

# Parameter Estimation for VSI-Fed PMSM based on a Dynamic PSO with Learning Strategies

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**Abstract:** A dynamic particle swarm optimization with learning strategy (DPSO-LS) is proposed for key parameter estimation for permanent magnet synchronous machines (PMSMs), where the voltage-source-inverter (VSI) nonlinearities are taken into account in the parameter estimation model and can be estimated simultaneously with other machine parameters. In the DPSO-LS algorithm, a novel movement modification equation with variable exploration vector is designed to effectively update particles, enabling swarms to cover large areas of search space with large probability and thus the global search ability is enhanced. Moreover, a Gaussian-distribution based dynamic opposition-based learning (OBL) strategy is developed to help the *pBest* jump out local optima. The proposed DPSO-LS can significantly enhance the estimator model accuracy and dynamic performance. Finally, the proposed algorithm is applied to multiple parameter estimation including the VSI nonlinearities of a PMSM. The performance of DPSO-LS is compared with several existing PSO algorithms, and the comparison results show that the proposed parameters estimation method has better performance in tracking the variation of machine parameters effectively and estimating the VSI nonlinearities under different operation conditions.

**Index Terms:** particle swarm optimization (PSO), dynamic, opposition-based learning (OBL), learning strategy, system identification, parameter estimation, voltage source inverter (VSI) nonlinearity, permanent magnet synchronous machines (PMSMs).

## I. INTRODUCTION<sup>1</sup>

IN recent years, permanent magnet synchronous machines (PMSMs) are widely employed in high-performance applications (such as industrial robots, servo drive system, high-speed rail, renew energy generation systems, and household appliances) due to their high efficiency, high-power density, and good dynamic response [1][2]. Accurate knowledge of the machine parameters such as winding resistance, direct axis inductances, quadrature axis inductances, and rotor PM flux linkage are required for

control system design [3][4], condition monitoring and fault detection [5][6]. Usually machine parameters are used as a normal operation indicator for the PMSM drive system. For example, high temperature can cause an increase in winding resistance and the variation of inductances may cause torque ripple. Similarly, demagnetization in permanent magnet flux may cause a decrease in the amplitude of fundamental back electromotive force (EMF) and will influence *d-q*-axis inductances of the machine, which in turn will have a direct impact on machines performance and power efficiency [7]. In real applications, these machine parameters are not known exactly as they vary with the load torque, the changes of temperature, and other environmental conditions. For example, the winding stator resistance is prone to change with the variation of temperature, and the rotor flux linkage created by PM may vary with the changes of temperature and/or operational condition [8] [9].

The PMSM parameters are a key factor for control system design, condition monitoring and fault diagnosis, and therefore estimation or direct measurement of the parameters are important. Traditionally, some measurement instruments such as thermal couplers, search coils and load test bench [10] [11] are employed to observe the machine parameters. However, there are some drawbacks in the direct measurement due to two reasons. Firstly, it is difficult to measure the machine parameters when PMSM operates; Secondly, even if direct measurement is possible, it would normally significantly increase the instruments cost and the complexity of the associated implementation. Some researchers proposed to use self-commissioning technique to estimate PMSM parameters under standstill state [12]. Unfortunately, this method cannot estimate all the needed parameters accurately on load, for example rotor PM flux linkage cannot be estimated at a standstill state. Thus, in practice system identification method is an ideal technology for directly estimating the needed parameters based on regularly measured signals instead of using additional measurement instruments [8]. Algorithms such as *recursive least-squares* (RLS) [13] [14], *extended Kalman filter* (EKF) [15] [16], *model reference adaptive system* (MRAS) [17] [18], finite-element method [19], adaptive estimation methods [20] and *artificial neural networks* (ANN) [21] are usually employed for the design of parameter estimators. Owing to linear parameterization for the RLS algorithm, the RLS estimator usually suffers from the noise characteristics and may lead to the reduction of solution accuracy [13]. In [15], an EKF was employed to estimate the winding resistance and rotor flux linkage. The results indicate that the estimator suffers from noise and instability, and thus cannot obtain accurate estimates for the actual parameter values. In [16], an EKF was proposed to estimate the rotor speed and position of

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PMSM. However, it is difficult to use in real applications because the algorithm is sensitive to noise. The MRAS estimators proposed in [17] and [18] cannot simultaneously estimate winding resistance, inductance and rotor flux linkage accurately. In the MRAS method, other parameters' nominal values specified in the motor manual are needed to estimate one parameter. In this case, the accuracy of identified parameters depends on the accuracy of the nominal value. In reality, the real parameter value usually depends on a variable operating condition caused by the changes of temperature and/or load. The FE (finite element) based parameters estimator proposed in [19] requires a high computational load and it may be challenging task to use this method to estimate PMSM parameters due to the complex computations. Some ANNs have also been proposed for estimating parameters of PMSM in [21]. Although the ANN method is known to be precise in parameter estimation, it usually needs a long data set to train and more knowledge for weight adjustment.

Some researchers proposed to inject perturbation signals into the drive system to obtain an extra number of state space equations of PMSM, and then and apply system identification methodologies to estimate machine parameters [8] [12] [22][23]. In the signal injection method, the designed estimator is based on the conventional  $d$ - $q$ -axis equation and the VSI (voltage source inverter) nonlinearities are often ignored. Since the used signals such as VSI voltages for the parameter estimator are usually measured from the output voltage of the PI regulator in a PMSM vector control system, those methods are prone to suffer from the effect of nonlinearity of VSI such as switch voltage drop, switching delay and dead zone response [24]. As a result, it cannot estimate the actual value of the machine parameters due to the ignorance of effects of the nonlinearities on parameters estimation. Some methods were proposed to compensate the effect of VSI nonlinearity (see e.g. [24]-[27]), but these methods need accurate PMSM parameter values. Because the VSI nonlinearity and machine parameters cannot be simultaneously estimated by using these methods, the errors caused by VSI nonlinearity are combined into the parameter estimator and this will affect the accuracy of parameter estimation. Thus, the VSI nonlinearity should be considered in estimating machine parameters.

Due to the easy implementation, low computational cost and fast convergence speed in dealing with practical industrial problems, particle swarm optimization (PSO) has recently been introduced as an attractive optimization techniques in system identification, optimal and control of power electronics [28]-[34]. The parameter estimation problem can be treated as a grey-box model based parameter optimization task and the issue of parameter cross-coupling can be effectively solved by using PSO. In [28], an improved PSO method for estimating the unknown composite load model parameters was proposed, where a new crossover operation was introduced to improve the convergence performance. In [29], another improved PSO was proposed for parameter estimation of an induction machine by modifying the movement equation of the standard PSO as linear time-varying parameters. A least mean square (LMS) method combined with PSO was presented to identify the parameters of an induction motor in [30]. In the field of PMSM

parameters identification, some researchers proposed a PSO-based parameter estimator for PMSM [31] [32], this kind of intelligent estimator is effective in estimating the *stator resistance* and disturbed load torque. In [31], a PSO algorithm combined with experimental measurements was proposed for the identification of PMSMs. Similarly, a PSO combined with self-commissioning scheme was used in [32] for the identification and optimization of PMSM parameters. It is known that the basic PSO is easy to get trapped in local minima, these basic PSO algorithms may not be able to exactly estimate multiple parameters simultaneously, such as *winding resistance*, *dq-axis inductances* and *permanent magnet flux*. In [33], a coevolutionary optimization methodology combined multiple cooperate PSO and *artificial immune system* (AIS) was developed to improve multi-parameter estimation performance of PMSM. To speed up the search process of particles, a method of GPU accelerated parallel co-evolutionary immune PSO was proposed for parameter estimation and temperature monitoring of a PMSM [34], for which the performance of the parameter estimates was greatly improved by combining PSO and a parallel computing technology. Nevertheless, the existing PSO-based parameters estimators of PMSM are based on the basic  $d$ - $q$ -axis equation which neglects the VSI nonlinearity, thus it cannot estimate the actual value of the machine parameters.

In this study, a dynamic particle swarm optimization with learning a strategy (DPSO-LS) is proposed to design the estimator of machine parameters and VSI nonlinearity in PMSM, in which the VSI nonlinearity is seen as a system parameter and can be estimated simultaneously with machine parameters. In the DPSO-LS, a novel movement modification equation with variable exploration vector is designed to update particles, it permits some particles with large probability to cover large areas of search space and thus the global search ability is enhanced. Moreover, a dynamic opposition-based learning (OBL) operator using Gaussian-distribution is developed to help *pBest* jump out local optima. OBL is a reinforcement learning strategy using computing and counter computing simultaneously, and is widely used to accelerate the convergence properties of many evolutionary algorithms [35][36]. The proposed algorithm is applied to the estimation of multiple machine parameters and VSI nonlinearity of PMSM. The results indicate that it can track parameter variation with the changing operation condition effectively. A comparison of the performance of DPSO-LS with several existing PSO algorithms is carried out, and it demonstrates that the proposed parameters estimation method can better track the variation of machine parameters and estimating the VSI nonlinearities under different operation conditions.

In summary, the major contributions of this paper include:

- 1) A dynamic estimator using dynamic PSO combined with a dynamic OBL scheme is proposed for simultaneous estimation of the machine parameters and VSI nonlinearities of PMSM. The VSI nonlinearity is seen as system parameters and can be estimated by the designed estimator, which takes into consideration of the influence of distorted voltage from the VSI and thus the accuracy of the estimation of machine parameters is improved. The proposed estimator can

simultaneously estimate machine parameters and VSI nonlinearity without any priori knowledge of the PMSM.

2) In order to enhance the accuracy and the dynamic performance of the estimator, a novel movement modification equation using a variable exploration vector is designed to update the velocity of particles. Moreover, a dynamic OBL mechanism with Gaussian distribution is introduced to overcome the blindness of the *pBest* stochastic evolution and enables it jump out the local optimality. The proposed estimator has a fast convergence rate, a good accuracy and a good dynamic response property.

3) The proposed estimator has also taken into account the identifiability of all the parameters to be estimated and the VSI nonlinearities. Furthermore VSI nonlinearities can be estimated individually from the *d-q*-axis equation with  $id=0$  control and  $id \neq 0$  (current injection condition), respectively.

The remainder of this paper is organized as follows. An estimator model for the machine parameters and VSI nonlinearities of a PMSM is described in section II. A DPSO-LS algorithm is proposed in section III, where a scheme to determine the parameters of the estimator and the optimization procedure and steps are described. Experimental results and the analysis are given in section IV. Finally, some concluding remarks are presented in section V.

## II. PMSM MODEL AND DESIGN OF PARAMETER ESTIMATION MODEL

### A. PMSM Model and VSI Nonlinearity

The *d-q*-axis voltage equations of the PMSM are usually employed for the parameter estimation of the machine [8], which are given as:

$$\begin{cases} \frac{di_d}{dt} = -\frac{R}{L_d}i_d + \frac{L_q}{L_d}\omega i_q + \frac{u_d}{L_d} \\ \frac{di_q}{dt} = -\frac{R}{L_q}i_q - \frac{L_d}{L_q}\omega i_d + \frac{u_q}{L_q} - \frac{\psi}{L_q}\omega \end{cases} \quad (1)$$

$$T_e = 1.5P[\psi i_q + (L_d - L_q)i_d i_q] \quad (2)$$

where  $\omega$  is the electrical angular velocity,  $u_d$ ,  $u_q$ ,  $i_d$ , and  $i_q$ , are *d-q*-axis stator voltage and current,  $P$  is the number of pole pairs, the parameter set  $\{R, L_d, L_q, \psi\}$  is unknown and needs to be identified from measured data. (1) can be discretized as follows when the machine is under the steady-state:

$$\begin{cases} u_d(k) = Ri_d(k) - L_q\omega(k)i_q(k) \\ u_q(k) = Ri_q(k) + L_d\omega(k)i_d(k) + \psi\omega(k) \end{cases} \quad (3)$$

Taking into account the influence of VSI nonlinearity, (3) could be rewritten as:

$$\begin{cases} \dot{u}_d(k) + Dd(k)V_{dead} = u_d(k) \\ \dot{u}_q(k) + Dq(k)V_{dead} = u_q(k) \end{cases} \quad (4)$$

where  $\dot{u}_d$  and  $\dot{u}_q$  are the *dq*-axis reference voltages and measured from the PI regulators (V),  $Dd$  and  $Dq$  can be expressed as [25]-[27]:

$$\begin{bmatrix} Dd(k) \\ Dq(k) \end{bmatrix} = 2 \begin{bmatrix} \cos(\theta) & \cos(\theta - \frac{2\pi}{3}) & \cos(\theta + \frac{2\pi}{3}) \\ -\sin(\theta) & -\sin(\theta - \frac{2\pi}{3}) & \sin(\theta - \frac{\pi}{3}) \end{bmatrix} \begin{bmatrix} \text{sign}(i_{as}) \\ \text{sign}(i_{bs}) \\ \text{sign}(i_{cs}) \end{bmatrix} \quad (5)$$

where  $i_{as}$ ,  $i_{bs}$ ,  $i_{cs}$  are the stator *abc* three-phase currents (A).

$$\text{sign} = \begin{cases} 1, & i \geq 0 \\ -1, & i < 0 \end{cases} \quad (6)$$

In discrete time domain, the steady-state PMSM equation including the distorted voltage due to VSI nonlinearity can be expressed as

$$\dot{u}_d(k) + Dd(k)V_{dead} = Ri_d(k) - L_q\omega(k)i_q(k) \quad (7a)$$

$$\dot{u}_q(k) + Dq(k)V_{dead} = Ri_q(k) + L_d\omega(k)i_d(k) + \psi\omega(k) \quad (7b)$$

The variable  $V_{dead}$  is the distorted voltage caused by the VSI nonlinearities, and can be represented as

$$V_{dead} = \frac{T_{dead} + T_{on} - T_{off}}{T_s} (V_{dc} - V_{sat} + V_d) + \frac{V_{sat} + V_d}{2} \quad (8)$$

where  $T_{dead}$ ,  $T_{on}$ ,  $T_{off}$ ,  $V_{dc}$ ,  $V_{sat}$  and  $V_d$  are the dead-time period, turn-on, turn-off times of the switching device, the actual and measured real-time dc bus voltages, the saturation voltage drop of the active switch and the forward voltage drop of the freewheeling diode, respectively. The switching times and voltage drops in the switching device may vary during operations and difficult to measure due to the changes of current, frequency, DC link voltage, operating conditions, dead-time period, and temperature. Therefore, it is important to accurately estimate and compensate the  $V_{dead}$  in order to ensure the accuracy of estimated PMSM parameter values.

### B. PMSM Parameter Estimator Design

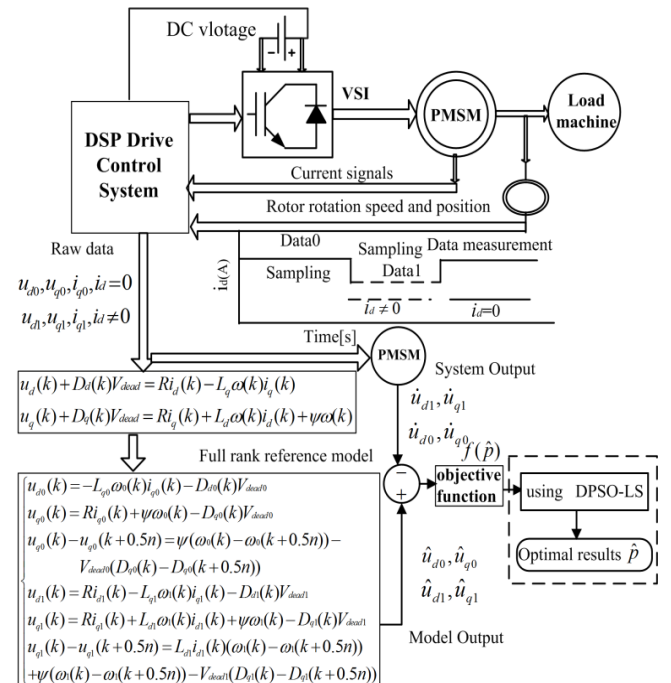


Fig. 1. Schematic diagrams of estimation and mathematical model.

First of all, the VSI nonlinearity is seen as parameters that can be estimated simultaneously with other machine parameters by the designed estimator using the proposed DPSO-LS algorithm. To obtain more equations,  $i_d$  is set to be zero for decoupling the flux and torque control, and a very short period of negative  $i_d$  (i.e.  $i_d < 0$ ) is then injected to obtain a full rank reference model. The symbols  $id_0$  and  $id_1$  indicate that the  $d$  axis is injected with the current  $id=0$  and  $id \neq 0$ , respectively (see Fig. 1). In Fig.1, under normal operation condition, the PMSM is under a control state with  $id=0$ , the Data0 (the data associated with  $id=0$ ) are firstly measured and then a short pulse of negative  $id < 0$  is injected, and the corresponding data, Data1 (the data associated with  $id \neq 0$ ), are recorded after 2ms of injection, both with the same sampling width and sampling number.

The parameters of machine are assumed to be constant as the duration of injected pulse current is very short due to mechanical inertia and fast response of current loop PI controller. In this case, the influence of injecting a short pulse of  $id$  on output torque can be neglected. Thus, the two sets of steady state data (Data0 and Data1) can be used for the estimation of multiple machine parameters since these parameters can be seen as constant within very short time. Note that  $V_{dead}$  is directly related to the current, so  $V_{dead0} \neq V_{dead1}$ . Thus, the distorted voltage  $V_{dead0}$  and  $V_{dead1}$  need to be estimated from the data. A total of six parameters (i.e.,  $R, L_d, L_q, \psi, V_{dead0}, V_{dead1}$ ) need to be estimated, therefore six equations need to be designed. From (7), it is ready to get (9a) and (9b) when  $id=0$ . When  $id \neq 0$ , (7) can be reformed as (9d) and (9e). The measured data are divided into two parts, the first part is indexed from 1 to  $0.5n$  and the second one is indexed from  $0.5n+1$  to  $n$ . Since  $i_q$  and  $i_d$  are kept as constants, it is reasonable that  $V_{dead}$  is regarded as a constant during the data measurement, two additional equations are designed as in (9c) and (9f) during the varying speed. The full rank reference model is given as

$$u_{d0}(k) = -L_{q0}\omega(k)i_{q0}(k) - D_{d0}(k)V_{dead0} \quad (9a)$$

$$u_{q0}(k) = Ri_{q0}(k) + \psi\omega(k) - D_{q0}(k)V_{dead0} \quad (9b)$$

$$u_{q0}(k) - u_{q0}(k + 0.5n) = \psi(\omega(k) - \omega(k + 0.5n)) - V_{dead0}(D_{q0}(k) - D_{q0}(k + 0.5n)) \quad (9c)$$

$$u_{d1}(k) = Ri_{d1}(k) - L_{q1}\omega(k)i_{q1}(k) - D_{d0}(k)V_{dead1} \quad (9d)$$

$$u_{q1}(k) = Ri_{q1}(k) + L_{d1}\omega(k)i_{d1}(k) + \psi\omega(k) - D_{q1}(k)V_{dead1} \quad (9e)$$

$$u_{q1}(k) - u_{q1}(k + 0.5n) = L_{d1}i_{d1}(k)(\omega(k) - \omega(k + 0.5n)) + \psi(\omega(k) - \omega(k + 0.5n)) - V_{dead1}(D_{q1}(k) - D_{q1}(k + 0.5n)) \quad (9f)$$

The estimation of the parameters can be addressed as an optimization problem where the system response to a known input is used to find the unknown parameter values of the model. The idea is to compare the system response with the parameterized model based on a cost function, which is defined to measure the similarity between the system response and the model response.

To approximate the dynamic parameters, it needs to define cost functions. In this study, the three cost functions or fitness functions, under control  $id = 0$ , are defined as

$$f_1(\hat{L}_q, \hat{V}_{dead0}) = \frac{1}{n} \sum_{k=1}^n \left| \dot{u}_{d0}(k) + D_{d0}(k)\hat{V}_{dead0} - \hat{u}_{d0}(k) \right| \quad (10)$$

$$= \frac{1}{n} \sum_{k=1}^n \left| \dot{u}_{d0}(k) + D_{d0}(k)\hat{V}_{dead0} + \omega(k)\hat{L}_q i_{q0}(k) \right|$$

$$f_2(\hat{R}, \hat{\psi}, \hat{V}_{dead0}) = \frac{1}{n} \sum_{k=1}^n \left| \dot{u}_{q0}(k) + D_{q0}(k)\hat{V}_{dead0} - \hat{u}_{q0}(k) \right| \quad (11)$$

$$= \frac{1}{n} \sum_{k=1}^n \left| \dot{u}_{q0}(k) + D_{q0}(k)\hat{V}_{dead0} - \hat{R}i_{q0}(k) - \omega(k)\hat{\psi} \right|$$

$$f_3(\hat{\psi}, \hat{V}_{dead0}) = \frac{1}{2n} \sum_{k=1}^n \left| \dot{u}_{q0}(k) - \dot{u}_{q0}(k + 0.5n) - (\hat{\psi}(\omega(k) - \omega(k + 0.5n))) \right| \quad (12)$$

Under control  $id \neq 0$ , another three fitness functions are given as

$$f_4(\hat{R}, \hat{L}_q, \hat{V}_{dead1}) = \frac{1}{n} \sum_{k=1}^n \left| \dot{u}_{d1}(k) + D_{d1}(k)\hat{V}_{dead1} - \hat{u}_{d1}(k) \right| \quad (13)$$

$$= \frac{1}{n} \sum_{k=1}^n \left| \dot{u}_{d1}(k) + D_{d1}(k)\hat{V}_{dead1} - \hat{R}i_{d1}(k) + \omega(k)\hat{L}_q i_{q1}(k) \right|$$

$$f_5(\hat{R}, \hat{\psi}, \hat{L}_q, \hat{V}_{dead1}) = \frac{1}{n} \sum_{k=1}^n \left| \dot{u}_{q1}(k) + D_{q1}(k)\hat{V}_{dead1} - \hat{u}_{q1}(k) \right| \quad (14)$$

$$= \frac{1}{n} \sum_{k=1}^n \left| \dot{u}_{q1}(k) + D_{q1}(k)\hat{V}_{dead1} - \omega(k)\hat{L}_d i_{d1}(k) \right|$$

$$f_6(\hat{R}, \hat{\psi}, \hat{V}_{dead1}) = \frac{1}{2n} \sum_{k=1}^n \left| \dot{u}_{q1}(k) - \dot{u}_{q1}(k + 0.5n) - (\hat{L}_d i_{d1}(k)(\omega(k) - \omega(k + 0.5n)) + \hat{\psi}(\omega(k) - \omega(k + 0.5n)) - \hat{V}_{dead1}(D_{q1}(k) - D_{q1}(k + 0.5n))) \right| \quad (15)$$

where  $n$  is the length of samples,  $\hat{u}_d$  and  $\hat{u}_q$  indicate the estimated voltages in  $dq$ -axis calculated through measured currents and the estimated parameters and VSI nonlinearities. Let  $\hat{p} = (\hat{R}, \hat{L}_d, \hat{L}_q, \hat{\psi}, \hat{V}_{dead0}, \hat{V}_{dead1})$ , then all the needed parameters can be identified simultaneously by minimizing the following objective function

$$f(\hat{p}) = \sum_{i=1}^6 a_i f_i \quad (16)$$

where  $a_i$ s are weighting coefficients. Note that the designed objective function (16) is related to the actual permanent magnet synchronous motor drive system which is highly nonlinear and time varying. The nonlinear objective function has many local optima and the used optimization method should be capable of identifying parameters dynamically and adaptively in solving such a problem. So, it is important to develop an efficient dynamic parameter tracking approach for the estimation of PMSM parameters and VSI nonlinearities.

### III. ESTIMATOR PARAMETER OPTIMIZATION WITH DPSO-LS

#### A. Principle of the Basic PSO Algorithm

PSO is a swarm-based intelligent optimization algorithm inspired by the ideas of mimicking behaviors of bird flocking foraging. Assuming that the problem is defined in a  $d$ -dimensional space, and each particle  $i$  is composed of two vectors, namely the velocity vector  $V_i = \{V_{i1}, V_{i2}, \dots, V_{id}\}$  and the position vector  $X_i = \{X_{i1}, X_{i2}, \dots, X_{id}\}$ , the searching scheme can be represented as

$$V_{id}(t+1) = \phi V_{id} + c_1 * rand_1() (pBest_{id}(t) - X_{id}(t)) + c_2 * rand_2() (gBest_d(t) - X_{id}(t)) \quad (17)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \quad (18)$$

where  $\phi$  is the inertia weight factor decreasing linearly,  $c_1$  and  $c_2$  are the acceleration coefficients,  $rand_1$  and  $rand_2$  are two uniformly distributed numbers generated randomly within  $[0,1]$ , respectively.  $pBest_{id}$  represents the  $i$ -th particle has found best position so far (individual best),  $gBest_d$  is the best position found among the entire population (global best).

### B. The Proposed DPSO-LS Algorithm

As mentioned in Section II, the objective function is multimodal and therefore requires that the proposed parameter optimization should be able to adaptively change their original trajectories to explore new search space when the solution of problem is changing. In order to solve this problem, a dynamic particle swarm optimization with a learning strategy (DPSO-LS) is proposed for machine parameter and VSI nonlinearity estimation.

The implementation of the learning strategy contains two key aspects. Firstly, a novel movement update equation is designed using a variable exploration vector to enhance the dynamic performance of PSO. Secondly, a dynamic OBL using adaptive Gaussian-distribution is proposed to overcome the blindness in the search of  $pBest$ s through stochastic evolution and enables it escape from local optima. It worth noting that the proposed DPSO-LS does not increase time complexity in comparison with the basic PSO. Actually, it is easy to implement to solve the optimization problem here, and to adapt to solve other similar problems.

The general steps of DPSO-LS are stated as follows.

#### Algorithm: DPSO-LS

**Step1:** Initialize population; set up parameters for DPSO-LS.

**Step2:** for  $i=1$  to  $N // 1 \leq i \leq N$ ,  $N$  is the number of particles  
 update  $particle_i$  velocity ( $V_i$ ) using the equation (19)  
 update  $particle_i$  position ( $X_i$ ) using the equation (20) }

Evaluate the fitness value ( $Fit(X_i)$ ) of  $particle_i$ ;

IF  $Fit(X_i) < Fit(pBest_i)$  then Update  $pBest_i$  ( $pBest_i \leftarrow X_i$ )

IF  $Fit(pBest_i) < Fit(gBest)$  Then Update  $gBest$  ( $gBest \leftarrow pBest_i$ )  
 End for

**Step3:** for  $i=1$  to  $N // 1 \leq i \leq N$ ,  $N$  is the number of  $pBest$

If  $rand < Oc // Oc$  is a learning probability

Then Gaussian distribution based dynamic OBL strategy for  $pBest_i$  using the equations (24)-(26) and the Fig. 2.

Evaluate the fitness value ( $Fit(X_i)$ ) of  $opBest_i$  (opposition  $pBest_i$ )

Update  $pBest_i$  ( $pBest_i \leftarrow pBest_i \cup opBest_i$ )

End for

**Step4:** Until a terminate condition is met, or else, returns to step2.

**Step5:** Output optimal results.

### C. Dynamic PSO Model

In recent years, many researchers focused on improving the performance of basic PSO [33] [34] (mainly on individual best position ( $pBest$ ) and the global best position ( $gBest$ )). If the particles converge fast, they will always shrink toward local regions within a few generations [33]. This phenomenon leads to a similar search behavior among the swarms and the loss of diversity in the population. If the particles are trapped in local regions, they will not be able to jump out due to their

homogeneous search behavior as well as the absence of an adaptive exploration ability [33]. To improve the performance of PSO, the particles should be able to adaptively change their original trajectories to explore new search space. The issue is how to guide particles to move toward different promising regions and enhance a broader exploration of the solution space. An improved movement modification equation with an adaptive exploration vector is proposed to update the velocity of particles ,i.e.,

$$V_{id}(t+1) = \phi V_{id} + c_1 * rand_1() (Pbest(t) - X_{id}(t)) + c_2 * rand_2() (gBest(t) - X_{id}(t)) + c_3 * rand_3() (R(t) - X_{id}(t)) \quad (19)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \quad (20)$$

The exploration vector ( $R(t)-X_{id}(t)$ ) is added to provide a broader exploration of the solution space for the  $i$ -th particle due to the use of adaptive variable exploration radius ( $R(t)$ ) which permits particles to cover large areas of search space with large probability.

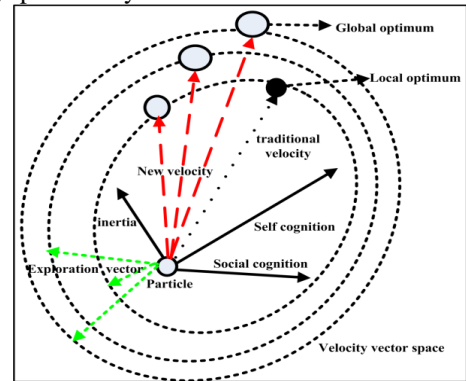


Fig.2. Illustration of PSO searching behavior with adaptive explore mechanism

The exploration radius  $R(t)$  learns adaptively as

$$R(t) = \frac{(X_{max}^d + X_{min}^d)}{2} + \frac{(X_{max}^d - X_{min}^d)}{2} \cdot e^{-\lambda t} \cdot \cos(2\pi u) \quad (21)$$

where  $u$  is a random in  $[0,1]$ ,  $X_{min}^d$  and  $X_{max}^d$  are the designated lower and upper bounds of the problem, respectively,  $\lambda$  is an adjustment parameter ( $\lambda$  is usually  $\geq 2$ ), and  $t$  is the iteration index. The modified velocity equation of PSO indicates that the swarm members are allowed to explore larger unvisited regions in the objective space (as illustrated in Fig.2). A large  $R(t)$  facilitates an exploration which induces the particles to leave their current regions and pushes the particles to search in the other regions. A small  $R(t)$  enhances the exploitation which refines the best solution of the particles by exploiting a small vicinity around this best solution. Obviously, the whole feasible solution space can be explored and covered as large as possible by this modified equation with adaptive variable exploration vector.

### D. A Dynamic OBL for $pBest$ s

In order to help  $pBest$  particles jump out the local optimal and accelerate the local search, in this study an adaptive Gaussian-distributed-based dynamic OBL strategy is proposed for a reinforcement learning of  $pBest$ .



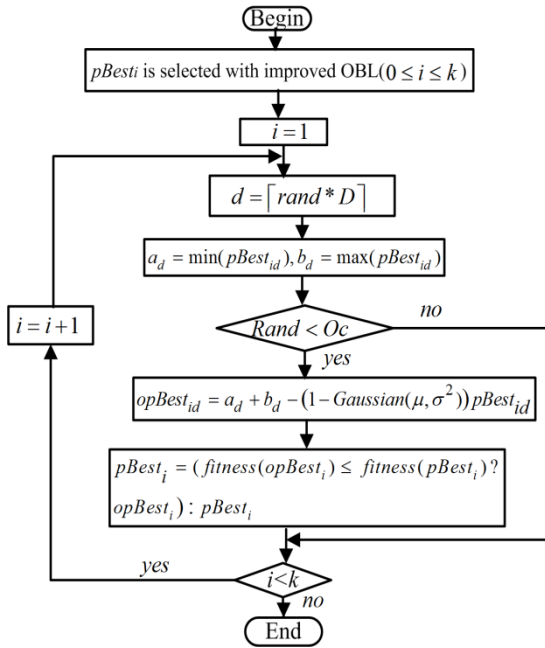


Fig.3. The schematic of dynamic OBL for  $pBests$ .

The opposition-based learning (OBL) is a machine learning method and was firstly introduced by Tizhoosh [35].

The key point for OBL is that it introduces a simple technique which allows the population-based algorithms to search for an optimal point in the opposite direction of the current search. Mathematical and experimental proofs show that opposite points are more beneficial than random points [36], and can be used to accelerate the convergence properties of other evolutionary algorithms. The basic idea of OBL is that a search in the opposite direction is carried out simultaneously when a solution is exploited in a direction, i.e.,

$$\tilde{x} = a + b - x \quad (22)$$

where  $x$  is a real number on the interval  $[a, b]$ , and  $\tilde{x}$  is the opposite number of  $x$ . This definition is also valid for D-dimensional space, where for  $x_1, x_2, \dots, x_D \in \mathbb{R}$  and  $x_i \in [a_i, b_i]$ , the D-dimensional point  $x_i$  is defined as

$$\tilde{x}_i = a_i + b_i - x_i \quad (23)$$

In order to overcome the drawbacks of the traditional OBL and enhance the  $pBest$  convergence speed, in this study a dynamic OBL strategy using adaptive Gaussian distribution is designed as

$$opBest_{id} = a_d(t) + b_d(t) - (1 - Gaussian(\mu, \sigma^2)) \cdot pBest_{id} \quad (24)$$

$$a_d(t) = \min(pBest_{id}), b_d(t) = \max(pBest_{id})$$

where  $Gaussian(\mu, \sigma^2)$  is a random number of a Gaussian distribution with a zero mean ( $\mu$ ) and a standard deviation ( $\sigma$ ). In order to obtain a better dynamic learning performance for  $pBests$ , it is assumed that  $\sigma$  decreases nonlinearly, for which a good choice may be given as

$$\sigma = \sigma_{\min} + (\sigma_{\max} - \sigma_{\min}) \left(1 - \frac{t}{T}\right)^2 \quad (25)$$

where  $\sigma_{\max}$  (fixed to one in this study) and  $\sigma_{\min}$  (fixed to zero) are the upper and lower bounds of  $\sigma$ , which specifies the learning scale to reach a new region. We adopt the

Box-Muller transform [37] to obtain a Gaussian distributed random variable, i.e.,

$$Gaussian(\mu, \sigma^2) = \mu + \sigma \sqrt{-2 \ln(1 - u_1)} \cdot \cos(2\pi u_2) \quad (26)$$

where  $u_1$  and  $u_2$  are uniformly generated random numbers in  $[0, 1]$ .

The schematic of the dynamic OBL for  $pBests$  is shown in Fig.3, where the symbol  $Oc$  is the learning probability, the symbol  $d$  is the randomly selected from total dimension ( $D$ ) as  $d = \lfloor rand * D \rfloor$ . Since not all dimensions are changed to their opposite values during OBL, useful information in the original individual may be preserved. The point and its opposite point are evaluated simultaneously in order to continue with the one that best fit, that is, if the  $fitness(pBest_i^{new})$  is better than  $fitness(pBest_i)$ , then the  $pBest$  position of  $i$ -th particle will be replaced with  $opBest_i$ ; otherwise, we continue with  $pBest_i$ . From the above description, it is quite clear that the  $pBest$  can be forced to jump to a new solution candidate with the improved OBL technique. This strategy provides a disturbance at  $pBest$ , the jump out performance is enhanced by this improved OBL with dynamic Gaussian distribution which is beneficial to guide particles' moving direction and enhance convergence speed.

## IV. EXPERIMENTAL RESULTS

### A. Hardware Control System and Software Platform

The parameter estimation process is divided into two main procedures, namely, the experimental data acquisition and data processing. To perform our experiments, a permanent magnet synchronous motor prototype and DSP vector control hardware platform are used as the experimental facility which is listed in Fig.4 and Table I. The current signals are obtained from the Hall transducers and then sampled by the DSP. The DC link is connected with the DC power source whose output is fixed to 36V. The sampling period is set to 83.3 $\mu$ s. The signals from the DSP are transmitted to a PC via serial protocol communication network and recorded in memory for

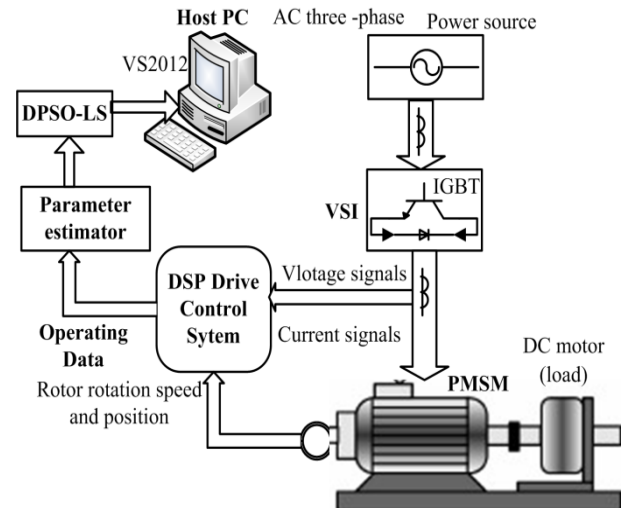


Fig.4. The schematic diagram of hardware and software platform for system identification and parameter estimation in PMSM

late use of parameter estimation using the proposed DPSO-LS algorithm, and this is carried out in a host computer installed with visual studio 2012 software.

A series of hybrid PSOs are used for a comparison with DPSO-LS. The hybrid PSOs algorithms used include OPSO (OBL for PSO) [35], HGAPSO (hybrid PSO with genetic algorithm) [38], HPSOWM (hybrid PSO with Wavelet Mutation) [39], CLPSO (comprehensive learning PSO) [40], A-CLPSO (An improved comprehensive learning PSO) [41] and APSO (adaptive Particle Swarm Optimization) [42], which are frequently used to test the performance of newly developed algorithms for dynamic optimization problems. To assess the quality of the estimated machine parameters and VSI nonlinearities based on the proposed DPSO-LS, a statistical analysis is performed and the associated mean, standard deviation and *t-test* values are calculated.

With the consideration of the balance between time cost and the precision of solutions, in this study the optimal setting of parameters for the proposed DPSO-LS is recommended as follows: the population size is 50, the inertia weight in (19) is on [0.90, 0.4] and decreases linearly, the two acceleration coefficients  $c_1$ ,  $c_2$  are 1.49445, the adjustment parameter  $\lambda$  set to 6 in equation (12), and the opposition learning probability ( $O_c$ ) is set to 0.38 in Fig.3. The optimal settings for other hybrid PSOs are the same as suggested in the associated references.

The basic settings of these PSOs are as follows: all the PSO algorithms using the same population size of 50, the maximum iteration is 300 and the number of runs is 30. All the hybrid PSOs are operated on the same hardware and software platform. All experiments are carried out on the

same computer equipped with Intel<sup>®</sup>-core<sup>™</sup>-i5-2450M and 4.0GB DDR3 RAM.

TABLE I  
DESIGN PARAMETERS AND SPECIFICATION OF PMSM

Rated speed	400rpm
Rated current	4A
DC link voltage	36v
Nominal terminal wire resistance	0.043
Nominal self inductance	2.91mh
Nominal mutual inductance	-0.330mh
Nominal <i>d</i> -axis inductance	3.24mh
Nominal <i>q</i> -axis inductance	3.24mh
Nominal amplitude of flux induced by magnets	77.6 mWb
Number of pole pairs	5
Nominal phase resistance ( $T=25^\circ\text{C}$ )	0.330 $\Omega$
Inertia	0.8e-5kgm <sup>2</sup>

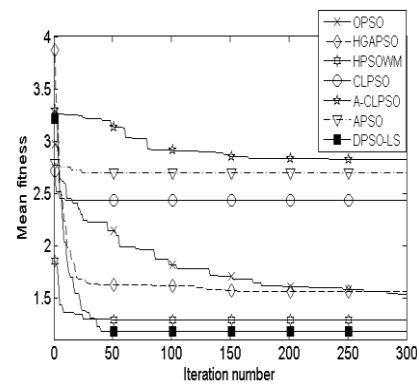


Fig.5. The fitness convergence curve of seven PSOs on multiple parameters and VSI nonlinearities identification of PMSM under normal temperature.

### B. Estimation of PMSM Parameters and VSI Nonlinearities under Normal Temperature

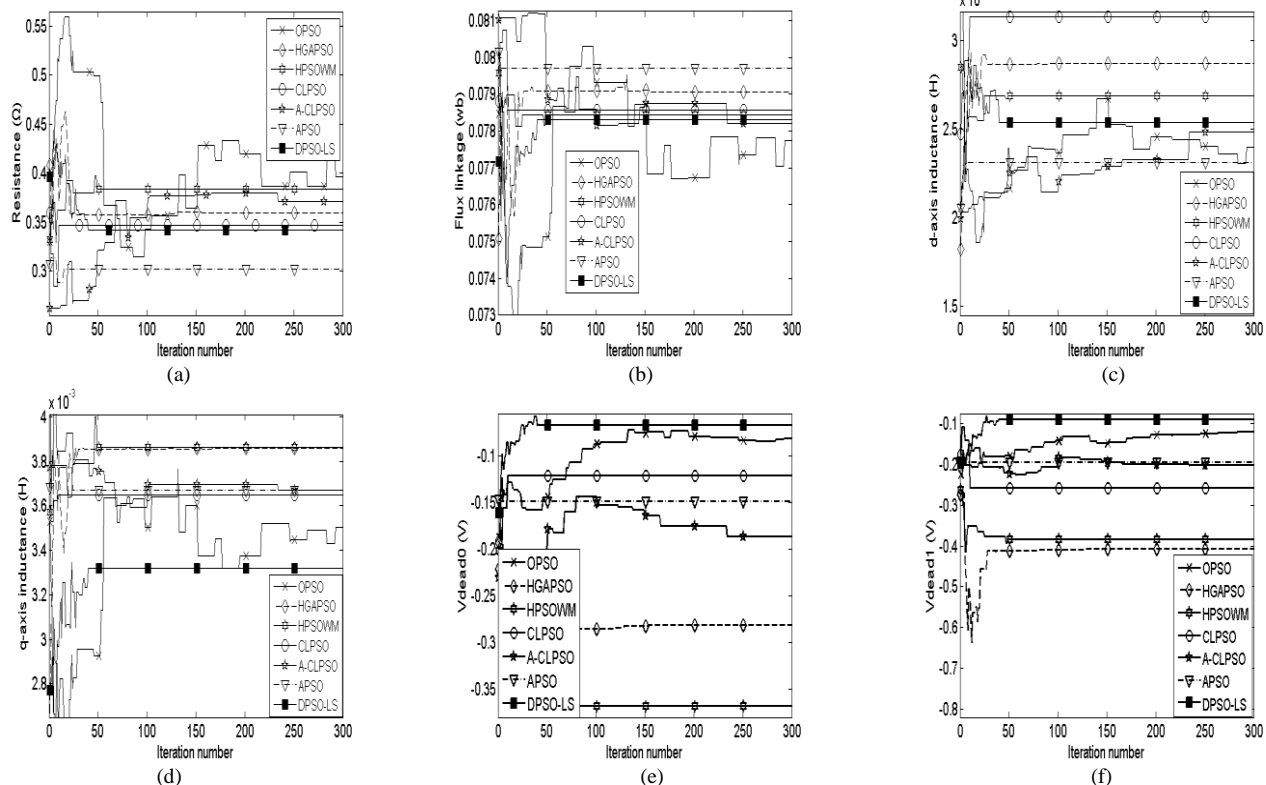


Fig.6. Identified parameters under normal temperature. (a) winding resistance. (b) rotor flux linkage (c) *d*-axis inductance. (d) *q*-axis inductance. (e)  $V_{dead0}$ . (f)  $V_{dead1}$ .

TABLE II.  
RESULT COMPARISONS AMONG SEVEN PSOs ON MULTIPLE PARAMETERS AND VSI NONLINEARITIES IDENTIFICATION OF PMSM UNDER NORMAL TEMPERATURE.

Estimated Parameters	OPSO	HGAPSO	HPSOWM	CLPSO	A-CLPSO	APSO	DPSO-LS
$R(\Omega)$	0.396	0.359	0.384	0.346	0.371	0.302	0.342
$\psi(wb)$	0.0777	0.0790	0.0784	0.0785	0.782	0.797	0.0783
$Ld(h)$	0.00239	0.00287	0.00269	0.00313	0.00248	0.00231	0.00254
$Lq(h)$	0.00350	0.00386	0.00386	0.00364	0.00367	0.00367	0.00332
$V_{dead0}$	-0.0819	-0.282	-0.368	-0.122	-0.187	-0.149	-0.068
$V_{dead1}$	-0.119	-0.407	-0.385	-0.257	-0.203	-0.195	-0.090
Mean	1.535	1.562	1.289	2.43	2.826	2.690	1.176
Std.dev	0.170	0.383	0.274	0.554	0.486	0.486	0.118
$t$ -value	6.623	5.305	1.818	13.603	19.604	17.988	0

The estimation of PMSM parameters using data measured from normal temperature environment are shown in Table II, and the convergence rates of different PSOs are shown in Fig.5, the estimated PMSM parameters convergence result are shown in Fig.6(a) to Fig.6(d). The estimated VSI nonlinearities of voltage under normal temperature condition (with  $i_d=0$  and  $i_d=-2$ ) are shown in Fig.6(e) and Fig.6(f). It is clear from Table II that DPSO-LS provides the best performance in terms of mean, standard deviation and  $t$ -test values (the confidence level is 90%). From Fig.5, the convergence speed of DPSO-LS is faster than other hybrid PSOs. The better performance of DPSO-LS can be explained in two aspects. Firstly, a novel movement modification equation using a variable exploration vector is designed to update the velocity of particles. Secondly, a dynamic *OBL* mechanism with adaptive Gaussian distribution is introduced to overcome the blindness in the search of  $pBest$  through stochastic evolution and enables it jump out the local optimal. As demonstrated in Table II, the estimated winding resistance (0.342Ω) with the consideration of the VSI nonlinearities is quite close to its nominal value (0.33Ω) under normal temperature. Also, the estimated flux linkage  $\psi$  (78.3mWb) by DPSO-LS is quite close to its nominal value (77.6mWb). The slight difference between the estimated and nominal values of machine parameters may be caused by nonlinearity on load condition. It is interesting that the estimated  $R$  without the consideration of VSI nonlinearities is much larger than that with the consideration of VSI nonlinearities, as the influence of VSI nonlinearity distort voltages ( $Dd.V_{dead}$  and  $Dq.V_{dead}$ ) introduce an error into the estimation of the machine parameters. The estimated distorted voltage  $V_{dead0}$  ( $i_d=0$ ) does not equal to  $V_{dead1}$  ( $i_d \neq 0$ ), and this confirms the fact that the  $V_{dead}$  is directly related to the current.

As shown in Fig.6 (e) and Fig.6 (f), the value of  $V_{dead0}$  ( $i_d=0$ ) and  $V_{dead1}$  ( $i_d \neq 0$ ) can be estimated simultaneously with other machine parameters based on the proposed estimator model. Furthermore, the VSI nonlinearities compensation can be simultaneously obtained by computing  $Dd.V_{dead}$  and adding the value of  $Dq.V_{dead}$  to the output of  $dq$ -axis PI regulators. Then, the compensation on  $V_{dead}$  slowly increases until  $V_{dead}$  approaches to zero, and this can help reduce the its influence on system stability.

In comparison with other hybrid PSOs, the estimates of the proposed DPSO-LS are more accurate and the estimated parameters for example motor resistance,  $dq$ -axis inductances

and the rotor flux rapidly converge to their right points. As can be seen from Fig.5, DPSO-LS converges to the optimum after about 50 generations of evolution while other hybrids shows poor convergence performance.

### C. Estimation of PMSM Parameters and VSI Nonlinearities under Varying Temperature Conditions

In order to check the performance of the proposed method for tracking the change of parameters under varying temperature conditions, experiments on a varying temperature condition are carried out. A heater is used to heat the prototype PMSM. The temperature variation experiments are divided into two steps.

- Continuously heating the PMSM for 20 minutes and recording experimental data.
- Estimating the machine parameters and VSI nonlinearities of PMSM.

The comparisons of the performance of different PSOs are shown in Table III, Fig.7. the estimated PMSM parameters convergence result are shown in Fig.8(a) to Fig.8(d). The estimated VSI nonlinearities of voltage under varying temperature conditions (with  $i_d=0$  and  $i_d=-2$ ) are depicted in Fig.8(e) and Fig.8(f). From Table III, it is clear that DPSO-LS outperforms other hybrid PSOs in terms of mean, standard deviation and  $t$ -test values. From Fig.7, it can be noticed that DPSO-LS has a faster convergence speed than other hybrid PSOs. Also, the steadiness of DPSO-LS is better than the other methods. Meanwhile, as can be seen from Table III and Fig.8(a)toFig.8(d) that the estimated winding resistance  $R$ ,  $d$ -axis inductance  $L_d$ ,  $q$ -axis inductance  $L_q$  and rotor flux linkage  $\psi$  vary with the changing temperature.

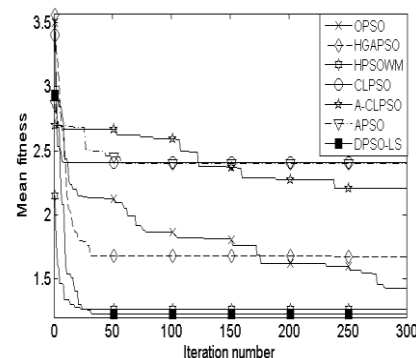


Fig. 7. The fitness convergence curve of several PSOs on PMSM parameter identification with heating 20 minutes by heater.



TABLE III.

RESULT COMPARISONS AMONG SEVEN PSOs ON MULTIPLE PARAMETERS AND VSI NONLINEARITIES IDENTIFICATION OF PMSM UNDER TEMPERATURE VARIATION (WITH CONTINUOUS HEATING 20 MINUTES).

Estimated Parameters		OPSO	HGAPSO	HPSOWM	CLPSO	A-CLPSO	APSO	DPSO-LS
$R(\Omega)$		0.478	0.480	0.434	0.467	0.489	0.462	0.438
$\psi(wb)$		0.0765	0.0778	0.0774	0.0762	0.0759	0.0766	0.0772
$L_d(h)$		0.00268	0.00342	0.00283	0.00202	0.00345	0.00294	0.00283
$L_q(h)$		0.00352	0.0080	0.00393	0.00319	0.00371	0.00347	0.00329
$V_{dead0}$		-0.0886	-0.361	-0.371	-0.173	-0.177	-0.098	-0.0772
$V_{dead1}$		-0.107	-0.569	-0.323	-0.220	-0.187	-0.192	-0.0957
Fitness	Mean	1.43	1.673	1.259	2.41	2.207	2.398	1.229
	Std.dev	0.228	0.702	0.156	0.624	0.528	1.02	0.127
	$t$ -value	3.359	3.988	0.545	11.621	10.856	7.650	0

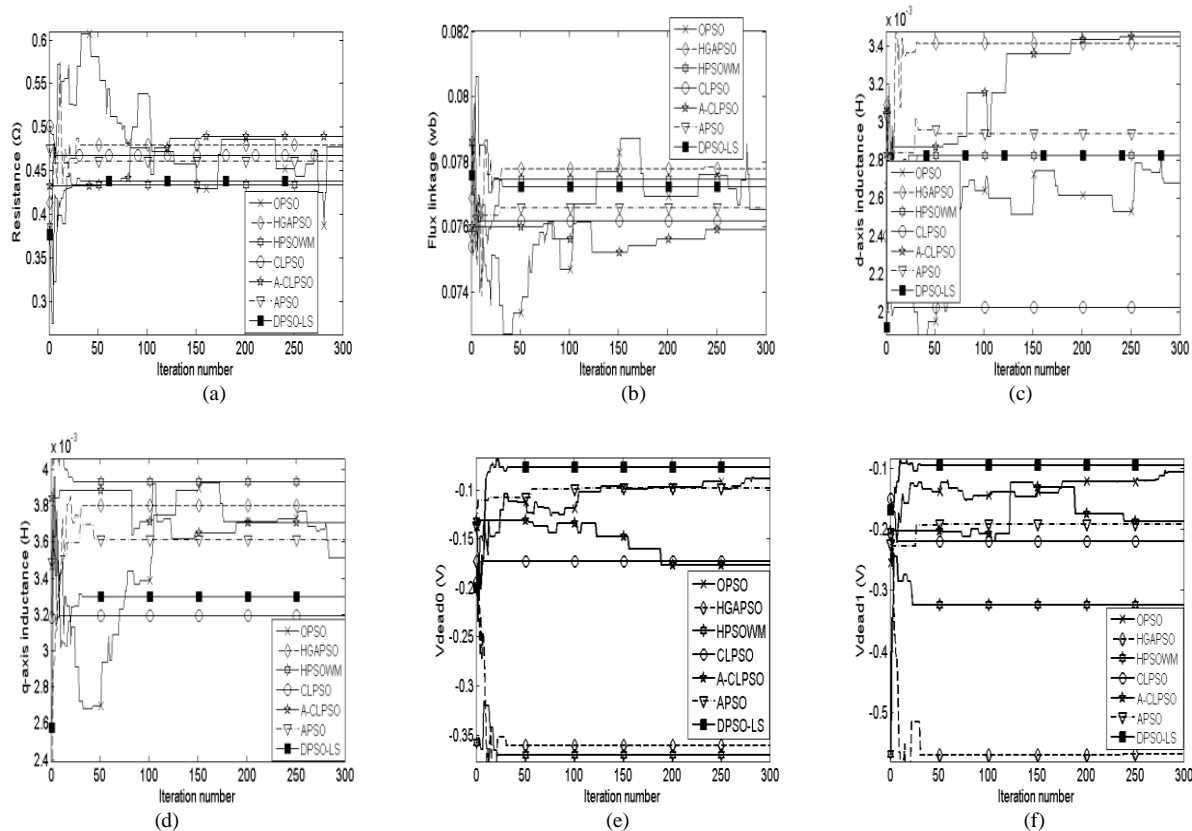


Fig. 8. Identified parameters with heating 20 minutes. (a) winding resistance. (b) rotor flux linkage. (c)  $d$ -axis inductance. (d)  $q$ -axis inductance. (e)  $V_{dead0}$ . (f)  $V_{dead1}$ .

For example, the estimated winding resistance value increases from 0.342 ( $\Omega$ ) to 0.438 ( $\Omega$ ) under heating temperature, the stator winding resistance value increases gradually when the temperature rises gradually due to the effects of the thermal metal. The estimated rotor flux linkage decreases from 78.3 ( $mWb$ ) to 77.2 ( $mWb$ ), the abrupt drop in the estimated rotor flux linkage after 20 minute heating can be explained by the fact that the residual flux density of the PM reduces when the temperature of NdFeB magnets increases [23].

It is interesting to note that for these PSO methods, the estimated value of  $L_q$  is larger than that of  $L_d$  in the surface-mounted PMSM. This is probably because  $L_d$  is significantly affected by the change of permanent magnet flux and reaches a magnetic saturation status, while  $L_q$  is not so sensitive as  $L_d$  to the change of the flux.

The estimated  $L_d$  and  $L_q$  also change when temperature varies, the reason is that the values of  $L_d$  and  $L_q$  are mainly

influenced by the flux density as the flux density has changed during the data measurement after 20-minute heating. Furthermore, from Fig.6(e), Fig.6(f), Fig.8(e) and Fig.8(f), it can be seen that the estimated  $V_{dead0}$  varies from -0.068 (v) to -0.072 (v), the estimated  $V_{dead1}$  varies from -0.090 (v) to -0.0957 (v) after 20 minute heating, and the estimated distorted voltage  $V_{dead0}$  ( $i_d=0$ ) does not equal to  $V_{dead1}$  ( $i_d \neq 0$ ), this can be explained by the that the VSI nonlinearity is also influenced by the temperature variation.

The comparison of dynamic tracking performance shows that DPSO-LS is better and statistically more robust than the other hybrid PSOs in terms of global search capacity and local search precision. This may be explained that the proposed dynamic search scheme, combined with the learning strategy, play a good role in finding the global optimum for the nonlinear multimodal optimization problem here.

## V. CONCLUSION

A novel parameter estimation method for PMSM electrical parameters and VSI nonlinearities has been proposed, in which the estimation of the needed parameters and the influence of VSI nonlinearities were taken into account simultaneously. Compared to the conventional estimation method using the  $d$ - $q$ -axis equations, the proposed estimator can provide more accurate estimation of the machine parameters with the consideration of VSI nonlinearities. The VSI nonlinearities can be considered as unknown system parameters and can be simultaneously estimated using the proposed method. Furthermore, the VSI nonlinearities can be estimated individually from the  $d$ - $q$ -axis equation with  $i_d=0$  control and  $i_d\neq 0$  (current injection condition), respectively. In order to enhance the accuracy and the dynamic performance of the estimator, a dynamic particle swarm optimization with learning strategy (DPSO-LS) is proposed to estimate the optimum parameters by minimizing the defined objective function. In the DPSO-LS, a novel movement modification equation with variable exploration vector and a Gaussian-distribution based dynamic *OBL* operator are developed to improve search performance of particles. The proposed DPSO-LS can significantly enhance the performance of the estimator and enables it to effectively track parameter variation with the changing operation conditions. Compared with several other existing PSO algorithms, the performance of DPSO-LS performs better in tracking the variation of machine parameters and estimating the VSI nonlinearities under different operation conditions.

The proposed parameters estimation method can be adapted and applied to condition monitoring, fault diagnosis for practical industrial PMSM drive systems, such as hybrid electric vehicles, renewable energy power generation. We would also carry out further investigations on the application of the method for flux weakening mode in our future work.

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