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Research Article

Parameter Identification of PMSM Using Immune Clonal Selection Differential Evolution Algorithm

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Permanent magnet synchronous motor (PMSM) models with accurate parameters are crucial to high performance PMSM control system designs. As the estimation of PMSM parameters is very difficult due to the *nonlinear* model complexity, a novel immune clonal differential evolution algorithm (ICDEA) is proposed to identify the electrical parameters of nonsalient pole PMSM. Clonal selection and receptor editing mechanism are introduced to ICDEA to increase the diversity of the population and improve searching capability. The effectiveness of the proposed identification method is verified by both simulation and experiment. The results show that the proposed algorithm has good convergence in simultaneously estimating stator resistance, dq-axis inductances, and rotor flux linkage. In addition, the convergence speed of ICDEA is compared with other differential evolution (DE) algorithms, which verifies that the ICDEA has better performances in global searching.

1. Introduction

Permanent magnet synchronous motor (PMSM) is widely used in high performance servo system due to its high power density and high efficiency. Meanwhile, control techniques such as field oriented control (FOC) and direct torque control (DTC) for controlling PMSM are also still developing and improving. In FOC, the parameters of current control loop will directly affect the overall performance of the system, and the greatest impact on the design of the current loop controller is the stator resistance and stator inductance. Therefore, identification of motor parameters accurately is important to design the current loop controller. In addition, parameters of speed loop and position loop controller are also influenced by the current loop control parameters. In DTC, electromagnetic torque and stator flux are used as control variables to directly control the torque and flux deviation through the hysteresis comparator. It is necessary to estimate the stator flux accurately, and the premise to estimate the stator flux accurately is to know the motor parameters exactly [1]. Common methods proposed for parameter identification include least squares [LS] method [2], model reference adaptive (MRA) method [3], extended Kaman filters (EKF) method [4], artificial intelligence methods (neural networks, fuzzy logic, genetic algorithms, etc.) [5], and evolutionary algorithms [6, 7].

The LS method is simple. When used in parameter identification, its objective function is the square of error between the measured results and the calculated results, and the minimum value of the objective function is zero. The LS method is suitable for online identification of motor parameter as its calculation amount is small. However, during the identification process, It is need to differentiate the objective function with respect to the motor parameter. The result of differentiation is easily affected by speed fluctuations or measurement noise which will lead to the deviation of the estimation result.

EKF method can avoid the problem of noise sensitivity and can estimate the state and parameters of the motor simultaneously. However, owing to large number of vector and matrix operations during the iterative process, the computation amount of this algorithm is great. In addition,

pretreatment of motor mathematical model is needed and this is complex when used in multiparameter identification. As in [8], the motor and load parameters including stator resistance, stator inductance, and torque constant are identified using neural network. Reference [9] used back-propagation neural network for speed estimation; this method does not require prior model training and offline training, and the whole training process is conducted online. However, the neural network methods cannot guarantee their own stability and the convergence of the identification results. In [10], an MRA parameter identification method is proposed. The motor resistance is set as design value on the data sheet, and then we identify the rotor flux and stator resistance; however, when the motor is running, the resistance is changing which will bring to great estimation error. In [11], Popov stability criterion was used to estimate PMSM parameter and the identification effect is better. But this method cannot estimate the parameters of the stator resistance, dq-axis inductance, and rotor flux linkage simultaneously. Evolutionary algorithm based on immune particle swarm optimization (PSO) was proposed in [12]; this method can identify stator resistance, stator flux, and inductance simultaneously and the result is accurate, but the method is too complex.

An immune clonal differential evolution algorithm (ICDEA) based estimation method for identifying the electrical parameters of a nonsalient pole PMSM is proposed. The proposed method does not need the nominal value of any parameters and can estimate the stator resistance, dq-axis inductance, and rotor flux linkage simultaneously. The proposed method is verified through both simulation and experiment test and shows good performance in estimation of the electrical parameters of PMSM.

2. Model of PMSM

Ignoring the iron loss, magnetic saturation, and magnet eddy current loss, the electrical model of a sinusoidal PMSM in synchronous rotating reference frame (dq-axis) can be expressed as follows:

$$\begin{aligned} \frac{di_d}{dt} &= -\frac{R_s}{L_d} i_d + \omega i_q + \frac{u_d}{L_d}, \\ \frac{di_q}{dt} &= -\frac{R_s}{L_q} i_q - \omega i_d + \frac{u_q}{L_q} - \frac{\psi}{L_q}\omega, \end{aligned} \tag{1}$$

where i_d, i_q, u_d, and u_q are the dq-component of stator current and voltage, respectively, ω is the rotor electrical angular speed, R_s, L_d, L_q, and ψ are the stator resistance, and d-axis and q-axis are the inductance and permanent magnet flux linkage, respectively.

In the proposed identification method, dq-axis current, dq-axis voltage, and rotor electrical speed are measured and stored after filtering by low-pass filter. The parameter identification can be based on steady state discrete model of PMSM [13] as shown in the following:

$$\begin{aligned} u_d(k) &= R_s i_d(k) - L_q \omega(k) i_q(k), \\ u_q(k) &= R_s i_q(k) + L_d \omega(k) i_d(k) + \psi\omega(k). \end{aligned} \tag{2}$$

The zero d-axis current control strategy ($i_d = 0$) is widely used in PMSM control. In this case, (2) can be simplified as

$$\begin{aligned} u_d(k) &= -L_q \omega(k) i_q(k), \\ u_q(k) &= R_s i_q(k) + \psi\omega(k). \end{aligned} \tag{3}$$

In (3), R_s, L_d, L_q, and ψ are the unknown parameters to be identified; other variables, such as dq-axis current, dq-axis voltage, and electrical speed, are measurable. As there are four parameters to be estimated and the rank of (2) or (3) is two, it can be regarded as rank deficient equation. To solve the rank deficient problem, in [14] LIU injects a short pulse of negative i_d current and simultaneously solves two sets of simplified PMSM state equations corresponding to $i_d = 0$ and $i_d \neq 0$ and gets a set of dq-axis equation as follows:

$$\begin{aligned} u_{d0}(k_0) &= -L_{q0}\omega(k_0) i_{q0}(k_0), \\ u_{q0}(k_0) &= R_s i_{q0}(k_0) + \psi_0\omega(k_0), \\ u_d(k_1) &= R_s i_d(k_1) - L_q\omega(k_1) i_q(k_1), \\ u_q(k_1) &= R_s i_q(k_1) + L_d\omega(k_1) i_d(k_1) + \psi\omega(k_1), \end{aligned} \tag{4}$$

where the variable and parameters with/without suffix "0" are referred to as $i_d = 0$ and $i_d \neq 0$, respectively.

3. Immune Clonal Selection Differential Evolution Algorithm (ICDEA)

3.1. Standard Differential Evolution Algorithm. Differential evolution (DE) algorithm was proposed by Storn and Price in 1997 and has received increasing attention due to its effectiveness and simplicity [15]. DE algorithm is a population-based evolutionary computing method and has the characteristic of memorizing of individual's optimal value, sharing internal information. Its basic operator includes mutation, crossover, and selection. It can be seen as a kind of greedy genetic algorithm with the idea of ensuring quality. In the initialization phase, the individuals are initialed with an average probability distribution within the search space. In the evolutionary stage, individuals undergo mutation, crossover, and selection until the stop condition is met. Each individual represents a candidate solution of objective function $f(x)$; its quality is evaluated through calculating the fitness function and the optimal individual is recorded and tracked.

The evolution process of DE starts with a population which includes NP individuals; each individual is a D dimensional vector and can be described as follows:

$$X_i^g = \left(x_{i1}^g, x_{i2}^g, \ldots, x_{iD}^g\right) \quad (i = 1, 2, \ldots, \mathrm{NP}). \tag{5}$$

The evolution process starts after the population is initialized randomly, and the process includes mutation, crossover, and selection operation. There are several mutation strategies according to the producing way of individual. Common mutation operator include DE/rand/1/bin and DE/best/1/bin. For each target individual X_{ig}, according to the mutation operator, a mutation vector $v_{i,j}^{g}$ is generated by adding the weight difference between a defined number of individual randomly selected from the previous population and another individual, which is described as

$$v_{i,j}^{g} = x_{r1,j}^{g} + F * \left(x_{r2,j}^{g} - x_{r3,j}^{g}\right), \tag{6}$$

or

$$v_{i,j}^{g} = x_{\text{best},j}^{g} + F * \left(x_{r1,j}^{g} - x_{r2,j}^{g}\right), \tag{7}$$

where $x_{\text{best},j}^{g}$ denote the best individual in current population, $r1, r2, r3 \in \{1, 2, \ldots, \text{NP}\}$ are integers randomly generated and mutually different and also different from i, and $F \in (0, 2)$ is the scaling factor, which is a positive constant and used to control the amplification of the differential of $x_{r1,j}^{g} - x_{r2,j}^{g}$ or $x_{r2,j}^{g} - x_{r3,j}^{g}$ and thus represents the level of mutation. Following the mutation operation, for each target individual X_{ig}, a new individual is generated by the following equation:

$$u_{i,j}^{g} = \begin{cases} v_{i,j}^{g}, & \text{rand}(j) \le \text{CR or } j = rn_i \\ x_{i,j}^{g}, & \text{otherwise,} \end{cases} \tag{8}$$

where $\text{CR} \in [0, 1]$ is called a crossover constant, rand(j) is the jth evaluation of a uniform random number generator with value between 0 and 1, and rn_i is a randomly selected index $\in 1, 2, \ldots, D$ and used to ensure that $u_{i,j}^{g}$ is different from $v_{i,j}^{g}$ [15].

"Greedy" selection strategy is used in selection phase to ensure the better individual can get into next generation. Individual of next generation is created according to the following formula:

$$x_i^{g+1} = \begin{cases} u_i^{g}, & f\left(u_i^{g}\right) < f\left(x_i^{g}\right) \\ x_i^{g}, & f\left(u_i^{g}\right) \ge f\left(x_i^{g}\right). \end{cases} \tag{9}$$

x_i^{g+1} is the new individual in the new population and $f(\,)$ is the fitness function. Only the value of fitness function of trial vector u_i^{g} is smaller than that of the target vector x_i^{g}; the next generation will be replaced by u_i^{g}.

3.2. Immune Differential Evolution Based on Clonal Selection Algorithm. As described above, DE algorithms use greedy search strategy in selection operation; that is, after mutation and crossover operation, only the individual with better fitness value can be chosen as offspring. This greedy mechanism can increase the convergence speed of the algorithm; however, it is easily trapped into local minimum and lead to the premature convergence. To deal with this problem,a DE algorithm based on immune clonal selection algorithm is proposed. In proposed algorithm, certain number of outstanding offspring individuals underwent clonal selection operation, which retains the excellent individuals as much as possible and thereby enhancing the convergence accuracy and diversity of the population. The inactive individual undergoes receptor editing operation to ensure the diversity of the population and to speed up the convergence rate of the algorithm.

3.3. Artificial Immune Algorithm. One reason for premature convergence in DE algorithm is that the population diversity declines rapidly during the iteration; this is called as gather phenomenon, which makes the difference between the individual's fitness get smaller and smaller and tend to concentrate on converging to one point, and the population cannot research in the solution space. Therefore, the algorithm falls into a local optimum and premature convergence phenomenon is appearing. In addition, as DE algorithm is a stochastic search method, if the problem is a multimodal function in which multiple local minima exist, the algorithm is easy to trap into local optimum and is difficult to find the global optimum. In order to improve the optimization capability to solve multimodal problem, clonal selection mechanism and the receptor editing mechanism are introduced.

3.4. Clonal Selection Algorithm. Clone selection algorithm (CSA) was presented by de Castro and Von Zuben in 2000 [16]. As a new kind of bionic intelligent algorithm, CSA has the property of fast convergence to the global optimizations. CSA introduces the mechanism of affinity maturation, clonal and memory based on the traditional bionic evolutionary algorithm and uses the corresponding operators that guarantee it converging to the global optimization. The basic steps of CSA are as follows:

Step 1. Generate a set of candidate solutions $X = \{x_{1d}, x_{2d}, \ldots, x_{nd}\}$.

Step 2. Clone the individual in population X; the clonal size is proportional to its affinity:

$$N_c = \sum_{i=1}^{n} \text{round}\left(\frac{\beta * n}{i} + b\right), \tag{10}$$

where round( ) denotes the rounding function, n is population size, and $\beta \in (0, 1)$; constant $b \geqslant 1$ is added to ensure that each antibody has a certain number. After clonal operation, a temporary population C is generated.

Step 3. Antibody population (C^*) is created through hypermutation to each individual in population C. Inspired by natural biological evolution, in the beginning stage of evolution, the mutation rate is larger to maintain the diversity of the population, whereas in the later stage of evolution,

the mutation rate declines gradually to improve the ability of local tuning. The mutation operator is defined as follows:

$$x_{id}^{\text{new}} = x_{id} + [rd > P_m]\,\eta x_{id} * \text{rand}(0,1) - [rd \le P_m]\,\eta x_{id} * \text{rand}(0,1), \quad [rd > P_m] = \begin{cases} 1 & [rd > P_m] \\ 0 & \text{otherwise}, \end{cases} \tag{11}$$

where rand(0, 1) is random number between 0 and 1, $P_m = 0.5$, $\eta(t) = 1 - r^{(1-g/g_{\max})a}$, $g_{\max}$ is the max number of evolutionary generations, a is normal number and its general value is set to 2, and $r \in (0,1)$. It can be seen from (11) that in the beginning of evolution, when r is small, $\eta(t) \approx 1$, mutation range is large and in the later stage of evolution, when g is near to $g_{\max}$, $\eta(t) \approx 0$, local search will be carried on within a small range local space.

Step 4. Immune selection operations: after clonal operation, the individual with optimum affinity is chosen to next generation. Through local selection, population compression is realized while ensuring the optimal solution in the antibody group is not deteriorating.

3.5. Receptor Editing Mechanism. Receptor editing mechanism [17] refers to the T-cell and B-cell receptor's structure change in specific condition and the affinity of receptor change accordingly. Receptor editing mechanism enriches the diversity of antigen receptors. In ICDEA algorithm, inactive cell receptor is distinguished at intervals of certain generation, and receptor editing is carried on to this inactive cell receptor through using nonlinear logistic sequence to realize the random and regular drift as the following formula:

$$X'_{id} = X_{id} + \frac{X_{id}^{\max} - X_{id}^{\min}}{m} + U_{r+1}. \tag{12}$$

$x_{\text{id}}^{\min}$, $x_{\text{id}}^{\max}$ are low bound and up bound, respectively, and m is normal constant and its value is determined by specific problems. U_{r+1} is mapping of chaotic sequence logistic and given by

$$U_{r+1} = \mu * U_r * (1 - U_r), \quad r = 0, 1, 2, \ldots, \quad 0 < U_0 < 1, \tag{13}$$

where μ is the control parameter of system; it has been proved by [18] that when $\mu = 4$ and $U_r \in (0.25, 0.5, 0.75, 1)$, the system described by (13) is completely chaotic and U_{r+1} is ergodic within 0 and 1.

3.6. Algorithm Procedure. The proposed ICDEA can be summarized as follows.

Step 1. Set the values of population size NP, maximum number of iterations $g_{\max}$, scaling factor F, and crossover probability CR; set the current number of iterations $g = 1$ and initialize each individual randomly according to the following formula:

$$x_{ij} = \text{rand}(0,1) * \left(x_j^u - x_j^l\right) + x_j^l, \tag{14}$$

where $i = 1, 2, \ldots$, NP; $j = 1, 2, \ldots, D$, and x_j^u and x_j^l are up bound and low bound on jth dimension.

Step 2. Calculate individual fitness and find the optimal fitness value and record the best individual in the current generation as X_{best}^g.

Step 3. If the optimal fitness value reaches theoretical optimal value or current number of iterations g is equal to $g_{\max}$, then output the outcome; otherwise, go to next step.

Step 4. Sort all individuals according to their fitness value. For the top one fourth of the outstanding individual, clonal selection operation is carried on; if the individual fitness value is better than the current generation of global optimal individual fitness, it is replaced with the individual global best individual X_{best}^g, whereas one fourth of individual with poor fitness undergo receptor editing operations every several generations.

Step 5. Randomly select two different individuals in the population and generate individual v_i^g through mutation operation according to (6).

Step 6. According to (8), generate test individual using crossover operation.

Step 7. Carry out selection operation according to(9)

Step 8. $g = g + 1$; return to Step 2.

4. Multiparameter Identification of PMSM Using ICDEA

Parameter identification of PMSM can be regarded as a system optimization problem. The identification principle is to find a set of parameters that minimize the error between the output of the theoretical model and the actual system. To use optimization algorithm for parameter identification, the model of PMSM can be described as the form of differential equations which is as follows [19]:

$$\dot{x} = f(p, x(t), u(t)), \quad y(t) = g(p, x), \tag{15}$$

where $x(t) = (i_d, i_q)$ is the state vector, $u(t) = (u_d, u_q)$ is the system input vector, $p = (R_s, L_d, L_q, \psi)$ is the parameter vector which is needed to identify, $y(t)$ is the measurable output vector, and $f(p, x(t), u(t))$ and $g(p, x)$ can be either linear or nonlinear function. The objective of parameter identification is to identify the unknown parameter vector p as accurately as possible; an equipollent tracking model of the system is established as follows:

$$\dot{\hat{x}} = f(\hat{p}, x(\hat{t}), u(t)), \quad y(\hat{t}) = g(\hat{p}, \hat{x}). \tag{16}$$

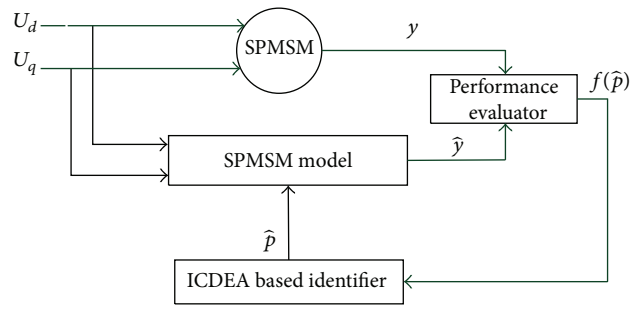


Figure 1: Components of the ICDEA based parameters identification.

Table 1: Time complexity of the proposed identification algorithm.

Step	Time complexity
Initial parameters	O (NP × D)
ICDEA-based parameters estimation	O (NP × $G_{\max}$ × (NP + D))
SPMSM model calculation	O (NP^2)
Fitness calculation	NP

where $\hat{p}$ is the estimated value of p. The structure of the ICDEA based parameter identification of PMSM is illustrated in Figure 1.

First, $u(t) = (u_d, u_q)$ is fed into both the system to be identified and the desired system; the outputs of both of the system and its desired system are input to the performance evaluator and then the fitness will be calculated; the calculated fitness is input to the ICDEA based identifier to estimate the unknown parameter vector; the estimated parameter will be used to update the system model. The above process will be repeated until the error between output of system and its model reaches the desired error limit or the preset maximum iteration number is equal to its preset maximum.

As described above, PMSM parameter identification is an identification problem with nonlinearity structure. Four parameters, stator resistance, dq axis inductance, and linkage flux are to be estimated. The fitness function is constructed according to (2), (3), and Figure 1 [20]. Consider

$$\begin{aligned} f(\hat{p}) = \sum_{k=1}^{n} & w_1 \left| u_{d0}(k) - \hat{u}_{d0}(k) \right| \\ & + w_2 \left| u_{q0}(k) - \hat{u}_{q0}(k) \right| \\ & + w_3 \left| u_d(k) - \hat{u}_d(k) \right| \\ & + w_4 \left| u_q(k) - \hat{u}_q(k) \right|, \end{aligned} \tag{17}$$

where w_1, w_2, w_3, w_4 are weight value and n is the number of sample data. Equation (17) is a function of the estimated parameters with multiple local optima. As traditional algorithms usually have difficulties in optimizing complex nonlinear systems with multiple local optima, the fitness function is optimized using the proposed ICDEA to search

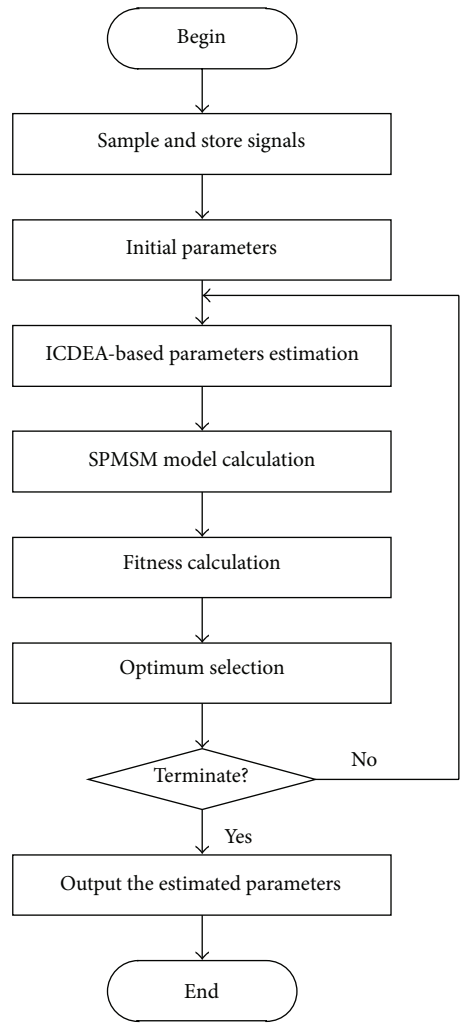


Figure 2: Flow chart of the ICDEA based parameters identification.

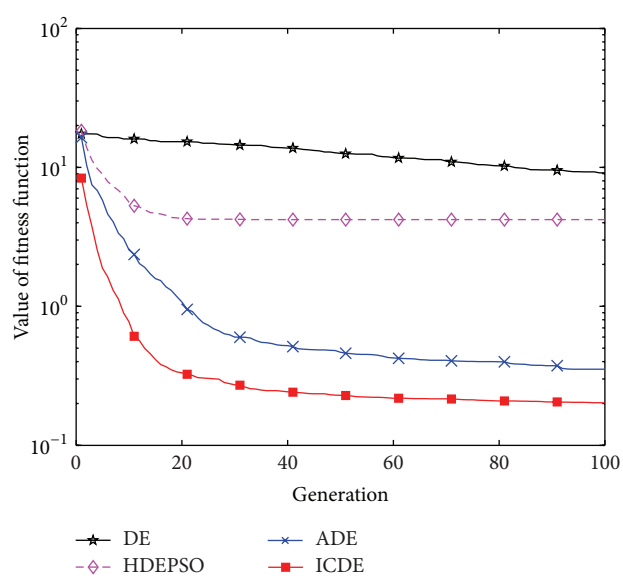
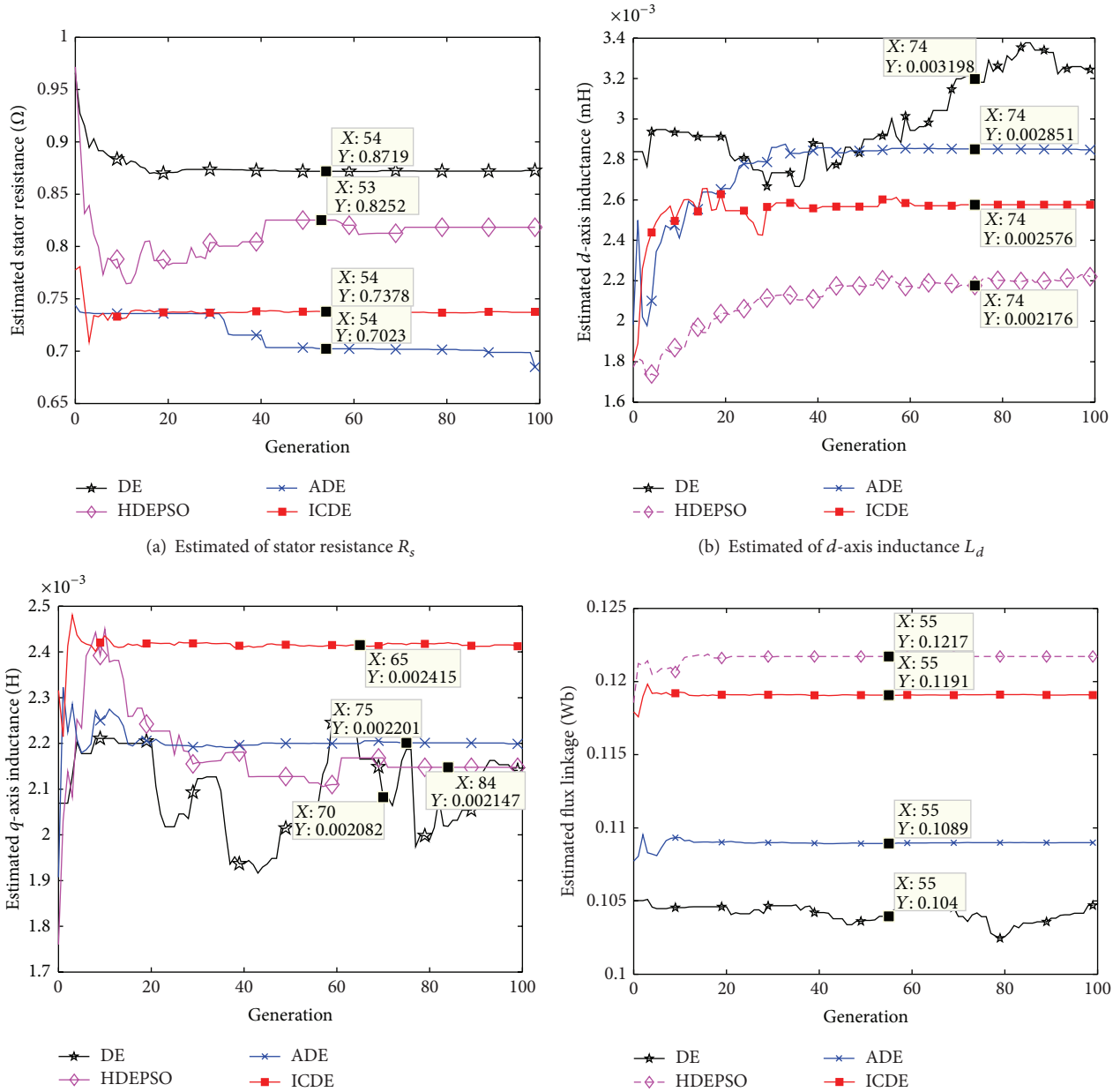


Figure 3: Optimization process of the fitness function (simulation).



(a) Estimated of stator resistance R_s

(b) Estimated of d-axis inductance L_d

(c) Estimated of q-axis inductance L_q

(d) Estimated of flux linkage ψ

FIGURE 4: Identified parameters (simulation).

for better identification of PMSM electrical parameters. The flow chart of the ICDEA based parameters identification is illustrated in Figure 2. The time complexity of each step is presented in Table 1.

5. Simulation and Experimental

5.1. Simulation. A nonsalient poles PMSM is simulated in Matlab to demonstrate the performance of the proposed ICDEA applied to PMSM parameter identification. In the simulation, the PMSM is applied to vector control drive system with cascaded PI controllers which are widely used in industrial motor drive system. Similar structure is used in our experimental test platform. Nominal parameters of the simulated PMSM are listed in Table 2.

To compare with others algorithms, different DE algorithms include DE [21] and adaptive differential evolution (ADE) [22]; hybridizing differential evolution and particle swarm optimization (HDEPSO) [23] are applied to the PMSM electrical parameter identification. During simulation, all the algorithms iterate 100 generations; the parameters of simulated PMSM are chosen to be identical to the test motor datasheet parameters. Figure 3 shows the optimization

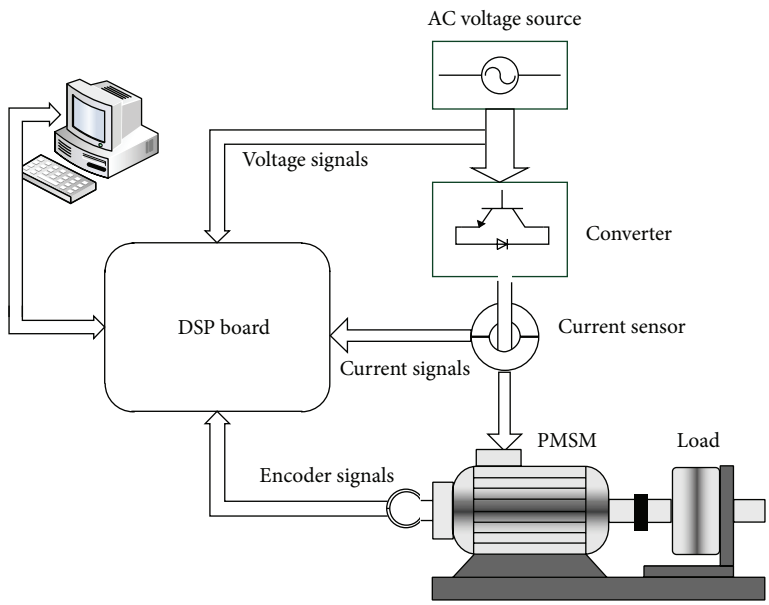
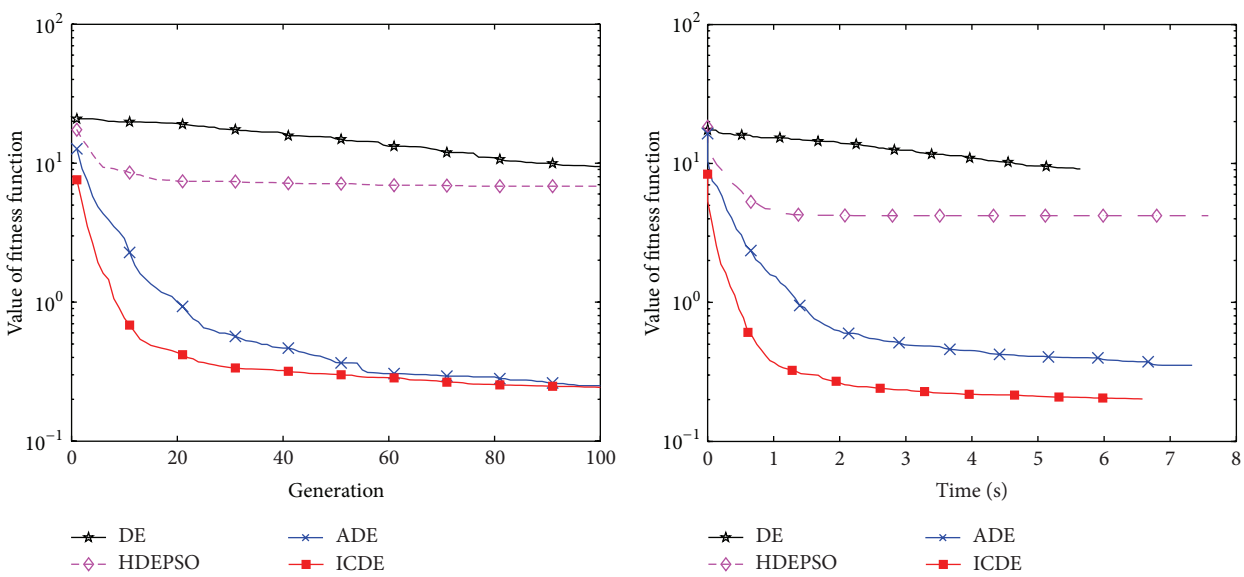


Figure 5: System setup of experimental platform.



(a) Fitness value change with generation

(b) Fitness value change with time

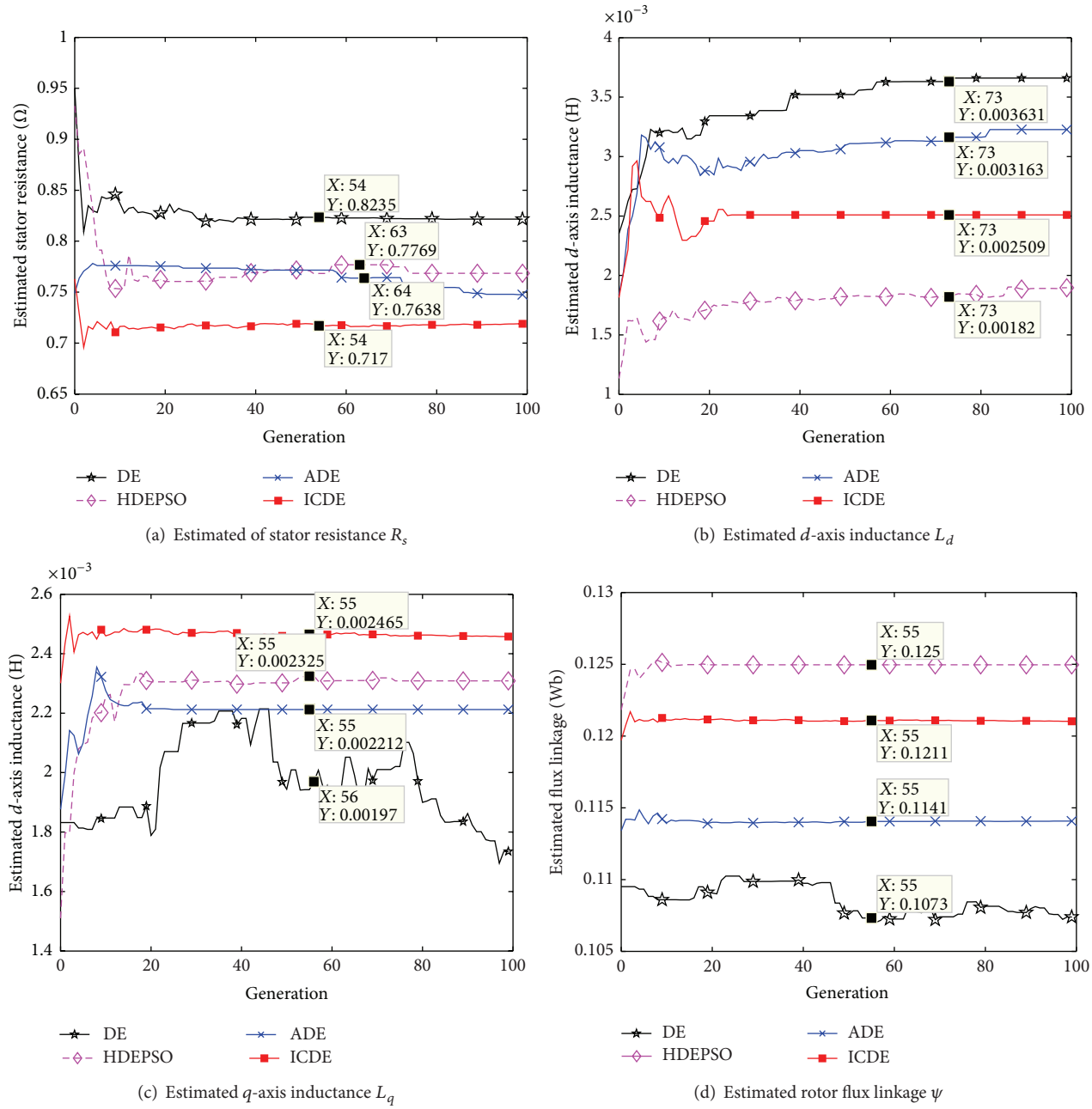
Figure 6: Optimization process of the fitness function (experimental).

process of the fitness function (cost) and the optimization process of the identified parameters R_s, L_d, L_q and ψ are shown in Figure 4.

It can be seen from Figures 3 and 4 that the convergence rate of proposed ICDEA is significantly faster than DE, ADE, and HDEPSO, and the algorithm is capable of identifying the electrical parameter of PMSM accurately.

5.2. Experimental Verification. To further verify the effectiveness of the proposed estimation method, experiments are performed on a platform of PMSM drive system. The experimental data were obtained on a PMSM fed from vector control drive and coupled to an identical DC motor as its load. The DSP (TMS320LF28335) based hardware test bed is displayed in Figure 5, specification for PMSM is identical to Table 2.

In the experiment, the motor was started and rotated at its rated speed. Data including dq-axis current, dq-axis voltage, and electrical speed are sampled and memorized. During the identification process, the data are sent to the computer to



(a) Estimated of stator resistance R_s

(b) Estimated d-axis inductance L_d

(c) Estimated q-axis inductance L_q

(d) Estimated rotor flux linkage ψ

Figure 7: Identified parameters (experimental).

calculate iteratively. The procedure is similar to that of the simulation described previously, except that the real data are utilized.

The convergence rates of different evolution algorithms are shown in Figure 6(a). Figure 6(b) shows the fitness value variation of DE, HDEPSO, ADE, and ICDE, respectively, which shows that the ICDE can converge to the global optimum about 4 s and it is more effective than the other three DE algorithms.

Optimization process of the identified parameters is shown in Figure 7. The identification results are present in Table 3. It can be seen from the experiment results that the ICDEA is the best identification algorithm compared with DE, ADE, and HDEPSO.

6. Conclusion

A new hybrid DEA named ICDEA is proposed for PMSM electrical parameters identification. ICDEA incorporates clonal selection, receptor editing, and DEA. Both simulation and experiment results are provided to verify the effectiveness of the proposed method. Comparing with other different DEA shows that the ICDEA has better optimization capability and has good convergence in simultaneously estimating

Table 2: PMSM specification.

Parameter	Value (unit)
Rated power P_r	2.6 (kW)
Rated speed n	2500 (rpm)
Rated voltage U_r	220 (V)
Rated current I_r	10 (A)
Torque constant K_t	1.0 (N·m/A)
Stator resistance R_s	0.73 (Ω)
Nominal d-axis inductance L_d	2.45 (mH)
Nominal q-axis inductance L_q	2.45 (mH)
PM flux ψ	117.9 (mWb)
Moment of inertia J	$1.94e-3$ (kgm^2)
Pole pairs n_p	4

Table 3: Experimental results.

		DE	HDEPSO	ADE	ICDE
R_s (Ω)	Min.	0.8090	0.7531	0.7476	0.6959
	Max.	0.9500	0.7938	0.7782	0.7629
	Avg.	**0.8260**	**0.7743**	**0.7659**	**0.7175**
ψ (Wb)	Min.	0.1070	0.1218	0.1134	0.1197
	Max.	0.1102	0.1253	0.1149	0.1217
	Avg.	**0.1087**	**0.1249**	**0.1141**	**0.1211**
L_d (H)	Min.	0.0024	0.0011	0.0018	0.0018
	Max.	0.0037	0.0019	0.0032	0.0030
	Avg.	**0.0034**	**0.0018**	**0.0030**	**0.0025**
L_q (H)	Min.	0.0017	0.0015	0.0019	0.0023
	Max.	0.0022	0.0023	0.0024	0.0025
	Avg.	**0.0020**	**0.0021**	**00022**	**0.0024**
Fitness	Avg.	14.9338	7.5423	1.0274	0.5515
	Std. dev.	3.6926	1.5753	1.8840	0.9770

PMSM electrical parameters such as stator resistance, dq axis inductances, and rotor flux linkage. As the proposed method is used for nonsalient pole PMSM (assuming that $L_d = L_q$), it still needs further research for parameter identification of salient pole PMSM.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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