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Optimal Energy Control of Double-Stator Induction Motor Regime Using Particle Swarm Optimization

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Abstract

In this paper a problem of energy optimization of a Double Stator Induction Motor (DSIM) is considered. Using the concept of a Rotor Field Oriented Control (RFOC); the DSIM Blondel-Park model is used as dynamic constraints in an optimal control problem. A cost function consists of linear combination of magnetic energy, copper losses and mechanical power is minimized. From the Particle Swarm Optimization (PSO) algorithm, a time-varying expression of a minimum-energy rotor flux is obtained. Compared to the constant rotor flux approach, it is proved that higher performances are achieved. The simulation results show the satisfactory behavior of the proposed identification algorithm.

Keywords: Double-stator induction machine; Field-oriented control; Particle swarm optimization; Optimal control; Energy minimization

Introduction

The absolute biggest chances to save energy and diminish working costs in structures and modern offices come from advancing electric engine frameworks. As a general rule, the most piece of power expected moves through engines principally enlistment engines. The DSIM is the prevailing innovation utilized today because of its superior presentation, its high dependability and its speed and force abilities. The regular RFOC technique working at steady rotor motion standard fixed at its standard level gives maximal effectiveness when the framework works at its standard working point. A long way from this, the machine's proficiency diminishes; it can result from a force greatness change. In this way different methods of motion activity are expected to arrive at framework with ideal exhibitions [1].

In numerous applications, effectiveness enhancement of DSIM presents a significant component of control particularly for independent electrical footing. The extremely broad utilization of DSIM suggests that in the event that misfortunes in DSIM drives can be decreased by only a couple of percent, it will significantly affect the all out electrical energy utilization. In high powerful exhibitions control like field-arranged control and direct force control, the motion is normally kept up with steady equivalent to its ostensible worth [2-4]. In this present circumstance the enlistment engine run effectively around the ostensible point. At the point when the heap is decreased extensively, the effectiveness is likewise significantly diminished.

Numerous scientists have been accounted for a few systems utilizing various factors to limit misfortunes in the machine. Among these works, the people who were keen on meta-heuristic methodologies [5-9]. In this specific circumstance, I.Ya. Braslavsky, et al. proposed a hereditary calculation to find the negligible misfortune motion direction [10]. They were keen on incessant beginning electrical drives. Ahmad Moghadam and Ali Reza Seifi offer another way to deal with the issue of Ideal Receptive Power Control Factors arranging (ORPVCP) of an enlistment engine [11]. The fundamental thought is division of Burden Length Bend (LDC) into a few time stretches with steady dynamic power interest in every span and afterward tackling the Energy Misfortune Minimization (ELM) issue. They acquire an ideal introductory arrangement of control factors of the framework so that is substantial forever stretches and can be utilized as an underlying working state of the framework. In this paper, the ELM issue has been addressed by the Straight Programming (LP) and the Fluffy Direct Programming (Fluffy LP) and developmental calculations. The outcomes are contrasted and the proposed Fluffy TLBO strategy.

In the creators present a methodology for proficiency enhancement of a vector controlled enlistment engine drive [12]. The ideal motion delivering current is acquired utilizing a fake brain organization. The counterfeit brain network model is laid out utilizing Matlab/Simulink and in light of the heap force and speed information of a backhanded vector-controlled acceptance engine drive [13]. The difference in iron center misfortune opposition because of motion and recurrence variety is thought about [14]. Reenactment consequences of the proposed approach show a critical improvement in energy saving and productivity enhancement. Similarly, in the creators present a definition of a sequencing issue with the double objectives of changing the parts usage at various workstations of the sequential construction system and shifting the responsibility related with every workstation [15]. This paper presents a Discrete Molecule Multitude Streamlining (DPSO) calculation, a Memetic calculation (Mama), a Weighted aggregate Multi-Objective Hereditary Calculation (MOGAW) and a Non-ruled Arranging Hereditary Calculation (NSGA-II) to settle an in the nick of time sequencing issue where these targets are to be improved all the while. Exploratory outcomes

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show that discrete molecule multitude streamlining beats different calculations in regard of an examination metric.

Liu X, et al. take care of an ideal control issue for a class of time-invariant exchanged stochastic frameworks with multi-exchanging times, where the goal is to limit an expense utilitarian with various costs characterized on the states [16]. In light of the math of variety, the creators determine the slope of the expense utilitarian as for the turning times on a particularly basic structure, which can be straightforwardly utilized in inclination drop calculations to find the ideal exchanging moments.

Notwithstanding these investigations, this paper gives a Molecule Multitude Improvement (PSO) commitment. The proposed approach is utilized as improvement looking through calculation because of its benefits over different methods for lessening the levelized cost of energy. PSO calculation utilizes as "populace" the directions of the reference rotor transition. The issue is characterized and objective capability is presented taking in thought wellness values awareness in molecule swarm process. The prevalence of the proposed approach has been shown by contrasting the outcomes and the regular RFOC technique [17].

The body of this paper is coordinated as follows: Area 2 is primarily expected to portray the full DSIM model. Segment 3 is committed to introduce the energy-power cost capability. We grow in segment 4, the PSO approach and we present a reproduction results contrasting and the regular RFOC. Area 5 finishes up the paper.

Materials and Methods

Double-star induction motor model

The DSIM is built with two symmetrical three-phase armature winding systems, electrically displaced by 30°. Its rotor has a conventional structure. Figure 1 shows the position of the natural frame relative to the common reference frame.

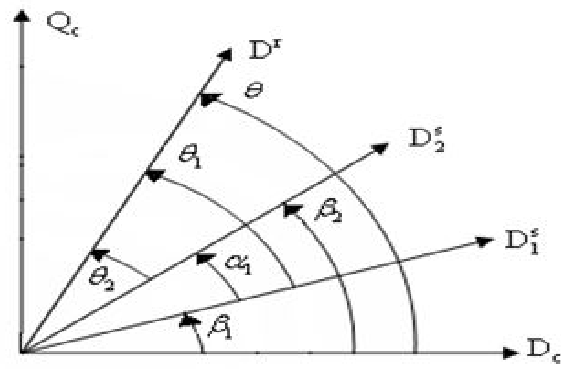

Figure 1: Position of the natural frame relative to the common reference frame.

The full-order model of the DSIM viewed from the synchronous rotating reference frame is given by the following system.

$$\begin{cases} \dot{I}_{s(d,q)} = -\left(\gamma I + (\dot{\rho} + p\Omega)J\right) I_{s(d,q)} \\ \dot{\varphi}_{r(d,q)} = -(aI + \dot{\rho}J)\varphi_{r(d,q)} + bI \\ \dot{\Omega} = -\frac{K_l}{J_m} + \frac{y}{J_m} \end{cases} \quad (1)$$

with

$$I_{s(d,q)} = \begin{pmatrix} I_{s1d} + I_{s2d} \\ I_{s1q} + I_{s2q} \end{pmatrix} = \begin{pmatrix} I_{sd} \\ I_{sq} \end{pmatrix};\ V_{s(d,q)} = \begin{pmatrix} V_{sd1} + V_{sd2} \\ V_{sq1} + V_{sq2} \end{pmatrix} = \begin{pmatrix} V_{sd} \\ V_{sq} \end{pmatrix};\ \varphi_{r(d,q)} = \begin{pmatrix} \varphi_{rd} \\ \varphi_{rq} \end{pmatrix};$$

$$\sigma_1 = 1 - \left(\frac{M^2}{L_r L_s}\right);\ \sigma_2 = 1 - \left(\frac{M^2}{L_r L_{sp}}\right);\ \gamma = \frac{1}{\sigma_1 L_s + \sigma_2 L_{sp}}\left(R_s + \frac{M^2}{L_r^{\ 2}} R_r\right);$$

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix};\ J = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix};\ a = \frac{R_r}{L_r};\ b = aM;$$

By noting $\omega_s=\rho$ is the sleep frequency, R_s and R_r are stator and rotor resistances, L_s and L_r are stator and rotor inductances; M is the magnetizing inductance, L_{sp} is the principal cyclic inductance. J_m is the total moment of inertia of the rotor, K_i is the load torque constant. I_{sd1}, I_{sd2}, I_{sq1} and I_{sq2} are respectively the direct and quadrature current of stator 1 and stator 2. V_{sd1}, V_{sd2}, V_{sq1}, V_{sq2} are respectively, the stator voltages in d-q axis of each stator, p is the poles number, Y is the electromagnetic torque expressed as follows:

$$Y = C_r \cdot \left(I_{s1} + I_{s2}\right)^t_{(d,q)} \cdot J \cdot \varphi_{r(d,q)} \quad (2)$$

Generally speaking, the control law strategy aims to force the system to satisfy specified closed-loop differential equations. Here, the stator current is taken as an input control of the system. A high gain control current loop is chosen in order to simplify the optimization algorithm [18]. Such choice permits to apply a reduced order current fed DSIM model; the current loop is given [19].

$$V_{s(d,q)} = \frac{\sigma_1 L_s + \sigma_2 L_{sp}}{\varepsilon}\left(U - I_{s(d,q)}\right) \quad (3)$$

and a reduced model of the DSIM is built as follows:

$$\begin{cases} \dot{\varphi}_{r(d,q)} = -\left(aI + \dot{\rho}J\right)\varphi_{r(d,q)} + bU \\ \dot{\Omega} = -\frac{K_l}{J_m} + \frac{cU^t J \varphi_{r(d,q)}}{J_m} \end{cases}$$

(4)

with

$$U = \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} = \begin{pmatrix} I_{sd} \\ I_{sq} \end{pmatrix};\ c = \frac{3}{2} p \frac{M}{L_r}$$

Results and Discussion

Energy model of a double-star induction motor

The instantaneous active power in the d-q rotating frame is given by:

$$P_a = \tfrac{3}{2}\left(V_{s(d,q)}\right)^t I_{s(d,q)} \tag{5}$$

The relation between stator and rotor currents can be given as follows:

$$I_{r(d,q)} = \frac{1}{L_r}\left(\varphi_{r(d,q)} - L_s I_{s(d,q)}\right) \tag{6}$$

From equations (1) and (6), the input power is given by:

$$\begin{aligned} P_a = {} & \tfrac{3}{2}(\sigma_1 L_s + \sigma_2 L_{sp}).\left(\left(\dot{I}_{s(d,q)}\right)^t\left(I_{s(d,q)}\right)\right) + \frac{1}{L_r}.\left(\left(\dot{\varphi}_{r(d,q)}\right)^t\left(\varphi_{r(d,q)}\right)\right) \\ & -\tfrac{3}{2}\left[\left(R_s\left(\dot{I}_{s(d,q)}\right)^t\left(I_{s(d,q)}\right)\right) + \left(R_r\left(\dot{I}_{r(d,q)}\right)^t\left(I_{r(d,q)}\right)\right)\right] + \Omega Y \end{aligned} \tag{7}$$

Finally, the instantaneous active power can be defined as the following sum:

$$P_a = \frac{\partial}{\partial t} W + P_J + P_m \tag{8}$$

By means of a field-oriented control drive:

$$\varphi_{r(d,q)} = \begin{bmatrix} \varphi_r \\ 0 \end{bmatrix}$$

The derivate of stored magnetic can be expressed as follows:

$$\frac{\partial}{\partial t} W = \tfrac{3}{2}\left(\left(\frac{\sigma_1 L_s + \sigma_2 L_{sp}}{2}\right).\left(u_1^2 + u_2^2\right) + \frac{1}{2L_r}\varphi_r^2\right) \tag{9}$$

We define also the total copper losses as:

$$P_J = \tfrac{3}{2}\left[\left(R_s\left(\dot{I}_{s(d,q)}\right)^t\left(I_{s(d,q)}\right)\right) + \left(R_r\left(\dot{I}_{r(d,q)}\right)^t\left(I_{r(d,q)}\right)\right)\right] \tag{10}$$

By using equations (1) and (6), those losses can be expressed with respect to U and φ_r as follows:

$$P_J = \tfrac{3}{2}\left(\left(R_s + R_r\left(\frac{M}{L_r}\right)^2\right).\left(u_1^2 + u_2^2\right) - \frac{3}{2}\frac{R_r}{L_r^2}\varphi_r^2 - \frac{3}{2L_r}\frac{d\varphi_r^2}{dt}\right) \tag{11}$$

The mechanical power of the DSIM is given as follows:

$$P_m = \Omega Y \tag{12}$$

In term of rotor variables and torque current, we get:

$$P_m = \tfrac{3}{2}\frac{M}{L_r}\varphi_r I_{sq} \tag{13}$$

An optimal control consists on minimization of a cost function. In this case, the cost function can be defined as the integral of an index f (I_{sd}, I_{sq}, φ_r, Ω) given as follows:

$$J = \int_0^T f(I_{sd}, I_{sq}, \varphi_r, \Omega)\,dt \tag{14}$$

The index corresponds to the weighted sum:

$$f\left(I_{sd}, I_{sq}, \varphi_r, \Omega\right) = \alpha_1 W_L + \alpha_2 P_J + \alpha_3 P_m \tag{15}$$

The weighting factors (α_1, α_2, α_3) are used to scale power-energy combined convex criteria terms defined above.

Using equations (4), (6), (7) and (9), the cost function is given as follows:

$$\begin{aligned} J_r = {} & \alpha_1\left(\left(\sigma_1 L_s + \sigma_2 L_{sp}\right).\left(u_1^2 + u_2^2\right) + \frac{1}{2L_r}\varphi_r^2\right) + \alpha_2\left(\left(R_s + R_r\frac{M}{L_r}\right)\left(u_1^2 + u_2^2\right) + \frac{R_r}{L_r}\varphi_r^2\right) \\ & -\frac{\alpha_2}{L_r}\frac{d}{dt}\varphi_r^2 + \alpha_3 p\frac{M}{L_r}\varphi_r u_2 \end{aligned} \tag{16}$$

The integral $\int_0^T\left(-\frac{1}{L_r}\frac{d}{dt}\left(\varphi_r^2\right)\right)dt = \frac{1}{L_r}\left(\varphi_r(0) - \varphi_r(T)\right)$,

Has no effect in the optimizing problem and can be omitted it from the integral. Considering the new control vector.

$$U = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

The system described by (2) can be defined as follows:

$$\begin{cases} \dot{\varphi}_r = a\varphi_r + bu_1 \\ \dot{\Omega} = -\dfrac{K_l}{J_m}\Omega + \dfrac{cu_2}{J_m}\varphi_r \end{cases} \tag{17}$$

Find the optimal control variables (u_1^*) and (u_2^*) that minimize the following cost function:

$$J_r = \int_0^T \left(r_1 u_1^2 + r_2 u_2^2 + q_1 \varphi_r^2 + q_2 \varphi_r u_2 \Omega \right) dt \quad (18)$$

with $r_1 = \frac{3}{4}\left(\sigma_1 L_s + \sigma_2 L_{sp}\right)\alpha_1 + \frac{3}{2}\left(Rs + R_r \left(\frac{M}{L_r}\right)^2 \right)\alpha_2;\quad r_2 = r_1 + r_0\alpha_3$

$$q_1 = \frac{3}{4}\frac{\alpha_1}{L_r} - \frac{3}{2}\frac{R_r}{L_r^2}\alpha_2 + \alpha_3 q_0;\quad q_2 = \frac{3}{2}\frac{M}{L_r}\alpha_4$$

Where the weighting factors r_1, r_2, q_1 and q_2 must be positives.

Energy optimization *via* PSO algorithm

PSO calculation is a populace based streamlining strategy motivated by the movement of a bird rush, or fish tutoring. Such gatherings are social associations whose general conduct depends on a correspondence among individuals from some kind or another and participation. All individuals comply with a bunch of basic principles that model the correspondence inside the group and between the herd and the climate [20]. The worldwide way of behaving, in any case, is undeniably more perplexing and for the most part effective. For example, a group is generally effective at finding the best spot for taking care of, same which appears to be difficult to accomplish by any single part [21].

An individual from the group is classified "molecule", in this way a herd is an assortment of particles. The well known term "flying the particles" signifies the investigation of the pursuit space. Each molecule knows its ongoing position and the best position visited starting from the primary fly [22]. PSO performs investigation by ceaselessly detecting (perusing) the hunt space at neighborhood level. The data gathered by the particles is focused and arranged to track down the best part (called worldwide best). The new best part and the ongoing best part are thought about and the best one is kept as worldwide best. Its position is conveyed to all run individuals in this way in the following fly the particles know where the best spot lies in the pursuit space. Finding the following best spot is the principal errand of the group for which investigation and in this way populace variety is significant. In this situation the group investigates the space however stays stable in the wake of shifting its flying course (fourth standard). Simultaneously, in any case, all rush individuals are drawn in by the place of the worldwide best (Figure 2).

The two fundamental conditions which administer the working of PSO are that of speed vector and position vector are given by:

$$v_{id} = w.v_{id} + c_1.r_1.\left(p_{id} - x_{id}\right) + c_2.r_2.\left(p_{gd} - x_{id}\right) \quad (19)$$

$$x_{id} = x_{id} + v_{id} \quad (20)$$

Acceleration constants c_1, c_2 and inertia weight are the predefined by the user and r_1, r_2 are the uniformly generated random numbers in the range of (0, 1).

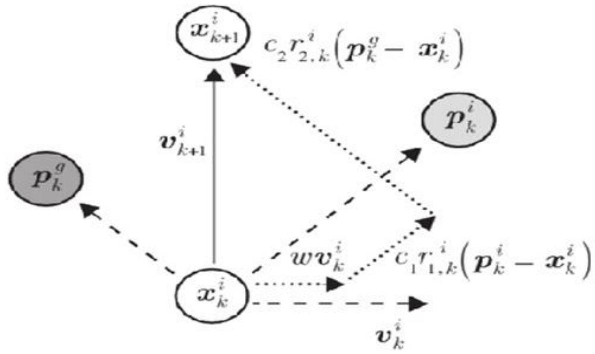

Figure 2: Depiction of position updates in particle swarm optimization.

The objective of optimization problem is to look for the values of the variables being optimized, which satisfy the defined constraints and maximize or minimize the fitness function. In this work consumption energy defined in equation (18) is used as fitness function.

Then, PSO is used to find the optimal rotor flux φ_r from the energy model of DSIM under variable load and speed. The flux φ_r^* is defined as a third order polynomial that depends on time t such as:

$$\varphi_r^* = p_3.t^3 + p_2.t^2 + p_1.t + p_0 \quad (21)$$

A concept consists on researching parameters p_0, p_1, p_2 and p_3, in bounded intervals previously defined, which enable reconstructing the optimal value of the rotor flux.

The simulations results are carried out on a three-phase DSIM, 380 V, 20 KW, 50 Hz and 4 poles, squirrel cage induction motor. The motor parameters are R_s=0.4 Ω, R_r=0.096 Ω, L_r=8.9 mH and L_s=81.2 mH. The mechanical parameter are J_m=0.6 and K_i=0.7. The load torque is assumed to be proportional to the reference speed with K_t=0.7 is the constant of proportionality. Study is carried out over a period of 2 seconds. The other parameters set in PSO algorithm are given in the Table 1.

Table 1: Strategy parameters for identification of PSO model.

Swarm size	30
Iterations	20
c_1	1.5
c_2	1.5
w_1 (Inertia weight at the start of PSO run)	0.4
w_2 (Inertia weight at the end of PSO run)	0.9

The best particle's position vectors corresponding to our cost function are represented by Figure 3.

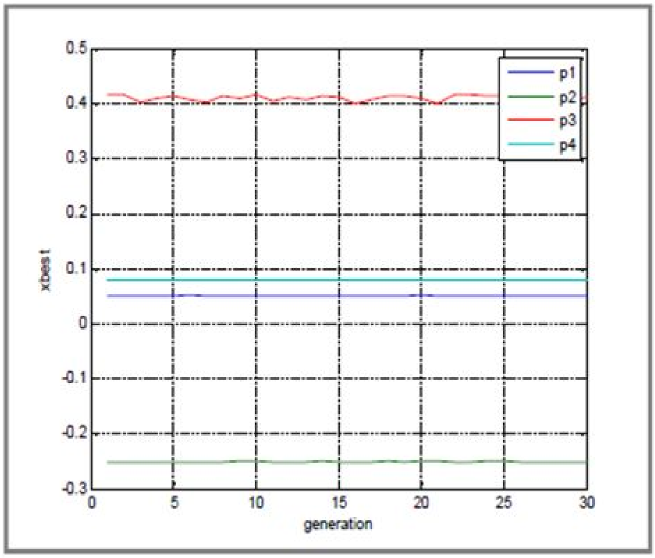

Figure 3: Best particle's position vectors corresponding to energy function.

Figure 4 show the evolution of the absorbed energy. We can observe a decreasing of absorbed energy values given by PSO flux solution compared with the classic RFOC.

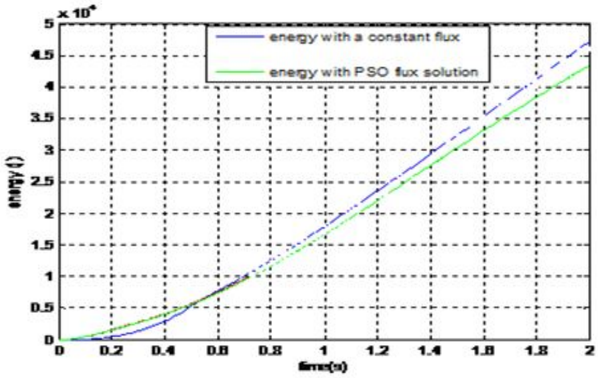

Figure 4: Comparison of energy curves at different control: With a constant flux (in blue) and with PSO flux solution (in green).

Table 2 presents the gain in energy of each method compared to the classic RFOC.

Table 2: Results of PSO optimization for different generation.

Energy using CST flux (j)=44777		
Simulation	**Energy using PSO (j)**	**Minimization via PSO (%)**
1	42847	-4.31
2	42116	-5.94
3	42314	-5.5
4	42351	-5.41
5	42557	-4.95
6	41836	-6.56
7	42692	-4.65
8	42368	-5.38
9	42638	-4.77
10	42652	-4.74
Average	42437.1	-5.221

The proposed fuzzy PSO optimization procedure has compared to a conventional vector control operating at rated rotor flux. These obtained results are then introduced in a lookup table and finally inserted in the control block. The energy minimization is greatly improved over a region wide range when using this method compared with the conventional method. The PSO results are greatly improved particularly over the light load region through which habitually the optimization values are relatively low.

Conclusion

An energy enhancement technique for a twofold stator enlistment engine control utilizing molecule multitude improvement is introduced in this paper. This technique comprises to find the ideal rotor motion. The connection between ideal rotor transition and engine misfortune minimization in the enlistment engine vector control framework is researched. It is pointed that the engine energy minimization can be accomplished by limiting all out misfortunes by and by. Recreation results were explored with a consistent transition activity and ideal motion utilizing molecule multitude improvement. PSO-based approach permitted a lot of lower energy utilization and an improved effectiveness than different techniques.

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