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Improved PSO Algorithm based Flux Optimization Strategy in Induction Machine Drive Systems

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***Abstract*— This paper proposes an improved particle swarm optimization (PSO) algorithm based flux optimization strategy in energy efficient control of induction machine (IM) drive systems. The improved PSO algorithm is based on a time-varying inertia weight. The inertia weight is started with a large value and linearly decreased that leads to a better performance. When the inertia weight is small, the PSO algorithm behaves like a local search algorithm. Conversely, when the inertia weight is large, the PSO algorithm behaves like a global search algorithm. On the other hand, a larger inertia weight facilitates a global exploration and a smaller inertia weight tends to facilitate a local exploration. This results in the best convergence capability and search performance for the PSO algorithm in searching for an optimal rotor flux reference for energy efficient control of the IM drive system. Simulation results confirm the effectiveness of the proposed flux optimization strategy in energy efficient control of the IM drive system.**

***Index Terms*—Flux optimization, induction machine drive systems, particle swarm optimization algorithm.**

I. INTRODUCTION

Regarding energy saving and environmental pollution reduction, the optimization in control and operation of induction machine (IM) drive systems has received significant attention in recent years. Basically, the IM operational efficiency is high for rated conditions of the load, speed and flux. Nevertheless, the IM drive systems usually operate at light loads most of the time. In this case, if the rated flux is still maintained at light loads, the core loss will increase dramatically. This results in poor IM efficiency. In order to solve this problem, it is well-known that the IM efficiency can be improved by reducing the flux level when it operates at light load conditions [1]. Various approaches have been researched to enhance the IM efficiency at light loads. The model-based control approach uses an IM loss model to define an optimal flux for each operational point at a given load torque and machine speed. A neural network [2]-[7], a genetic algorithm [8]-[9] and a particle swarm optimization algorithm [10] have allowed an optimal flux level to be defined for energy efficient control using the IM loss model. In the model-based control approach, the IM loss model is usually formed by the IM loss components such as the stator and rotor copper losses, core loss, stray loss and mechanical losses [4]-[6] and [9]-[10].

This paper proposes an improved particle swarm optimization (PSO) algorithm based flux optimization strategy in energy efficient control of the IM drive system in a certain load and machine speed. Furthermore, this paper also presents another loss model for the flux optimization strategy which is not formed by the IM loss components, such as the stator and rotor copper losses, core loss, stray loss and mechanical losses. Simulations and comparisons are performed to confirm the effectiveness of the proposed strategy for remaining an optimal efficiency.

The remainder of this paper is organized as follows. The IM model for flux optimization strategy is presented in Section II. The new application of the improved PSO algorithm for flux optimization strategy in efficient energy control of induction machine drive systems is proposed in Section III. The simulation results then follow to confirm the validity of the proposed technique in Section IV. Finally, the advantages of the new technique are summarized through comparison with the PSO algorithm.

II. INDUCTION MACHINE MODEL

In the model-based control approach, most of the previous energy efficient control strategies were based on the model of the IM loss components which are the stator and rotor copper losses, core loss, stray loss and mechanical losses. This paper introduces a loss model for the flux optimization of the IM which is more general and simpler than others. This loss model is described as follows.

In this case, this paper is considered in the steady-state and *d*-axis rotor indirect field-oriented control conditions. Thus the IM mathematical model is described as follows.

$$v_{qs} = R_s i_{qs} + \omega_e L_s i_{ds} \tag{1}$$

$$v_{ds} = R_s i_{ds} + \omega_e \left(\frac{L_m^2 - L_s L_r}{L_r} \right) i_{qs} \tag{2}$$

$$i_{qs} = \frac{1}{R_r} \frac{L_r}{L_m} (\omega_e - \omega_r) \psi_{dr} \tag{3}$$

$$i_{ds} = \frac{1}{L_m} \psi_{dr} \tag{4}$$

$$T_e = \frac{3}{2} \frac{p}{2} \frac{L_m}{L_r} \psi_{dr} i_{qs} \tag{5}$$

From (3) and (5), the IM synchronous speed is given by:

$$\omega_e = \omega_r + \frac{4}{3} \frac{R_r T_e}{p} \frac{1}{\psi_{dr}^2} \tag{6}$$

Substituting (3)-(4) and (6) into (1)-(2), the *d*-*q* axis stator voltages become:

$$v_{qs} = \frac{4}{3} \frac{T_e}{p} \left(\frac{R_r L_m + R_s L_s}{L_m} \right) \frac{1}{\psi_{dr}} + \frac{L_s}{L_m} \omega_r \psi_{dr} \tag{7}$$

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$$v_{ds} = \frac{R_s}{L_m}\psi_{dr} + \frac{4}{3}\frac{T_e}{p}\left(\frac{L_m^2 - L_s L_r}{L_m}\right)\omega_r \frac{1}{\psi_{dr}} + + \frac{16}{9}\frac{T_e^2 R_r}{p^2}\left(\frac{L_m^2 - L_s L_r}{L_m}\right)\frac{1}{\psi_{dr}^3} \quad (8)$$

From (3)-(4), (6), (7)-(8), assuming that the stator and rotor inductances are the same, the input power of the IM is then given as follows:

$$P_{in} = v_{qs}i_{qs} + v_{ds}i_{ds} = = \frac{R_s}{L_m^2}\psi_{dr}^2 + \frac{16}{9}\frac{T_e^2}{p^2}\left(\frac{R_r L_m^2 + R_s L_s^2}{L_m^2}\right)\frac{1}{\psi_{dr}^2} + \frac{4}{3}\frac{T_e}{p}\omega_r \quad (9)$$

In addition, the output power of the IM is described as follows:

$$P_{out} = \omega_m T_e = \frac{2}{p}\omega_r T_e \quad (10)$$

Eventually, from (9)-(10), the total IM loss is:

$$\Delta P = P_{in} - P_{out} = = \frac{R_s}{L_m^2}\psi_{dr}^2 + \frac{16}{9}\frac{T_e^2}{p^2}\left(\frac{R_r L_m^2 + R_s L_s^2}{L_m^2}\right)\frac{1}{\psi_{dr}^2} - \frac{2}{3}\frac{T_e}{p}\omega_r \quad (11)$$

It can be realized that the IM efficiency can be improved by minimizing the total IM loss which is dominated by the stator and rotor copper losses and core loss. The stator and rotor copper losses are reduced by decreasing the stator and rotor currents respectively which results in increased IM flux. As a consequence, the core loss is then increased. Obviously, there is a conflict between the copper losses and core loss. When the copper losses are decreased, the core loss is increased [11]. Nevertheless, there is an optimal IM flux at which the total IM loss is minimized for a given load torque and machine speed. This paper proposes an improved PSO algorithm to determine the optimal IM flux reference during operation presented in next section.

III. Improved PSO Algorithm Based Flux Optimization

The particle swarm optimization (PSO) algorithm is a population-based stochastic optimization method which was developed by Eberhart and Kennedy in 1995 [12]. The algorithm starts by initializing a population of random solutions called particles and searches for optima by updating generations through the velocity and position update equations.

The velocity update equation is given by:

$$\boldsymbol{v_i}(k+1) = w\boldsymbol{v_i}(k) + c_1 r_1(\boldsymbol{pbest_i}(k) - \boldsymbol{x_i}(k)) + + c_2 r_2(\boldsymbol{gbest}(k) - \boldsymbol{x_i}(k)) \quad (12)$$

$1 \le i \le M$ and $1 \le k \le n$

The position update equation is given by:

$$\boldsymbol{x_i}(k+1) = \boldsymbol{x_i}(k) + \boldsymbol{v_i}(k+1) \quad (13)$$

In the velocity update equation, $\boldsymbol{v_i}(k)$ is the k^{th} current velocity of the i^{th} particle whereas $\boldsymbol{x_i}(k)$ is the k^{th} current position of the i^{th} particle; v_i is usually clamped in the range [-v_{max}, v_{max}] to reduce the likelihood that a particle might leave the search space. In case of this, if the search space is defined by the bounds [-x_{max}, x_{max}] then the v_{max} value will be typically set so that $v_{\max} = m x_{\max}$, where $0.1 \le m \le 1.0$ [13].

$pbest_i(k)$ is the best position found by the i^{th} particle (personal best) whereas $gbest(k)$ is the best position found by a swarm (global best, best of the personal bests).

c_1 and c_2 are acceleration coefficients of the cognitive and social components respectively; c_2 regulates the step size in the direction of a global best particle and c_1 regulates the step size in the direction of a personal best position of that particle, c_1 and $c_2 \in [0, 2]$.

r_1 and r_2 are two independent random sequences which are used to influence the stochastic nature of the algorithm, $r_1 \in$ U(0, 1) and $r_2 \in$ U(0, 1).

Obviously, the PSO algorithm is simpler and easier to implement than other evolutionary algorithms, as it only has a few parameters to adjust, especially in solving discontinuous, multimodal and non-convex problems. However, in local optima problems, the particles sometimes become trapped in undesired states during the evolution process which leads to the loss of the exploration abilities. Because of this disadvantage, premature convergence can happen in the PSO algorithm which affects the performance of the evolution process. This is one of the major drawbacks of the PSO algorithm which needs to be improved for the evolution process performance of the PSO algorithm. It can be realized that the inertia weight in the PSO algorithm is considered as a trade-off factor for the local and global search abilities of the algorithm. In order to understand and control its behavior, Shi and Eberhart investigated the effect of w values in the range [0, 1.4] as well as in a linear time-varying domain [14]-[15]. Their results indicated that choosing w as a constant in the range [0.9, 1.2] results in a faster convergence. Additionally, the inertia weight can also be linearly decreased instead of a fixed constant value. In [15], the inertia weight is started with a large value of 0.9 and linearly decreased to 0.4 that leads to a better performance in most of the experiments conducted. When the inertia weight is small, the PSO algorithm behaves like a local search algorithm. Conversely, when the inertia weight is large, the PSO algorithm behaves like a global search algorithm. This also means that a larger inertia weight facilitates a global exploration and a smaller inertia weight tends to facilitate a local exploration [16]. Thus the modified inertia weight should be described as follows:

$$w_k = \left(w_{final} - w_{initial}\right) \times \frac{k}{n} + w_{initial} \quad (14)$$

where

w_k is the modified inertia weight;

w_{final} and $w_{initial}$ are the final and initial values respectively of the inertia weight.

It is obvious that the modified inertia weight is a time-varying value.

The PSO algorithm with a time-varying inertia weight is applied to the flux optimization strategy in energy efficient control. In this application, the particles represent the rotor flux reference of the IM. Each particle has its position, $\{\boldsymbol{\psi}_{dri}\}$ and velocity, $\{\boldsymbol{v}_{\psi_{dri}}\}$.

The i^{th} particle position and velocity are limited as follows:

$$\psi_{dri(min)} \le \psi_{dri} \le \psi_{dri(max)} \quad (15)$$

and

$$v_{\psi_{dri(\min)}} \le v_{\psi_{dri}} \le v_{\psi_{dri(\max)}} \quad (16)$$

The best position of the i^{th} particle { $\boldsymbol{pbest}_{\psi_{dri}}(k)$ } and the best position over the swarm { $\boldsymbol{gbest}_{\psi_{dr}}(k)$ } are obtained at each k^{th} iteration using the fitness function (11).

Eventually, the improved PSO algorithm stops at the n^{th} maximum iteration number and the optimal rotor flux reference is obtained as follows.

$$\psi_{dr\_optimal} = gbest_{\psi_{dr}}(n) \quad (17)$$

The simulations are implemented in the next section to validate the proposed PSO algorithm for flux optimization strategy in energy efficient control of the IM drive system.

IV. Simulation Results

Simulations are performed using MATLAB/SIMULINK software for the flux optimization strategy in energy efficient control of the 3 Hp IM drive system, fed by a voltage source inverter. The specifications and parameters of the simulated IM are in Table I.

The improved PSO algorithm is applied for the flux optimization strategy in energy efficient control of the IM drive system in which the particle number of a generation is set to 50 and the maximum iteration number is set to 100. The cognitive and social coefficients, c_1 and c_2 are set to 2 respectively. The two independent sequences, r_1 and r_2 are set to random values in U(0, 1). The inertia weight, w is started with a large value of 0.9 and linearly decreased to 0.4. The flow chart for flux optimization strategy of the IM drive system is described as in Fig. 1.

Fig. 2 shows the IM efficiency corresponding to the rated rotor flux reference which is constant regardless of the IM load variation. When the IM load is 80% of the rated load in the period, t = 0.5–2 s, the IM efficiency is high, 73.1%. At t = 2 s, the IM load starts decreasing to 60%, 50%, 40% and 20% of the rated load and the IM efficiency then decreases to 68.8%, 66.2%, 62.2% and 45.1% respectively. When the IM load decreases, the output power decreases and the input power is constant. As a consequence, the IM efficiency decreases.

In order to keep high IM efficiency, the input power is required to decrease and this can be achieved by changing the rotor flux reference to its optimal value.

Fig. 3 shows that the IM always has high efficiency. The rotor flux reference alters to adapt to the IM load variations. There is a significant improvement in the IM efficiency, Fig. 3, which is compared to the IM efficiency using the rated rotor flux reference, Fig. 2, especially at light loads. The IM efficiency is 45.1% at the lightest load whereas it is 83.5% using the optimal rotor flux reference obtained by the improved PSO algorithm.

Figs. 4-5 are the best fitness of the PSO and improved PSO algorithms versus the iteration step number and show the convergence capability of each algorithm. It can be observed that there is a basic difference between the PSO and improved PSO algorithms in the inertia weight. This results in a significant improvement in the convergence value of the improved PSO algorithm as shown in Figs. 4-5.

The convergence value of the PSO algorithm is 0.24417 whereas that of the improved PSO algorithm is 1.127×10^{-7}. The modification in the improved PSO algorithm has improved the performance as well as avoiding premature convergence in the PSO algorithm as illustrated in Figs. 4-5.

These analyses show that the improved PSO algorithm is better than the PSO algorithm in term of the convergence value for the flux optimization in energy efficient control of the IM drive system. This confirms the validity and effectiveness of the improved PSO algorithm in this novel application.

V. Conclusion

This paper proposes a novel flux optimization strategy in energy efficient control of the IM drive system obtained by the improved PSO algorithm. The improved PSO algorithm is one of the PSO algorithm variants, which modifies the inertia weight in the velocity update equation of the PSO algorithm as a linear time-varying parameter. The inertia weight is started with a large value and linearly decreased to a smaller value that leads to a better performance in the evolution progress. When the inertia weight is large, the PSO algorithm behaves like a global search algorithm. Conversely, when the inertia weight is small, the PSO algorithm behaves like a local search algorithm. This also means that a larger inertia weight facilitates a global exploration and a smaller inertia weight tends to facilitate a local exploration.

The simulation results show that the IM efficiency is significantly improved, especially for light loads using the flux optimization strategy obtained by the proposed PSO algorithm regardless of load variations.

It can be realized that the obtained IM efficiency by using the proposed PSO algorithm is always remained optimal and better than that obtained by using the PSO algorithm. Furthermore, the convergence speed and value of the proposed PSO algorithm are better than the PSO algorithm.

Table 1. IM specifications and parameters

Number of phases	3
Connection	Star
Number of poles	4
Rated power	3 Hp (~ 2.24 kW)
Line voltage (RMS)	230 V
Line current (RMS)	9 A
Rated speed	1430 rpm
Rated torque	14.96 N m
Rotor construction	Wound rotor with slip rings
Stator resistance	0.55 Ω
Stator inductance	0.068 H
Magnetizing inductance	0.063 H
Rotor resistance	0.72 Ω
Rotor inductance	0.068 H
Moment of inertia	0.05 kg m^2

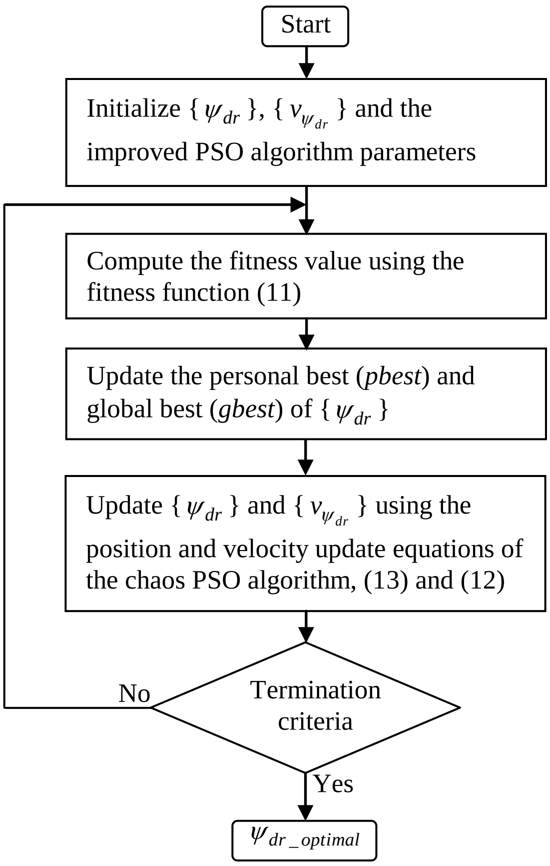

Fig. 1 Flow chart for flux optimization strategy of the IM drive system

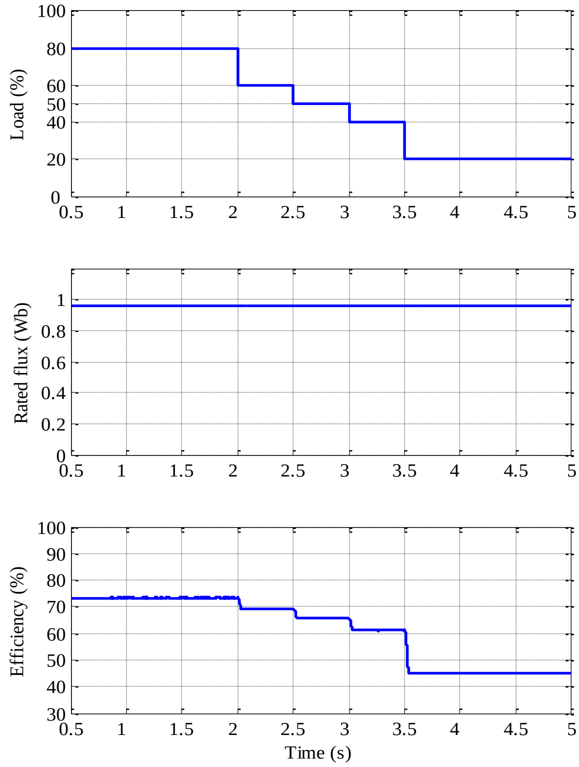

Fig. 2 IM efficiency with the rated rotor flux reference

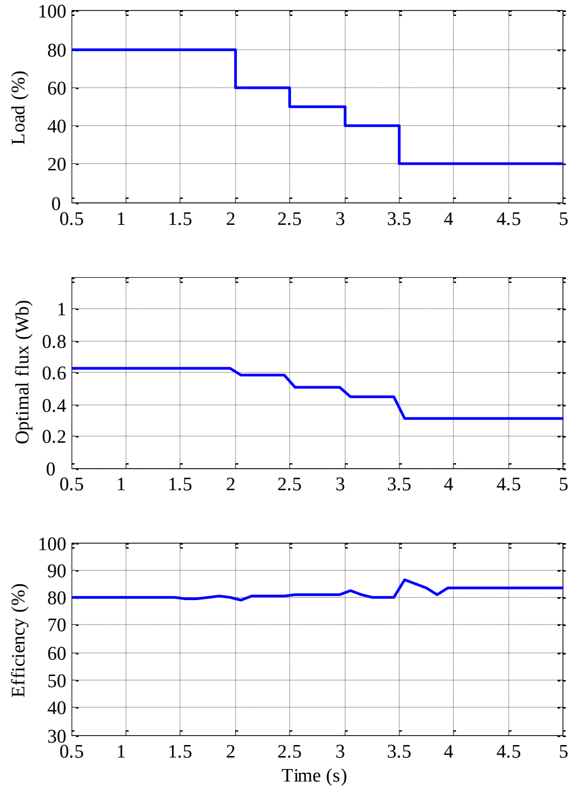

Fig. 3 IM efficiency with the flux optimization strategy obtained using the improved PSO algorithm

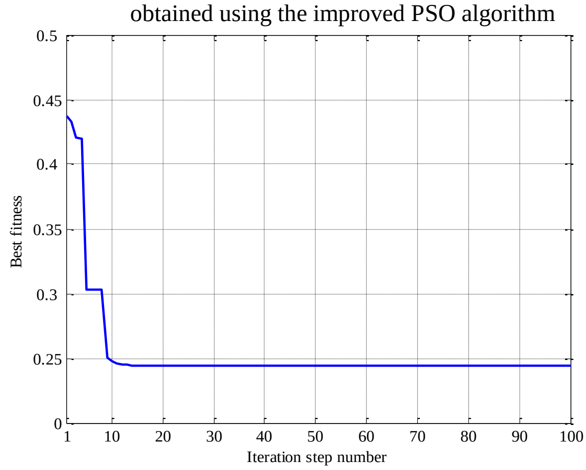

Fig. 4 Best fitness versus the iteration step number of the PSO algorithm

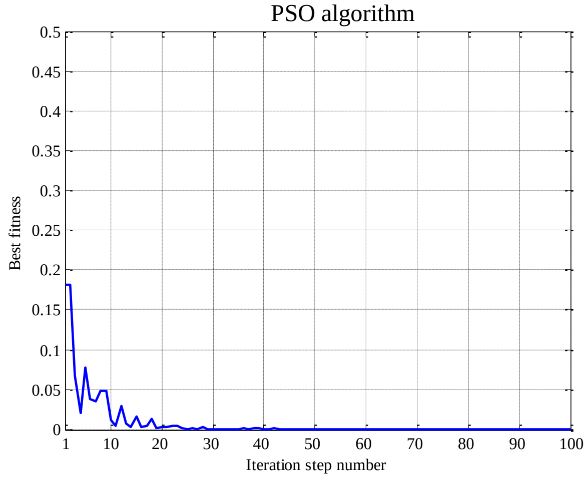

Fig. 5 Best fitness versus the iteration step number of the improved PSO algorithm

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