{qs}^s = R_s i_{qs}^s + \sigma L_s p i_{qs}^s + L_m p i_{dm}^s + \omega_e \left(\sigma L_s i_{ds}^s + L_m i_{dm}^s\right) \quad (6)$$

$$v_{dr}^s = R_r i_{dr}^s + \sigma L_r p i_{dr}^s + L_m p i_{dm}^s - (\omega_e - \omega_r)\left(\sigma L_r i_{qr}^s + L_m i_{qm}^s\right) \quad (7)$$

$$v_{qr}^s = R_r i_{qr}^s + \sigma L_r p i_{qr}^s + L_m p i_{qm}^s + (\omega_e - \omega_r)\left(\sigma L_r i_{dr}^s + L_m i_{dm}^s\right) \quad (8)$$

The d-axis and q-axis components of magnetic flux are given as;

$$\psi_{ds}^s = \sigma L_s i_{ds}^s + L_m i_{dm}^s \quad (9)$$

$$\psi_{qs}^s = \sigma L_s i_{qs}^s + L_m i_{qm}^s \quad (10)$$

$$\psi_{dr}^s = \sigma L_r i_{dr}^s + L_m i_{dm}^s \quad (11)$$

$$\psi_{qr}^s = \sigma L_r i_{qr}^s + L_m i_{qm}^s \quad (12)$$

The induced voltage on the magnetizing branch is given as;

$$v_{di}^s = L_m p i_{dm}^s - \omega_e L_m i_{dm}^s \quad (13)$$

$$v_{qi}^s = L_m p i_{qm}^s + \omega_e L_m i_{qm}^s \quad (14)$$

The interaction between stator current and magnetic flux components give electromagnetic torque in d-q coordinate frame as;

$$T_{em} = \frac{3}{2} P \frac{L_m}{\sigma L_{r+L_m}} \left[\psi_{qr}^s\left(i_{ds}^s - i_{dfe}^s\right) - \psi_{dr}^s\left(i_{qs}^s - i_{qfe}^s\right)\right] \quad (15)$$

The total loss is given by;

$$P_{loss} = \frac{3}{2}\left[R_s\left(i_{ds}^s + i_{qs}^s\right) + R_r\left(i_{ds}^s + i_{qs}^s\right) + \frac{1}{R_f}\left(v_{di}^s + v_{qi}^s\right)\right] \quad (16)$$

or, $P_{loss} = P_{js} + P_{jr} + P_{fe}$ (17)

Where, P_{js} = stator copper loss; P_{jr} = rotor copper loss; P_{fe} = core loss including eddy current and hysteresis loss.

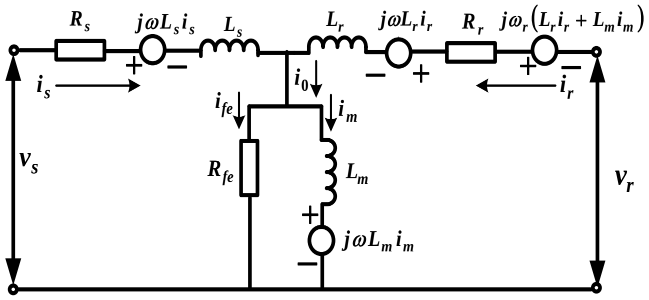


Figure 1: Equivalent circuit model of induction motor in T-form with iron loss.

INPUT POWER MEASUREMENT

The drive is equipped with DC voltage and current sensors to evaluate *P*in accurately. The motor is run in closed loop speed control without load, such that the contribution of the rotor copper losses is negligible. The currents, voltages and input powers are recorded when steady-state conditions are reached.

LOSS MINIMIZATION OF IM DRIVE

The improved dynamic performance with minimum loss is the important requirements for the IM drive. Therefore, loss minimization schemes using GA algorithm [45, 46] } have been incorporated in the outer loop of the control scheme. The vector control not only has the advantage of providing excellent dynamic performance, but also, enables decoupled control of torque and flux through d-axis (flux-producing) and q-axis (torque-producing) currents in the steady state. This makes the inclusion of the loss minimization algorithm simple [24]. The drive loss is calculated from the difference between the power input to the inverter and the shaft power output. The reference flux current, i_{ds}^* }is generated by the optimization algorithm, while the torque component of current is acquired from the speed control loop. In the transient state, when either the speed command or the load torque is changed, the nominal value of the i_{ds}^* comes into play.The transient speed is easily detected when the speed error signal ($\Delta\omega_e$) reaches the maximum value 0.5 rad/s and the energy optimization algorithm starts settling the i_{ds}^{*} to the required optimal value. The optimal value of i_{ds}^{*} generates the optimized required flux without affecting the output power. The optimal value of flux reduces the power loss of the drive system thus fulfilling objective of the proposed work. The detailed schematic diagram for estimation of speed with loss minimization algorithm is shown in Figure 2.

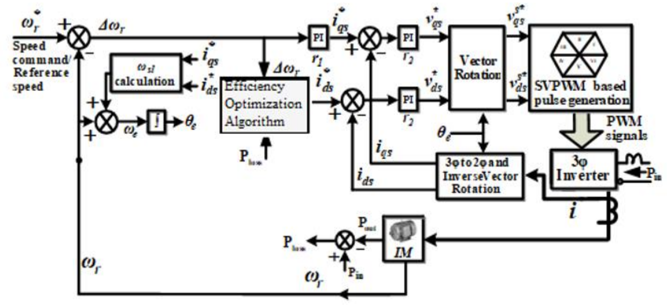


Figure 2: Schematic diagram of vector controlled IM drive and efficiency optimization scheme.

SYSTEM STABILITY ANALYSIS

To carry out the stability analysis of any system, the variables must be time-invariant [15]. The IM model in synchronously rotating (ω_e)} reference frame has been expressed as

$$\begin{bmatrix} \dot{i}_{ds} \\ \dot{i}_{qs} \\ \dot{\psi}_{dr} \\ \dot{\psi}_{qr} \end{bmatrix} = \underbrace{\begin{bmatrix} -p_1 & \omega_e & p_2 & p_3\omega_r \\ -\omega_e & -p_1 & -p_3\omega_r & p_2 \\ p_4 & 0 & -p_5 & \omega_{sl} \\ 0 & p_4 & -\omega_{sl} & -p_5 \end{bmatrix}}_{A} \begin{bmatrix} i_{ds} \\ i_{qs} \\ \psi_{dr} \\ \psi_{qr} \end{bmatrix} + \frac{1}{\sigma L_s} \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}}_{B} \begin{bmatrix} v_{ds} \\ v_{qs} \end{bmatrix} \quad (18)$$

$$\begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}}_{C} \begin{bmatrix} i_{ds} \\ i_{qs} \\ \psi_{dr} \\ \psi_{qr} \end{bmatrix} \quad (19)$$

where, $p_1 = \frac{1}{\sigma L_s}\left(R_s + \frac{L_m^2}{L_r \tau_r}\right)$, $p_2 = \frac{1}{\sigma L_s}\left(R_s + \frac{L_m}{L_r \tau_r}\right)$, $p_3 = \frac{1}{\sigma L_s}\left(\frac{L_m}{L_r}\right)$, $p_4 = \left(\frac{L_m}{\tau_r}\right)$ and $p_5 = \left(\frac{1}{\tau_r}\right)$

In the state space domain, (1-2) can be represented as

$$\dot{x} = Ax + Bu \quad (20)$$

$$y = Cx \quad (21)$$

where, *A*, *B*, *C* are obtained from (18)-(19) and $x = \begin{bmatrix} i_{ds} & i_{qs} & \psi_{dr} & \psi_{qr} \end{bmatrix}^T$, $u = \begin{bmatrix} v_{ds} & v_{qs} \end{bmatrix}^T$, $y = \begin{bmatrix} i_{ds} & i_{qs} \end{bmatrix}^T$

Linearizing the state space equation around a stable operating point say x_0, the small signal representation is as

$$\Delta\dot{x} = A\Delta x + \Delta A x_0 \quad (22)$$

$$\Delta y = C\Delta x \quad (23)$$

$$\text{or, } \Delta y = C(sI - A)^{-1}\Delta A x_0 \quad (24)$$

$x_0 = \begin{bmatrix} i_{ds0} & i_{qs0} & \psi_{dr0} & \psi_{qr0} \end{bmatrix}^T$ represents the operating point.

For checking the feasibility of the algorithm for rotor speed estimation, ΔA is calculated in terms of $\Delta\omega_r$ as;

$$\Delta A = \begin{bmatrix} 0 & 0 & 0 & p_3 \\ 0 & 0 & -p_3 & 0 \\ 0 & 0 & 0 & -1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \Delta\omega_r \quad (25)$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad (26)$$

Using eqns(25) and (26), the expression of Δy in eqn(24) becomes;

$$\Delta y = \begin{bmatrix} \Delta i_{ds} \\ \Delta i_{qs} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} (sI - A)^{-1} \begin{bmatrix} 0 & 0 & 0 & p_3 \\ 0 & 0 & -p_3 & 0 \\ 0 & 0 & 0 & -1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} i_{ds0} \\ i_{qs0} \\ \psi_{dr0} \\ \psi_{qr0} \end{bmatrix} \Delta\omega_r \quad (27)$$

$$\text{Let, } (sI - A)^{-1} = \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & c_{34} \\ c_{41} & c_{42} & c_{43} & c_{44} \end{bmatrix}$$

The transfer function of $\frac{\Delta i_{ds}}{\Delta\omega_r}$ and $\frac{\Delta i_{qs}}{\Delta\omega_r}$ obtained from eqn(27) can be represented as

$$\frac{\Delta i_{ds}}{\Delta\omega_r} = \frac{(c_{14} - p_3 c_{12})\psi_{dr0}}{|sI - A|} \quad (28)$$

$$\frac{\Delta i_{qs}}{\Delta\omega_r} = \frac{(c_{24} - p_3 c_{22})\psi_{dr0}}{|sI - A|} \quad (29)$$

where, $adj(sI - A) = [C_{ij}]$ and *i*, *j* varies from 1 to 4.

From Figure 2, the following expressions have been derived:

$$v_{ds}^{*} = \left(k_{p3} + \frac{k_{i3}}{s}\right) \times \left(i_{ds}^{*} - i_{ds}\right) = r_2\left(i_{ds}^{*} - i_{ds}\right) \quad (30)$$

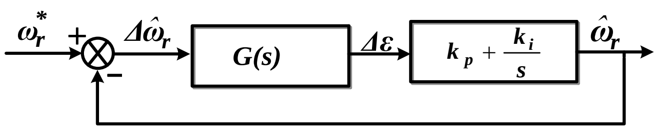


Figure 3: Closed loop representation of speed estimator

$$v_{qs}^{*} = \left(k_{p2}+\frac{k_{i2}}{s}\right)\left\{\left(k_{p1}+\frac{k_{i1}}{s}\right)\times\left(\omega_r^{*}-\omega_r\right)-i_{qs}\right\} = r_2\left\{r_1\left(\omega_r^{*}-\omega_r\right)-i_{qs}\right\} \quad (31)$$

where, $r_1 = \left(k_{p1}+\frac{k_{i1}}{s}\right) =$ transfer function of the speed PI controller, $r_2 = \left(k_{p2}+\frac{k_{i2}}{s}\right) =$ transfer function of current PI controllers, as seen from Figure 2.

To check feasibility of the algorithm for speed estimation, ΔA is calculated in terms of $\Delta\omega_r$ with an aim of obtaining $\Delta i_{ds}/\Delta\omega_r$ and $\Delta i_{qs}/\Delta\omega_r$. From the small signal error equation,, $\Delta\varepsilon/\Delta\hat{\omega}_r$ is represented as:

$$\frac{\Delta\varepsilon}{\Delta\hat{\omega}_r} = k_2\frac{\Delta i_{ds}}{\Delta\omega_r} + k_3\frac{\Delta i_{ds}}{\Delta\omega_r} + \left(k_5 - k_4\right) = G(s) \quad (32)$$

where, $k_2 = v_{qs0} - 2\sigma L_s\omega_{e0}i_{ds0} - 2\omega_{e0}\frac{L_m^2}{L_r}i_{ds0} + r_2 i_{qs0}$;

$k_3 = -v_{ds0} - 2\sigma L_s\omega_{e0}i_{qs0} - r_2 i_{ds0}$;

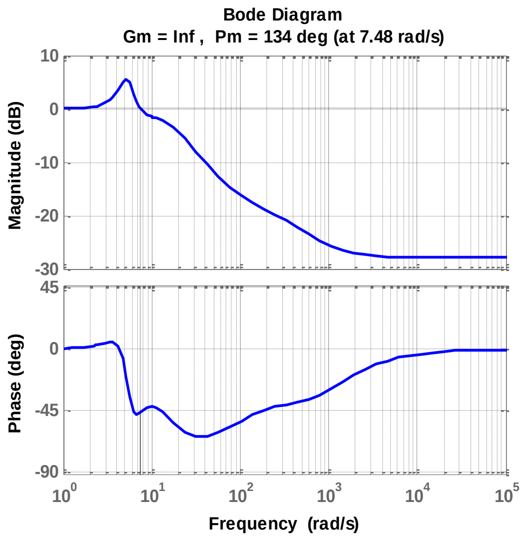
$k_4 = -\sigma L_s i_{ds0}^2 - \sigma L_s i_{qs0}^2 - \frac{L_m^2}{L_r}i_{ds0}^2$;

$k_5 = -\sigma L_s i_{ds0}^2 - \sigma L_s i_{qs0}^2 - \frac{L_m^2}{L_r}i_{ds0}^2 - r_1 r_2 i_{ds0}$;

The closed loop transfer function representation (Figure. 3) of the speed estimator is obtained as:

$$\frac{\hat{\omega}_r}{\omega_r^{*}} = G(s)\left(k_p+\frac{k_i}{s}\right)\Big/\left(1+G(s)\left(k_p+\frac{k_i}{s}\right)\right) \quad (33)$$

where, $\left(k_p+\frac{k_i}{s}\right) =$ is the transfer function of the PI controller. Equation 33 can be utilized for the small signal stability analysis with linearized machine equations for the proposed algorithms (GS, GA and PSO) based IM drive and is carried out for both the motoring and regenerating modes of operations. Since, the satisfactory performance of the drive in the low speed region is challenging, hence, drives stability study at a speed of 10 rad/s is reported. Figure 4 shows the bode plots as given in the figure captions for both the motoring and regenerating modes respectively. It is observed from the Bode plots that both the Gain Margin (GM) and Phase Margin (PM) are positive; representing a stable system for the IM drive system.



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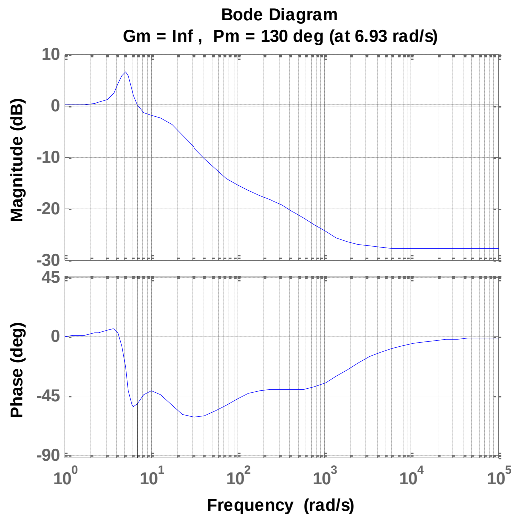

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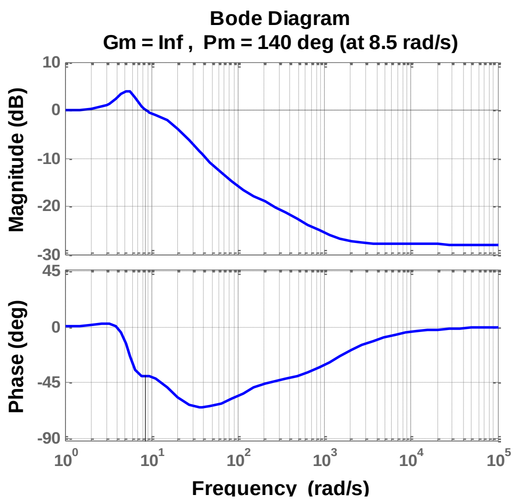

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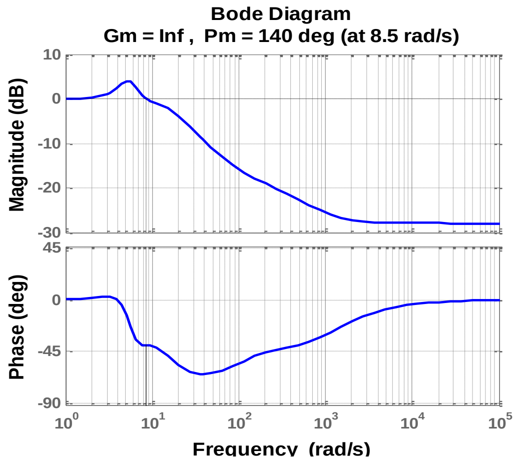

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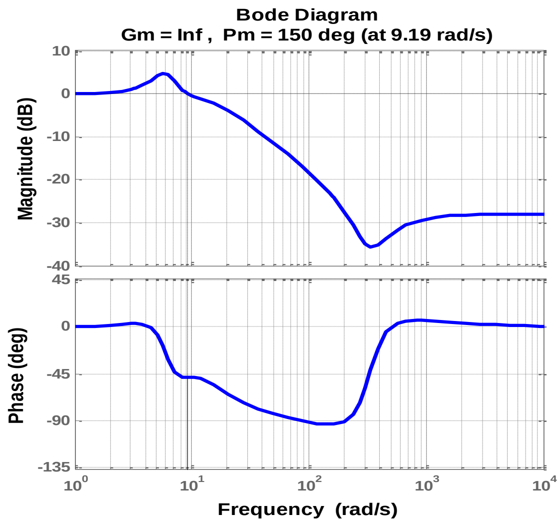

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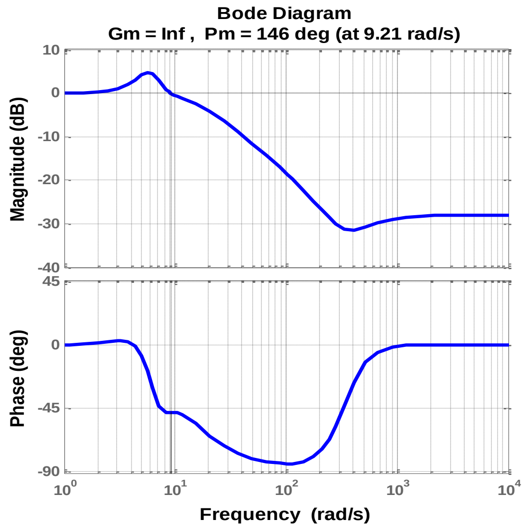


(f)

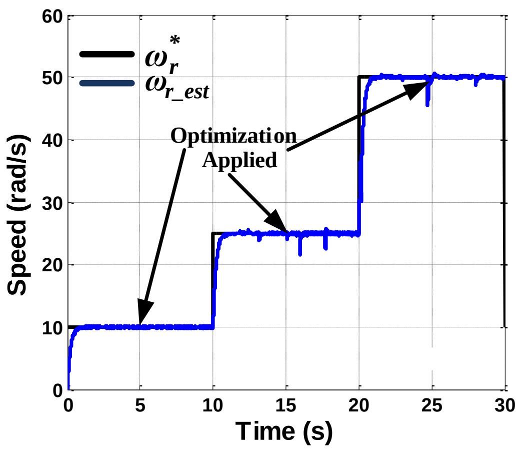
Figure 4: Bode plot of IM drive in motoring mode based on: (a) GS algorithm , (c) GA algorithm, (e) PSO algorithm, and in regenerating mode based on: (b) GS algorithm, (d) GA algorithm, (f) PSO algorithm.

SIMULATION RESULTS

The performance of the proposed algorithms for loss minimization of the vector controlled IM drive is verified in Matlab/Simulink for various test cases as described further in this section. The simulation results show the speed, rotor flux, stator current, and loss responses of the IM drive, before and after the optimization schemes are initiated for IM drive. The detailed specification of the 3-phase, 1.3 kW, IM drive is given in Appendix A.

Step change in rotor speed

Results of the GS, GA and PSO based optimization schemes, for the IM drive are studied in the motoring mode by a step change in the reference speed as shown in Figure. 5. An increasing step change in the speed command is applied at every 10 sec and the reference and actual speeds are shown for the whole speed range in Figure 5(a) , Figure 6(a) and Figure 7(a) for the GS, GA and PSO based optimization algorithms, respectively. Throughout the operation, a constant torque of 5 Nm is maintained. The flux components of the stator current (i_{ds}) is shown in Figure 5(b), Figure 6(b) and Figure 7(b). After every speed transient period, i_{ds} is adjusted to the optimal value by the algorithms. The flux orientation is also altered as the i_{ds} changes and is depicted in Figure 5(c), Figure 6(c) and Figure 7(c). The loss of the IM drive system is shown in Figure 5(d), Figure 6(d) and Figure 7(d). It can be observed that without efficiency optimization algorithm in the transient period, the drive loss is on the higher side as compared to the duration after optimization algorithm becomes functional. Also, the Figures reveal that the PSO based optimization scheme is more efficient in minimizing the losses as compared to the GS and GA based scheme.



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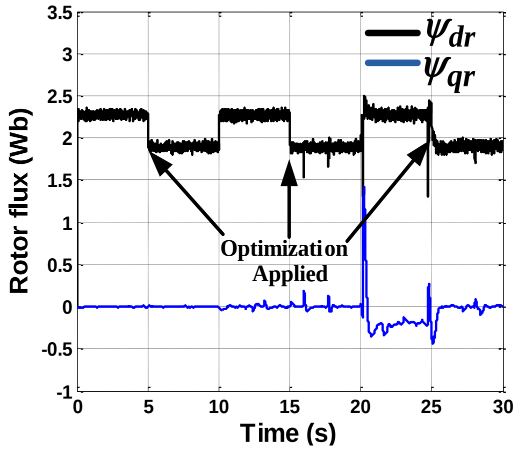

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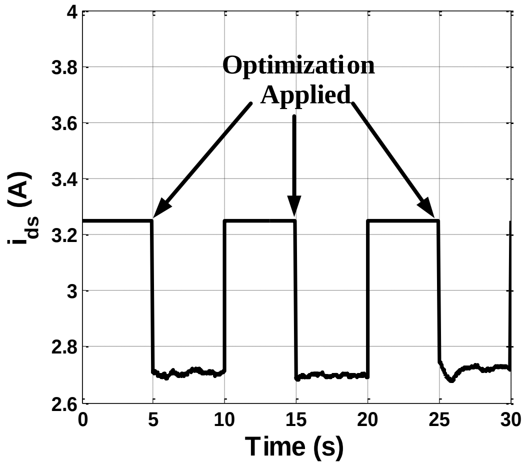

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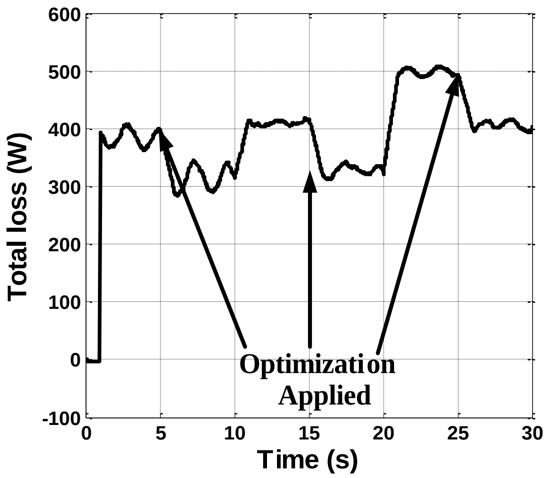
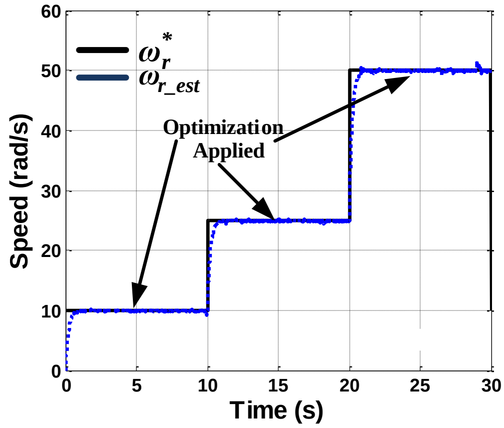


(d)

Figure 5: Simulation results of the IM drive with GS scheme for step change in rotor speed at 5 Nm load torque: (a) reference, estimated and actual speeds, (b) d- and q-axis rotor flux, (c) d-axis stator current, and (d) total loss of the drive.



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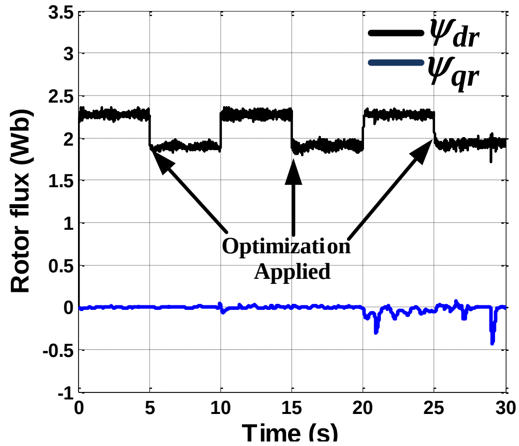

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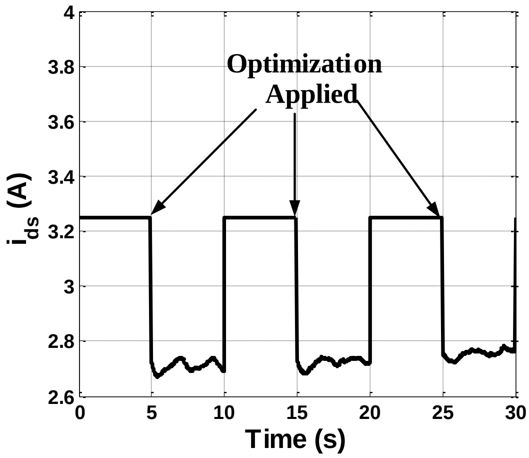

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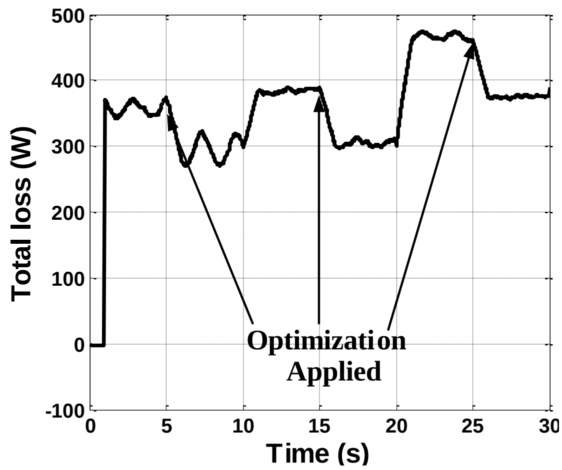
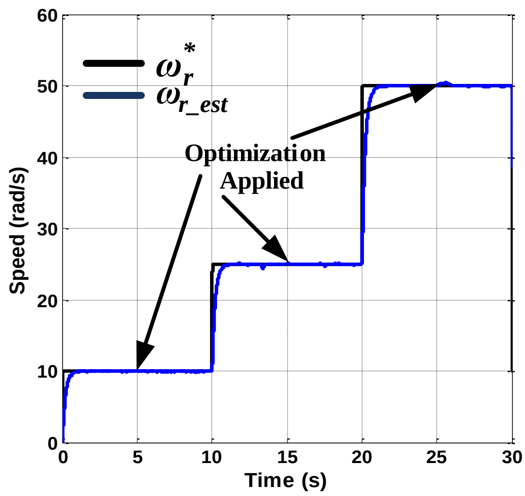


(d)

Figure 6: Simulation results of the IM drive with GA scheme for step change in rotor speed at 5 Nm load torque: (a) reference, estimated and actual speeds, (b) d- and q-axis rotor flux, (c) d-axis stator current, and (d) total loss of the drive.



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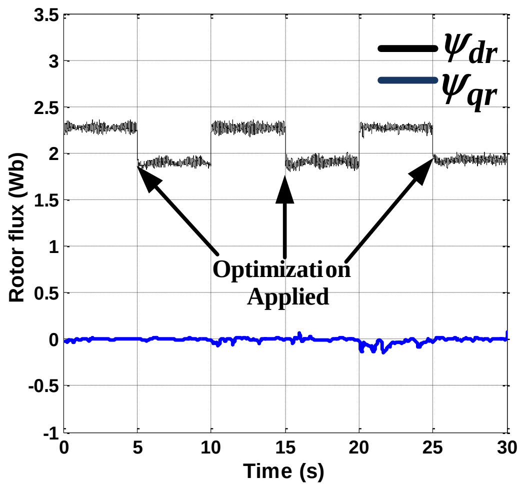

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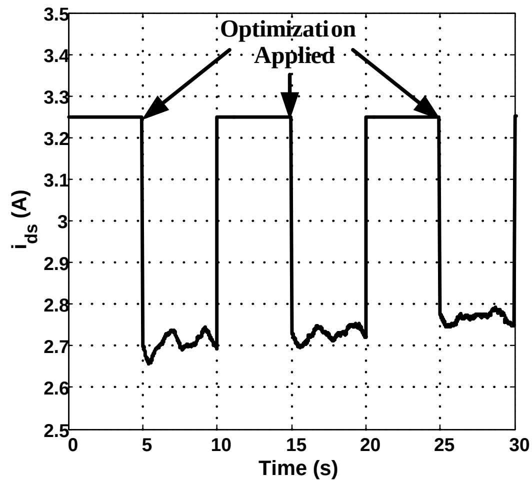

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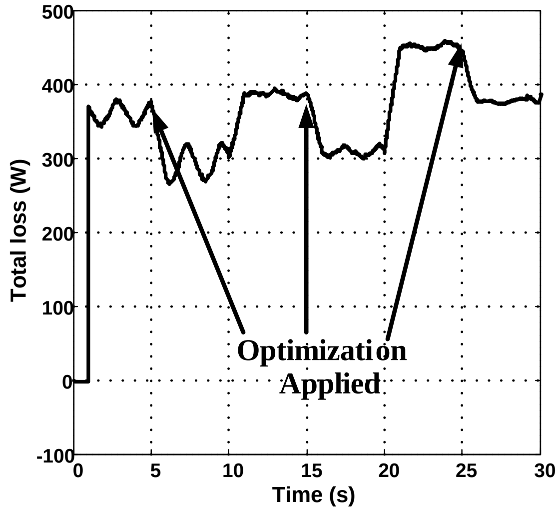
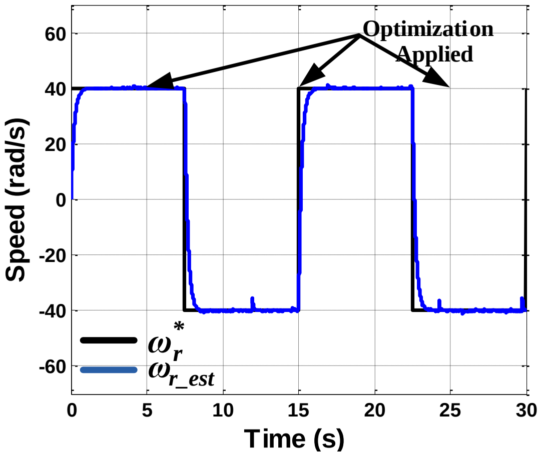


(d)

Figure 7: Simulation results of the IM drive with PSO scheme for step change in rotor speed at 5 Nm load torque: (a) reference, estimated and actual speeds, (b) d- and q-axis rotor flux, (c) d-axis stator current, and (d) total loss of the drive.

Regenerative mode operation: Second quadrant operation

The performance of the IM drive system in second quadrant is shown in Figure 8, Figure 9 and Figure 10. The estimated speed follows the actual speed satisfactorily Figure 8(a), Figure 9(a) and Figure 10(a)) for GS, GA and PSO loss optimization scheme. The optimization algorithm comes into play at 5 sec, 15 sec, and 25 sec. The optimal and non-optimal fluxes are shown in Figure 8(b), Figure 9(b) and Figure 10(b), respectively for aforesaid algorithms. The change in current during the entire time period is shown in Figure 8(c), Figure 9(c) and Figure 10(c). The decrement in loss when the optimization techniques (GS, GA and PSO) are working shown in Figure 8(d), Figure 9(d), and Figure 10(d). It can be observed from the results that PSO based optimization scheme is more efficient in reducing the loss than the GS and GA based scheme.



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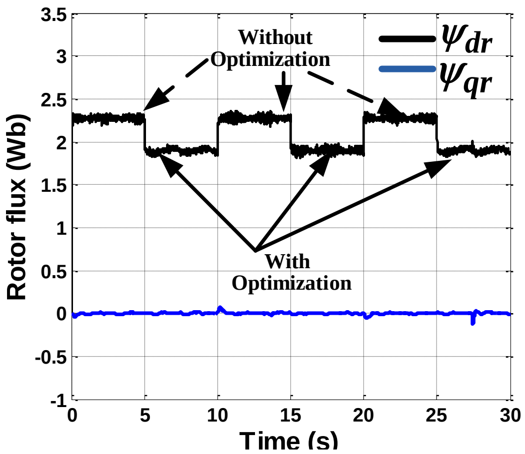

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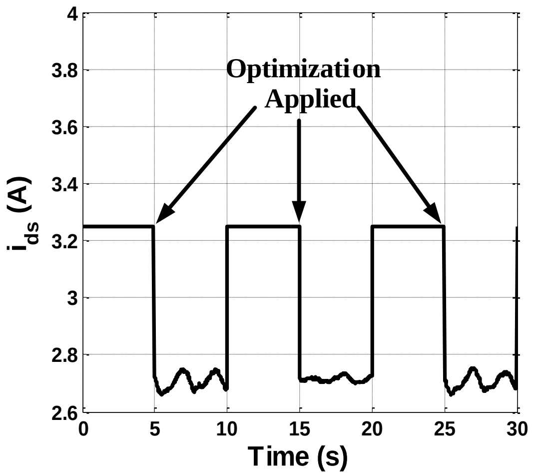

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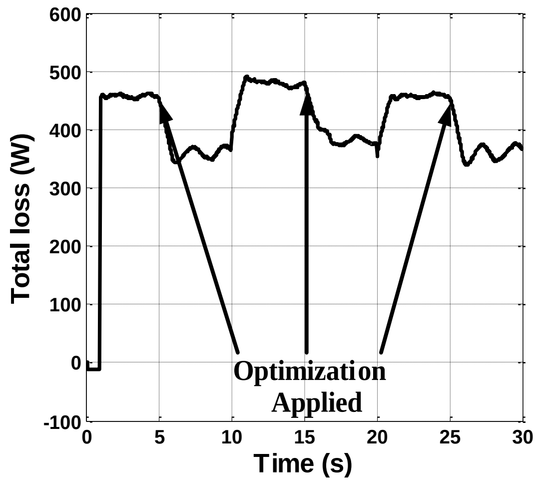
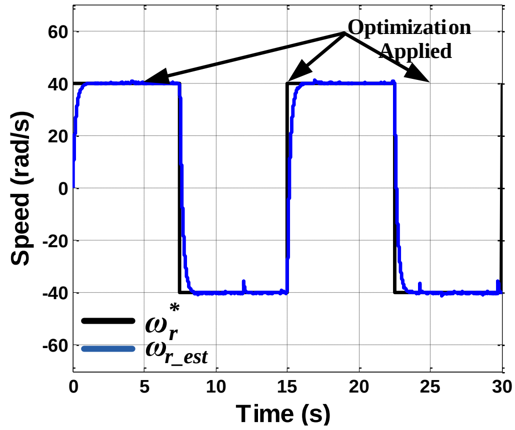


(d)

Figure 8: Simulation results of the IM drive with GS scheme for second quadrant operation at 5 Nm load torque: (a) reference, estimated and actual speeds, (b) d- and q-axis rotor flux, (c) d-axis stator current, and (d) total loss of the drive.



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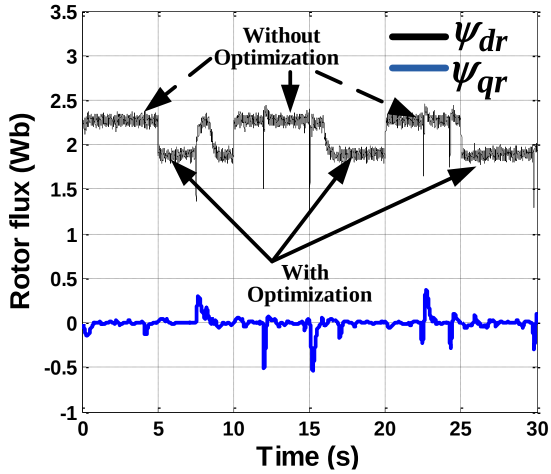

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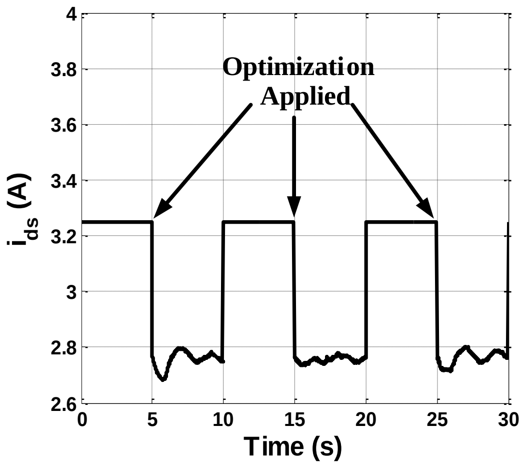

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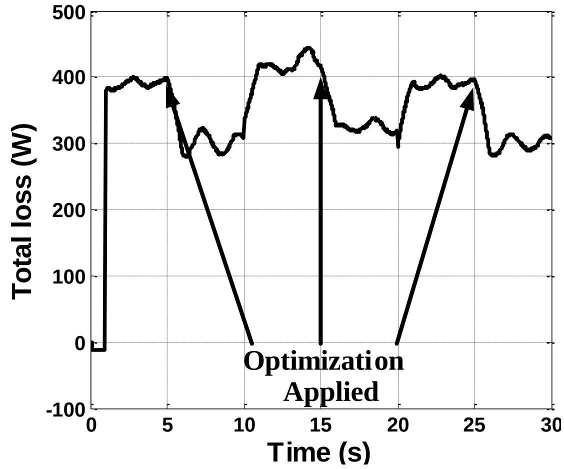
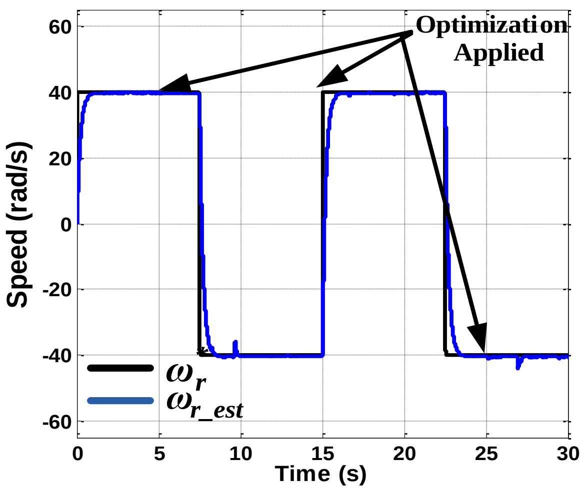
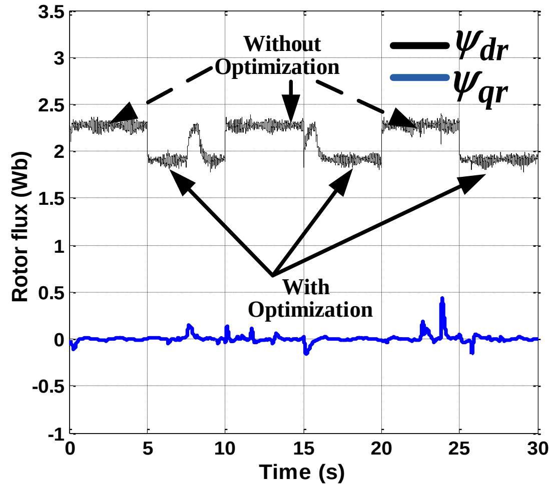


(d)

Figure 9: Simulation results of the IM drive with GA scheme for second quadrant operation at 5 Nm load torque: (a) reference, estimated and actual speeds, (b) d- and q-axis rotor flux, (c) d-axis stator current, and (d) total loss of the drive.



(a)



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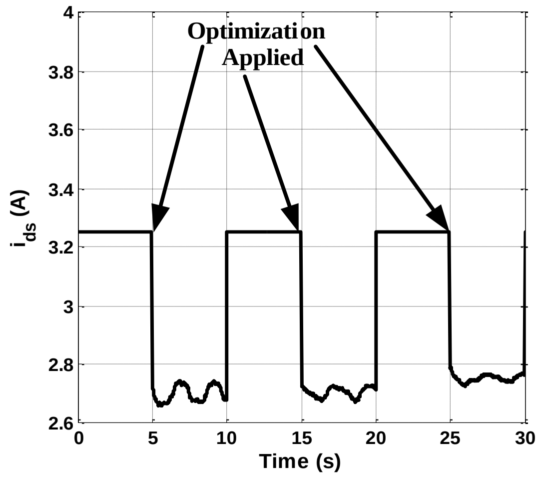

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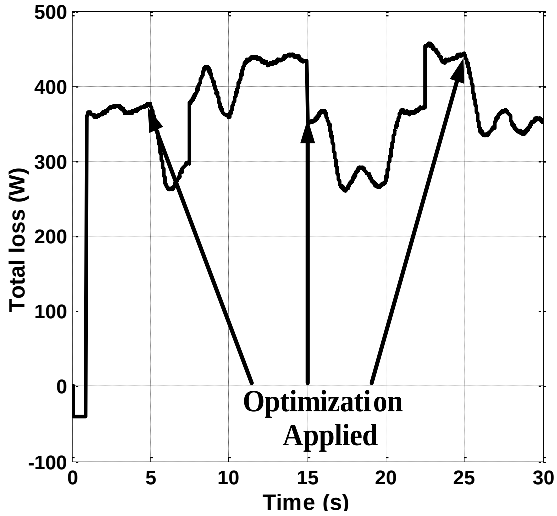

(d)

Figure 10: Simulation results of the IM drive with PSO scheme for second quadrant operation at 5 Nm load torque: (a) reference, estimated and actual speeds, (b) d- and q-axis rotor flux, (c) d-axis stator current, and (d) total loss of the drive.

In Table 1 loss minimization schemes are presented for different speed ranges at 5 Nm load torque (in motoring mode) and -5 Nm load torque (in regenerating mode). The Table summarizes the comparative results of loss minimization achieved with GS, GA and PSO techniques and without optimization techniques. From the table it is noticed that losses from PSO is more reduced as compared to both (GS and GA) the techniques. The Comparative diagram of total loss of the IM drive with and without optimization schemes is shown in Figure 11.

Table 1: Performance Assessment of IM drive operation in motoring and regenerating mode with and without GA based optimization.

Speed (rad/s)	Torque (Nm)	Loss (W), without optimization	Loss (W), with PSO optimization	Loss (W), with GA optimization	Loss (W), with GS optimization
50		485	359	380	460
40		423	341	363	403
30		396	323	346	383
20	**5**	364	310	330	355
10		341	291	300	331
5		327	283	296	311
0		318	276	285	298
0		322	270	281	306
5		331	286	291	319
10		350	296	302	341
20	**-5**	363	313	306	353
30		388	327	354	371
40		431	348	376	422
50		472	374	393	460

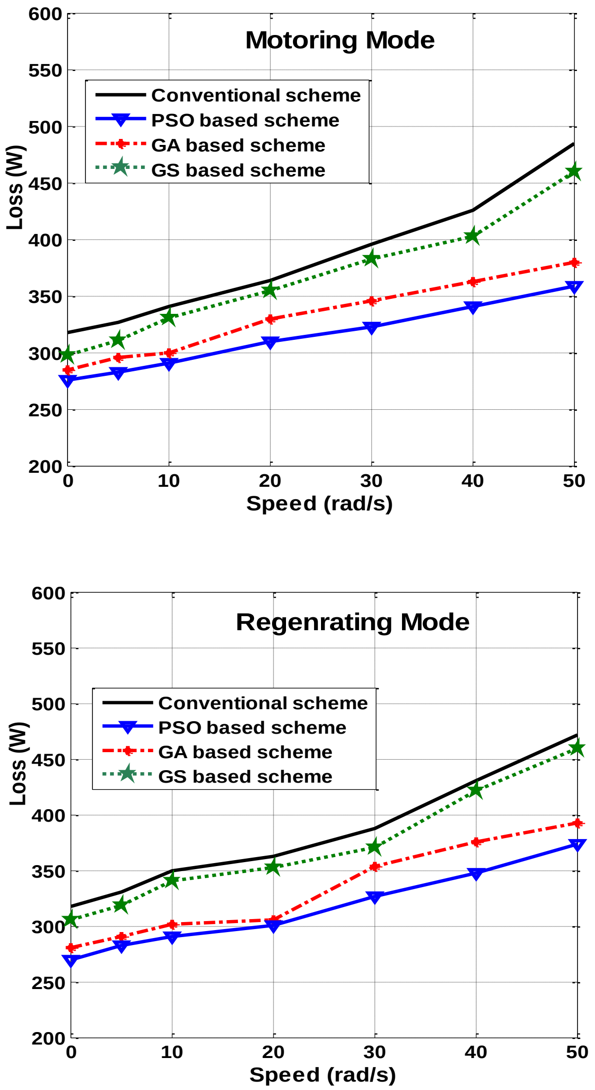

Figure 11: Comparison of total drive's loss for IM drive with GA and GS optimization scheme.

CONCLUSION

This paper presents a comparison between three different optimization schemes for high performance IM drive known as particle swan optimization (PSO) genetic algorithm (GA) and golden search (GS) method. The optimization schemes are applied to improve the overall efficiency of IM drive. The loss-minimization algorithms are developed considering the drive's loss for all the aforesaid schemes. The performance of the IM drive system considering PSO, GA and GS algorithms have been tested in simulation for different operating conditions. Moreover, the stability analysis of the IM drive system in the motoring and regenerating modes of operation confirms a stable drive operation for the schemes. The efficiency optimization algorithms generate the optimal value of i_{ds}^{*}. Hence, core loss of the drive system is minimized as the flux level is optimized. It is found from the results that the performance of the IM drive with the PSO based optimization algorithm remarkably reduces the loss of drive system and has better transient response compared to results obtained with GS and GA based optimization scheme.

APPENDIX A.1

A.1. MACHINE RATING AND PARAMETERS

Rated shaft power (P_r)	1.3 kW
Line-to-line voltage $(V_{LL\ rms})$	415 V, 50 Hz
Poles (P)	4
Magnetizing inductance (L_m)	0.7 H
Stator and rotor leakage inductance $(L_{ls} = L_{lr})$	0.0352 H
Stator resistance (R_s)	5.205 Ω
Rotor resistance (R_r)	4.075 Ω

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