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PMDC Motor Parameter Estimation using Bio-Inspired Optimization Algorithms

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Abstract**—The precise estimation of the motor parameter is essential to design the appropriate controller. The main goal of this paper is to estimate the parameters of permanent magnet DC (PMDC) motor used in a wheelchair, applying standard as well as a dynamic particle swarm optimization (PSO), ant colony optimization (ACO) and artificial bee colony (ABC) along with experimental methods. The electromechanical, mechanical and electrical parameters such as torque constant, back-emf constant, moment of inertia, viscous friction coefficient, armature inductance and resistance are estimated using both the experimental and optimization methods. The motor is modeled in Matlab/Simulink R2015a using the estimated motor parameters and studied the performance with different loading condition starting from no-load to full-load. The simulated results of motor performance with estimated parameters are compared with the experimental load test results. The results showed that the PMDC motor parameters estimated from dynamic PSO with varying inertia weight as well as artificial bee colony algorithm have comparatively very less speed and current error than standard PSO, dynamic PSO with constant inertia weight, and ant colony optimization algorithms. Further, parameters from dynamic PSO with varying inertia weight showed speed as well as current error less than 0.5% and the artificial bee colony algorithm shown current error slightly more than 0.5%. However, analysis of variance (ANOVA) tests shown no significant difference in current and speed performance with parameter estimated from artificial bee colony and dynamic PSO with varying inertia weight. Further, artificial bee colony algorithm convergence is faster than dynamic PSO with varying inertia weight. But parameters estimated from dynamic PSO with varying inertia weight are precise and may be appropriate for the design of the motor controllers.**

Index Terms**— Ant colony optimization, artificial bee colony, particle swarm optimization, PMDC motor, wheelchair**

I. INTRODUCTION

Several types of DC motors have been widely used in home and industrial applications. Advances in permanent magnet materials and desirable features such as light weight, low cost, low speed, etc. augmented the applications of permanent magnet DC (PMDC) motor particularly in wheelchair drive [1]-[2]. The accurate design of wheelchair drive controller is essential to provide safety and comfort to the wheelchair user [3]-[6]. However, the design of the precise controller for the motor using the conventional proportional-integral-derivative (PID) technique, intelligent control technique such as neural network, fuzzy, neuro-fuzzy, etc. require accurate modeling of the motor that considers the non-linear dynamics [7]-[9]. The estimation of motor parameters is also essential for condition monitoring, fault diagnosis, etc. However, the identification of non-linear dynamics is very complex and design of controller requires accurate parameters to model the motor. The poor estimation of motor parameters may lead to the controller with suboptimal performance and may eventually lead to instability and deterioration of the system.

Researchers have attempted different methods of parameter identification for various types of DC motors. Different approaches are widely developed for parameter estimation of DC motor [10]-[19]. However, in the case of PMDC motor not much parameter estimation techniques are reported in the literature. Techniques like frequency response method [20], gradient method [21], quantized identification method [22], recursive least squares method [23] are employed to estimate PMDC motor parameters.

The experimental method of parameter estimation is a difficult problem and requires the knowledge of the relationship between the parameter and environmental factors. The cost and time involved in experimental parameter estimation are high for setting up an experiment with necessary sensors, data acquisition equipment etc. Recently, the optimization algorithm gained interest in the system parameter identification due to the computational power of the personal computer. Researchers have developed genetic algorithm [24], adaptive tabu search technique [25], particle swarm optimization [26], etc. for parameter estimation of different types of motors. The bio-inspired optimization techniques have the advantage of finding global optimal by some operations to fit the objective function. Therefore, bio-inspired optimization techniques are preferred.

The authors have attempted particle swarm optimization (PSO) algorithm using the standard as well as dynamic approaches, ant colony optimization (ACO) and artificial bee colony (ABC) for estimation of PMDC motor parameters used in a wheelchair. The results of parameters estimated from

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optimization methods are validated with the experimental load test data. Furthermore, the performance of parameters estimated from the bio-inspired optimization techniques and experimental method are compared.

In this paper, section 2 describes the modeling of PMDC motor using electromechanical energy conversion principle. Section 3 details the experimental method of parameter estimation as well as bio-inspired optimization techniques. The results of various methods are discussed in section 4. Finally, the conclusion has been presented in section 5.

II. Mathematical Model Of PMDC Motor

The dynamic equations of a PMDC motor can be modeled based on the Kirchhoff's voltage law and the Newton's moment law using equations (1) - (4).

$$v_{arm} = L_{arm}\frac{di_{arm}}{dt} + R_{arm}i_{arm} + e_b \tag{1}$$

$$T_e = J\frac{d\omega}{dt} + f\omega + T_l \tag{2}$$

$$T_e = K_t i_{arm} \tag{3}$$

$$e_b = \omega K_b \tag{4}$$

The PMDC motor inputs are DC input voltage (v_{arm}) and load torque (T_l). The outputs are the angular speed (ω) and the armature current (i_{arm}). The block diagram representation of PMDC motor model from Laplace transform of equations (1) – (4) is shown in Fig. 1.

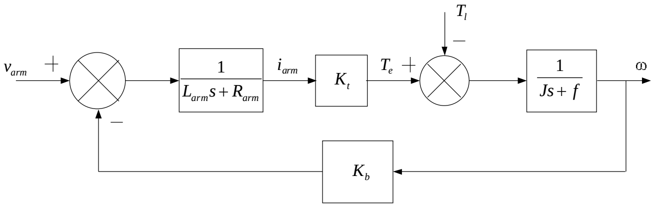

Fig. 1. PMDC motor model

The accurate design of the controller is possible in the simulation, only if the parameter of the PMDC motor model is known. The PMDC motor is modeled in Matlab/Simulink R2015a with the parameters estimated from different approaches discussed in section 3.

III. Motor Parameter Estimation

In order to model the motor, the parameters are estimated using experimental techniques as well as using bio-inspired optimization techniques. The subsequent section discusses the motor parameter estimation.

A. Experimental Techniques

The parameters of motor include electrical parameters - armature resistance, armature inductance; mechanical parameters - viscous friction coefficient, moment of inertia; and electromechanical constants - back-emf constant and torque constant which define the electrical to mechanical energy conversion. The parameters are estimated from experimental techniques without considering losses and temperature effect due to computation complexity.

1) Determination of armature resistance (R_{arm})

The determination of armature resistance in PMDC motor is complex. The usage of multi-meter to measure the armature resistance is typically very high owing to the connection between the brush and commutator along with the internal resistance of multi-meter. Moreover, the digital milliohm-meter also fails to measure the precise armature resistance. The stall test process has been proven to be a reliable technique and hence is employed for measurement of resistance.

A DC voltage is supplied to the motor, which restricts the armature rotation and draws 10% of the rated current or slightly more. Besides, the temperature of the winding also influences the resistance of the armature and not considered due to complexity. The voltage across the armature and armature current are measured for five different voltages when subjected to no-load conditions swiftly.

The electrical equation (1) is reduced to

$$v_{arm} = i_{arm}R_{arm} \tag{5}$$

At steady state, the voltage across the inductance is zero and brush drop is negligible. The armature resistance is calculated from the linear slope of the armature voltage and armature current.

2) Determination of armature inductance (L_{arm})

The armature inductance may be measured using two techniques; LCR (Inductance, Capacitance, and Resistance) meter and impedance method. However, the impedance method permits the measurement with changing field current. The field current is not possible to vary in PMDC to limit the armature current to one-tenth of the rated current to minimize the armature reaction. Therefore, in this work, the inductance is measured using an LCR meter.

3) Determination of back-emf constant (K_b)

The motor is supplied with a DC voltage enabling the armature rotation. The armature current, armature voltage, and speed are measured for different supply voltage across the armature under a no-load condition.

The back-emf (e_b) is calculated for different supply voltage using equation (1). Further, the back-emf of PMDC motor is proportional to an angular speed of the shaft and is calculated using equation (4) at steady state. The back-emf constant is estimated from the slope of the characteristics between back-emf and angular speed.

4) Determination of torque constant (K_t)

Under steady state condition, the electrical power (P_e) is equal to mechanical power (P_m).

$$P_e = P_m \tag{6}$$

The electrical power is calculated from the experimental measurements using the equation (7).

$$P_e = (v_{arm} - i_{arm}R_{arm})i_{arm} \tag{7}$$

The electromagnetic torque (T_e) is determined from the mechanical power and angular speed from the equation (8).

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$$T_e = \frac{P_m}{\omega} \tag{8}$$

The electrical power and hence the electromagnetic torque are calculated from the equation (7) and (8). The torque constant is determined from the slope of the characteristics between electromagnetic torque and armature current.

5) Determination of viscous friction coefficient (f)

Under the steady-state condition, the viscous friction coefficient (*f*) is determined from the linear slope of the characteristics between electromagnetic torque and angular speed using equation (9).

$$T_e = f\omega \tag{9}$$

6) Determination of moment of inertia (J)

To determine the moment of inertia of PMDC motor, retardation test is conducted. The PMDC machine is made to run at a speed just above the rated speed of the motor. Then the supply to the armature is cut off and the motor is allowed to reach the zero speed. The torque losses are supplied with energy stored in the moment of inertia. Therefore, the moment of inertia can be calculated using equation (10).

$$J = \frac{f\omega + A}{d\omega/dt} \tag{10}$$

Time for speed fall is recorded and the graph is plotted between the angular speed and time to obtain the slope of retardation curve.

B. Optimization Techniques

The experimental method of motor parameter estimation is time-consuming, complex and expensive for setting up the experiment. Nevertheless, precise estimation is essential for motor parameters during the design of the controller for the wheelchair. Figure 2 shows the block diagram of PMDC motor parameter estimation using optimization algorithms.

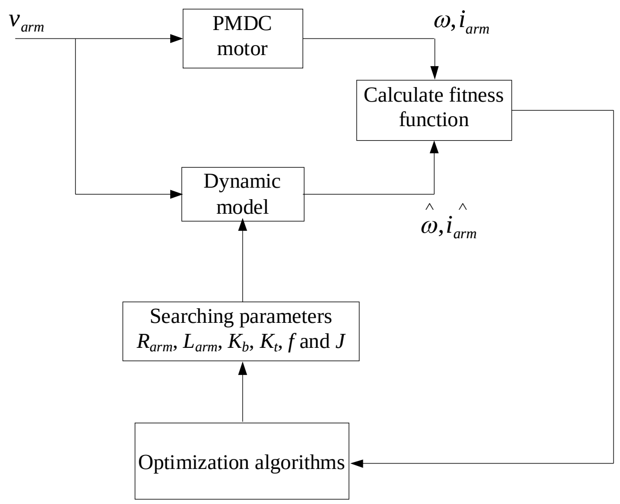

Fig. 2. Estimation of PMDC motor parameters using optimization algorithm

The PMDC motor parameter estimation is based on normalized angular speed error and current error, which compares the angular speed and current response of the real system with the response of PMDC motor model using estimated parameters.

The response of the real system is given by equation (11).

$$y = h(z,u) \tag{11}$$

where

$$u = [V_{arm} \quad T_l]$$
$$z = [R_{arm} \quad L_{arm} \quad K_b \quad K_t \quad f \quad J\ ]$$
$$y = [\omega \quad i_{arm}]$$

The response of estimated parameter model is given by equation (12).

$$\hat{y} = h(\hat{z}, u) \tag{12}$$

where

$$\hat{z} = \left[\hat{R}_{arm} \quad \hat{L}_{arm} \quad \hat{K}_b \quad \hat{K}_t \quad \hat{f} \quad \hat{J} \right]$$
$$\hat{y} = \left[\hat{\omega} \quad \hat{i}_{arm} \right]$$

The fitness evaluation function is based on mean square error calculated from normalized angular speed and normalized armature current response *y* of the real system and normalized estimated angular speed and normalized armature current response $\hat{y}$ of PMDC motor model using equation (13).

$$F(\hat{z}) = F_1(\hat{z}) + aF_2(\hat{z}) \tag{13}$$

where

$$F_1(\hat{z}) = \frac{1}{N}\sum_{j=1}^{N}\left\|\omega - \hat{\omega}\right\|^2$$ and
$$F_2(\hat{z}) = \frac{1}{N}\sum_{j=1}^{N}\left\|i_{arm} - \hat{i}_{arm}\right\|^2$$

The objective function $F(\hat{z})$ is equal to zero, only when $\hat{\omega} = \omega$ and $\hat{i}_{arm} = i_{arm}$ for *N* number of samples.

In this work, the authors attempted to minimize the objective function to estimate appropriate parameters of PMDC motor using the standard as well as dynamic particle swarm optimization algorithm, ant colony optimization algorithm, and artificial bee colony algorithm.

1) Standard Particle Swarm Optimization Algorithm

The particle swarm optimization (PSO) is one of the evolutionary population-based optimization techniques inspired by the behavior of bird flocks, fish schools etc. The PSO begins with the population of individuals called particles [27]-[31]. In PSO, each particle constitutes a number of parameters to be optimized known as a candidate solution in a multidimensional space. There are six parameters R_{arm}, L_{arm}, K_b, K_t, f and J to be estimated and therefore each particle is a point in six-dimensional search space. The population of particles is called the swarm. The PSO starts with the random initialization of swarm size and particle of the swarm. The swarm searches the optimal solution in a multidimensional parameter space starting with random position and zero velocity.

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The swarm moves in the search space depending on the fitness value estimated from the defined objective function. The particles in the swarm drive toward the best solution by adjusting the velocity based on own experience and other particle experience known as neighborhood solution at every time step in the parameter search solution. The velocity and hence the position of each particle are updated over a time in a number of iterations by evaluating the fitness function and comparing current solution with *pbest* and *gbest*. Mathematically the velocity and position of each particle *i*, in *j* dimensional parameter space are calculated using the equation (14)-(15).

$$v_{ij}^{k+1} = w * v_{ij}^{k} + c_1 * rand_1 * (pbest_{ij}^{k} - x_{ij}^{k}) + c_2 * rand_2 * (gbest_{j}^{k} - x_{ij}^{k}) \quad (14)$$

$$x_{ij}^{k+1} = x_{ij}^{k} + v_{ij}^{k+1} \quad (15)$$

The equation (14) constitutes of a momentum of the particle (w), iterative component (c_1), and the social component (c_2). The momentum of the particle is a function of inertia parameter, provides the access for the particle to move in the search space with the velocity of the particle v_{ij}. The iterative component otherwise known as the cognitive component, is based on the distance between the own best position (*pbest*) with the current position i.e. own distance. The social component is a function reflects the social behavior of the particle by considering the distance between best positions in a swarm (*gbest*) with the current position. The iterative and social components change the velocity of the particle and avoid hitting the boundary.

The six parameters, R_{arm}, L_{arm}, K_b, K_t, f, and J to be estimated is a particle and treated as a point in a six dimensional space. For the PSO algorithm, the i^{th} particle is represented as $\{R_{armi}, L_{armi}, K_{bi}, K_{ti}, f_i, J_i\}$. The position vector in PSO is given by equation (16).

$$\begin{bmatrix} R_{armi} & L_{armi} & K_{bi} & K_{ti} & f_i & J_i \end{bmatrix} = \begin{bmatrix} R_{arm1}^{k} & L_{arm1}^{k} & K_{b1}^{k} & K_{t1}^{k} & f_1^{k} & J_1^{k} \\ R_{arm2}^{k} & L_{arm2}^{k} & K_{b2}^{k} & K_{t2}^{k} & f_2^{k} & J_2^{k} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ R_{arm(M-1)}^{k} & L_{arm(M-1)}^{k} & K_{b(M-1)}^{k} & K_{t(M-1)}^{k} & f_{(M-1)}^{k} & J_{(M-1)}^{k} \\ R_{armM}^{k} & L_{armM}^{k} & K_{bM}^{k} & K_{tM}^{k} & f_M^{k} & J_M^{k} \end{bmatrix} \quad (16)$$

The response angular speed (ω) and armature current (i_a) are estimated using the armature voltage, load torque and current iterative parameter $\{R_{armi}^{k}, L_{armi}^{k}, K_{bi}^{k}, K_{ti}^{k}, f_i^{k}, J_i^{k}\}$ in a PMDC motor model. The fitness function (13) is evaluated to find the best position for the i^{th} particle (*pbest*) and the best position of the swarm (*gbest*) using normalized angular speed and armature current.

In this work, the positions of the i^{th} particle are random sequences, which are limited in the ranges $[x_{min}, x_{max}]$ using equation (17).

$$\begin{cases} R_{armi\,(\min)} \le R_{armi} \le R_{armi\,(\max)} \\ L_{armi\,(\min)} \le L_{armi} \le L_{armi\,(\max)} \\ K_{bi\,(\min)} \le K_{bi} \le K_{bi\,(\max)} \\ K_{ti\,(\min)} \le K_{ti} \le K_{ti\,(\max)} \\ f_{i\,(\min)} \le f_i \le f_{i\,(\max)} \\ J_{i\,(\min)} \le J_i \le J_{i\,(\max)} \end{cases} \quad (17)$$

These conditions strongly depend on the user's experience as well as the problem considered.

The best position found for the i^{th} particle is represented as $\{pbestR_{armi}^{k}, pbestL_{armi}^{k}, pbestK_{bi}^{k}, pbestK_{ti}^{k}, pbestf_i^{k}, pbestJ_i^{k}\}$. The best position found by the swarm is represented as $\{gbestR_{arm}^{k}, gbestL_{arm}^{k}, gbestK_b^{k}, gbestK_t^{k}, gbestf^{k}, gbestJ^{k}\}$. The parameter vector $\{R_{armi}^{k}, L_{armi}^{k}, K_{bi}^{k}, K_{ti}^{k}, f_i^{k}, J_i^{k}\}$ is set to $\{pbestR_{armi}^{k}, pbestL_{armi}^{k}, pbestK_{bi}^{k}, pbestK_{ti}^{k}, pbestf_i^{k}, pbestJ_i^{k}\}$ if the current iteration (k) parameter vector is better than previous iteration (k-1) *pbest* parameter vector. Similar to *pbest*, the parameter vector $\{R_{armi}^{k}, L_{armi}^{k}, K_{bi}^{k}, K_{ti}^{k}, f_i^{k}, J_i^{k}\}$ is set to $\{gbestR_{arm}^{k}, gbestL_{arm}^{k}, gbestK_b^{k}, gbestK_t^{k}, gbestf^{k}, gbestJ^{k}\}$ if the current iteration (k) parameter vector is better than previous iteration (k-1) *gbest* parameter vector. The velocity of the i^{th} particle is represented as $\{v_{Rarmi}, v_{Larmi}, v_{Kbi}, v_{Kti}, v_{fi}, v_{Ji}\}$. The velocity vector is calculated using (14) and the position of the i^{th} particle is updated through (15). The speed of convergence and number of iterations depends on the initialization range. This process is repeated until the user-defined goal is met. In this parameter estimation problem, the goal is that the k^{th} current iteration number reaches the maximum iteration number.

The solution of the parameter estimated at the end of iteration.

$$\begin{bmatrix} \hat{R}_{arm} & \hat{L}_{arm} & \hat{K}_b & \hat{K}_t & \hat{f} & \hat{J} \end{bmatrix} = \begin{bmatrix} gbest_{R_{arm}^{n}} & gbest_{L_{arm}^{n}} & gbest_{K_b^{n}} & gbest_{K_t^{n}} & gbest_{f^{n}} & gbest_{J^{n}} \end{bmatrix} \quad (18)$$

The standard PSO algorithm is obviously one of the simplest optimization algorithms. However, parameter convergence may not occur in standard PSO and affect the design of the controller. Therefore, the motor parameters are also estimated using dynamic PSO. In standard PSO, motor parameters are estimated for $c_1 = c_2 = 1$ and $w = 1$.

2) *Dynamic Particle Swarm Optimization Algorithm*

A dynamic particle swarm optimization (PSO) algorithm is based on time-varying cognitive (c_1) and the social component (c_2) with or without varying inertia weight. It is desirable to encourage searching the solution through the entire search space without trapping around local solution as well as making particle convergence towards the global solution. Proper control of c_1 and c_2 in addition to inertia weight w, will help to reach the optimal solution in an efficient way in PSO with varying inertia weight. It may be possible for individuals not get trapped in local minima at an early stage and converge towards the global solution at the latter stage using the iterative cognitive, social parameters with constant or varying inertia weight.

The time-varying representation of c_1, c_2 and w are given by equations (19)-(21).

$$c_1 = (c_{1Fv} - c_{1Iv}) \frac{k}{number\ of\ iteration} + c_{1Iv} \quad (19)$$

$$c_2 = (c_{2Fv} - c_{2Iv}) \frac{k}{number\ of\ iteration} + c_{2Iv} \quad (20)$$

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$$w = (w_1 - w_2)\frac{(number\ of\ iteration\ - k)}{number\ of\ iteration} + w_2 \quad (21)$$

The flowchart of the standard PSO, as well as dynamic PSO algorithms for estimation of PMDC motor parameters, is shown in Fig. 3.

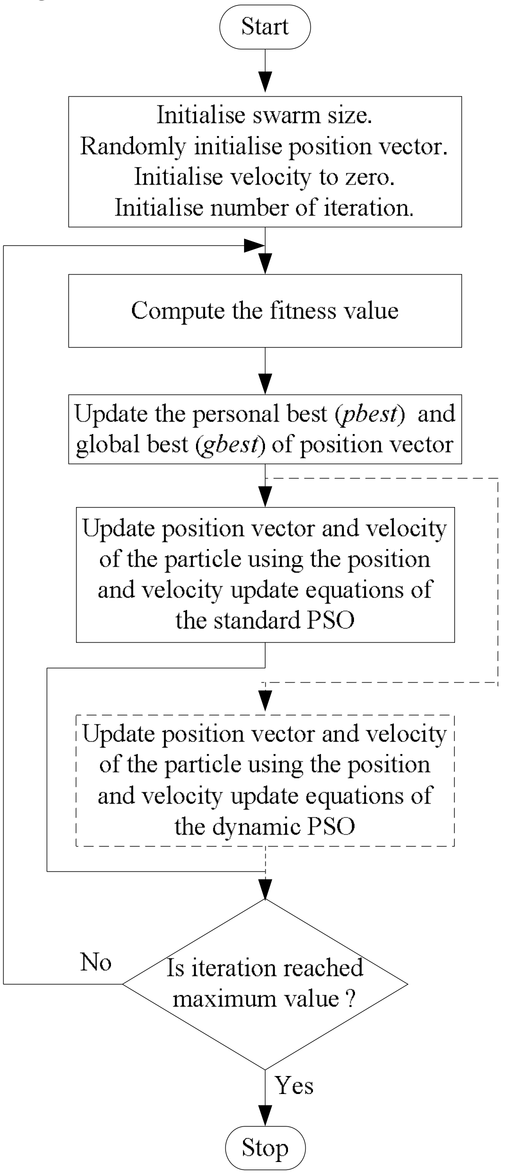

Fig. 3. Flowchart of the standard as well as dynamic PSO algorithm

3) *Artificial Bee Colony Algorithm*

In 2005, Karaboga [32-36] has developed an artificial bee colony (ABC) algorithm, a population-based search technique from scrounging behavior of bees for solving optimization problems. In ABC algorithm, the bees are divided as employed bees, onlooker bees, and scout bees.

The employed bees find the food sources position and share the information to onlooker bees at the hive. On the other hand, onlooker bees select the high-quality food sources based on nectar information and search further around the selected food sources. Scout bees independently search the new food sources to replace the abandoned food sources of employed bees.

The ABC algorithm begins with the initial population of food source positions (S_p). The i^{th} food source is defined with the d-dimensional vector $P_i = [p_{i,1}, p_{i,2}, \ldots, p_{i,d}]$ for $i = 1, 2, \ldots, S_p$. Each food source position/solution is generated using equation (22).

$$p_{ij} = p_{\min,\ j} + rand\ (0,1)\,(p_{\max,\ j} - p_{\min,\ j}) \quad (22)$$

where $j = 1, 2, \ldots, d$.

In ABC algorithm, each food source position corresponds to six PMDC motor parameters to be estimated. The position of the food sources is limited using equation (17). After initialization, all employed bees search for the food sources and generate candidate food source position/solution using equation (23).

$$v_{ij} = p_{ij} + \phi_{ij}(p_{ij} - p_{gj}) \quad (23)$$

where $g = 1, 2, \ldots, S_p$ and ϕ_{ij} is a random value in the range [-1, 1].

After generation of new food source position, the fitness of the new food source position is evaluated. The employed bees would replace the previous food sources position with new one; if the fitness value of the new food sources is better otherwise the employed bees retain the previous food source position. The employed bees share food source position and nectar information to onlooker bees.

An onlooker bees select the food sources depending on the probability value estimated using equation (24).

$$pr_i = \frac{fit_i}{\sum_{j=1}^{S_p} fit_i} \quad (24)$$

where fit_i is the fitness value of i^{th} food source position which depends on food source position. The number of food source position S_p is equal to the number of employed bees/onlooker bees.

The food source position is abandoned in case no improvement in the food source position is observed for predetermined number of cycles. Subsequently, scout bees discover the new food source position using equation (22). The new food source discovered by the scout bees will replace the abandoned one. This process of identification of best food source position is continued until the termination criteria is reached or the maximum number of iteration is reached. Figure 4 shows the flowchart of the ABC algorithm for estimation of PMDC motor parameters.

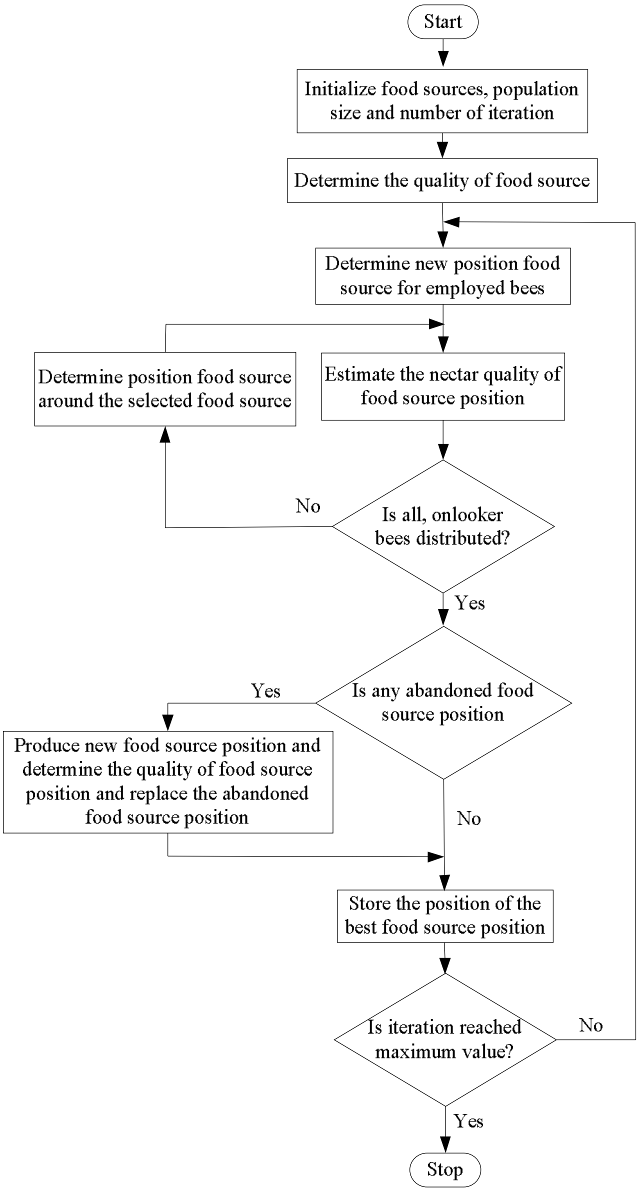

Fig. 4. Flowchart of the ABC algorithm

4) *Ant Colony Optimization Algorithm*

The Dorigo [37-40] has proposed ant colony optimization (ACO) from the inspiration of ant, to find an optimal path between food and nest. The optimal solution is found via the amount of pheromone on the ground. This concept has been used to estimate optimal value of PMDC motor parameter. The parameters are limited in the range and are given by equation (17). Each parameter is the vector corresponds to a layer/level. The upper and lower limits of the parameter depend on the user experience and divided into q number of nodes with possible values.

Ant colony optimization algorithm begins with initialization of ants and equal amounts of pheromone trail. The number of layers is six, constituting a motor parameter in each layer. Each layer consists of q nodes with permissible values assigned to each node using equation (17).

At each iteration, ant assumes the path using equation (25) to construct the probabilistic state transition rule for a complete solution. The state transition rule is mainly based on the state of pheromone.

$$p_{qs} = \frac{\tau_{qs}^{\alpha}}{\sum_{q=1}^{d} \tau_{qs}^{\alpha}} \tag{25}$$

The objective function is evaluated corresponding to the complete path to determine best and worst path of H ants. Subsequently, the optimal solution is obtained when all the ants follow the same best path.

If optimal solution is not obtained, the pheromone information is updated using equation (26).

$$\tau_{qs} = (1-\rho)\tau_{qs} + \frac{Q}{f_{best}} \tag{26}$$

with the updated pheromones, the process continues until the end of the iteration is reached. Figure 5 presents the flowchart of the ACO algorithm for estimation of PMDC motor parameters.

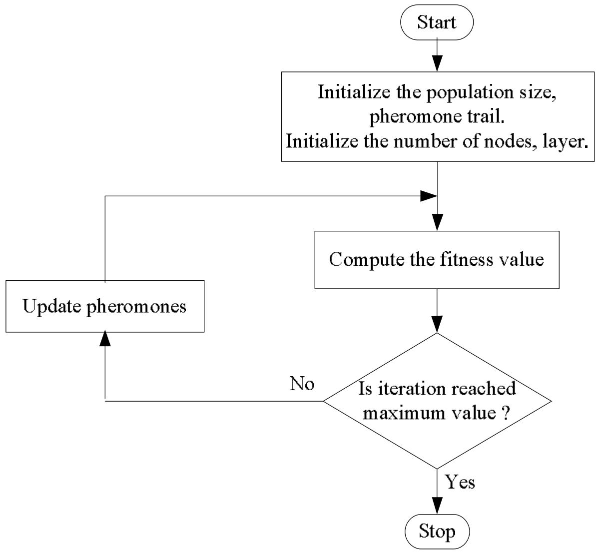

Fig. 5. Flowchart of the ACO algorithm

IV. Results and Discussion

In all algorithms of parameter estimation, the maximum number of iteration is set to 45, population size is set to 50, and parameters are calculated from the average of 30 runs. The other specific parameters of algorithms are:

1) *PSO settings:*

The PSO parameter considered for simulation is shown in Table 1. It can be observed that there is a difference among the standard PSO, dynamic PSO with constant inertia weight and dynamic PSO with varying inertia weight algorithms.

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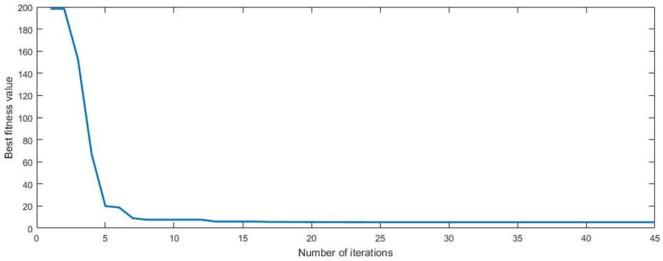
The cognitive and social parameters are time-varying variables in the velocity update equation of the dynamic PSO algorithm with constant inertia weight. Large cognitive and small social parameters are used in the beginning to enhance the global search and then small cognitive and large social parameters are used at the end to improve the convergence of the algorithm. Further, dynamic PSO is accelerated with varying inertia along with varying c_1 and c_2.



(c) Dynamic PSO with varying inertia weight algorithm

TABLE I
PARTICLE SWARM OPTIMIZATION PARAMETERS

Algorithms	initial particles positions	initial particles velocities	inertia weight, w	acceleration coefficients, c_1 and c_2	independent random sequences, r_1 and r_2
Standard PSO	random numbers € (0, 1)	0	w = constant = 1	$c_1 = c_2$ = constant = 1	random numbers € (0, 1)
Dynamic PSO with constant inertia weight	random numbers € (0, 1)	0	w = constant = 1	c_1 = varying = 2 to 0.1 c_2 = varying = 0.1 to 2	random numbers € (0, 1)
Dynamic PSO with varying inertia weight	random numbers € (0, 1)	0	w = varying = 0.9 to 0.4	c_1 = varying = 2 to 0.1 c_2 = varying = 0.1 to 2	random numbers € (0, 1)

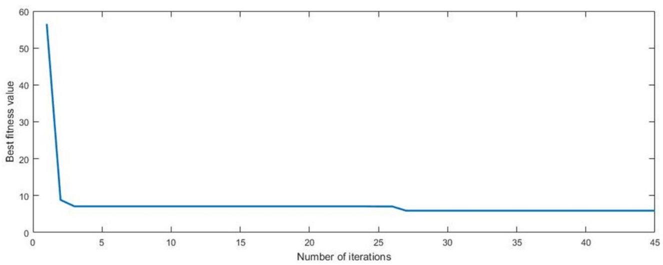
2) ABC settings:

The ϕ_{ij} is a random value and chosen as 0.5.

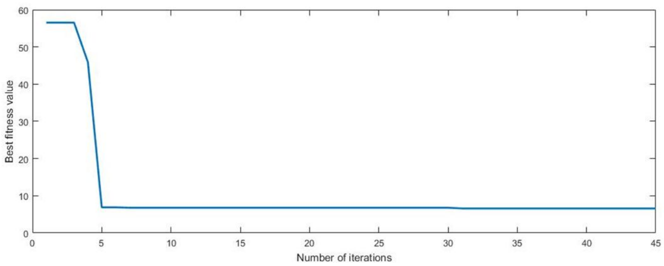
3) ACO settings:

The value of pheromone α is set to 1, a number of nodes are 100, and range of evaporation rate (ρ) is between 0 and 1. In this work, ρ is chosen as 0.2.

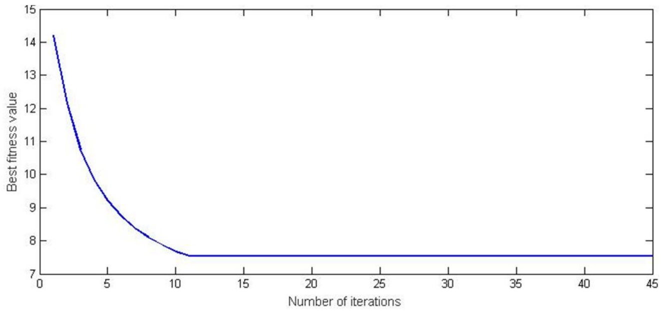
The convergence of the standard PSO, dynamic PSO with constant inertia weight and dynamic PSO with varying inertia weight algorithms, ACO and ABC against the iteration step number is shown in Fig. 6. The average convergence value and a number of iterations for optimization algorithms for 30 runs are shown in Table 2.



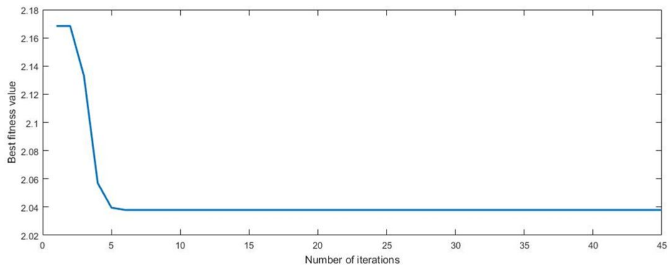
(a) Standard PSO algorithm



(b) Dynamic PSO with constant inertia weight algorithm



(d) Artificial bee colony algorithm



(e) Ant colony optimization algorithm

Fig. 6. Best fitness value versus number of iterations

TABLE II
AVERAGE CONVERGENCE VALUE AND NUMBER OF ITERATION FOR 30 RUNS

Algorithms	Value of final convergence	Number of iterations
Standard PSO	5.8102	25.68
Dynamic PSO with constant inertia weight	6.3889	30.46
Dynamic PSO with varying inertia weight	5.1957	21.63
Artificial bee colony	7.4883	11.76
Ant colony optimization	1.9381	6.16

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Table 3 shows the estimated PMDC motor parameters using standard PSO, dynamic PSO with constant inertia weight and dynamic PSO with varying inertia weight algorithms, ABC and ACO algorithms.

To determine the appropriate estimated parameters, the motor is simulated with varying load conditions and compared the results with actual load test results.

TABLE III
AVERAGE OF ESTIMATED PMDC MOTOR PARAMETERS FOR 30 RUNS

Parameters	Experimental tests	Standard PSO	Dynamic PSO with constant inertia weight	Dynamic PSO with varying inertia weight	Artificial bee colony	Ant colony optimization
R_a, Ω	0.162	0.162489396	0.160321476	0.158153937	0.157726954	0.160042088
L_a, H	0.000282	0.000280223	0.000280544	0.000281633	0.000319376	0.000321892
K_b, V/(rad/sec)	0.0503	0.048873126	0.049036542	0.049062757	0.049053501	0.049137374
K_t, Nm/Amps	0.05292	0.051867299	0.051481376	0.050617986	0.050746409	0.050848568
J, kg-m^2	0.00046	0.000469412	0.000456831	0.000463522	0.000460441	0.000475976
B, Nm/(rad/sec)	0.0001778	0.000246097	0.000231629	0.000218973	0.000226532	0.000197222

In order to analyze the estimated parameters, the load test is conducted on 24 V, 3 A, 320 W, 4600 rpm PMDC motor. From load test, armature current, voltage, and speed are noted for various loading conditions. The experimental setup for load test on PMDC motor with LEM LV 25-P voltage transducer, LEM LA 55-P current transducer, MOC 7811 optoisolator, and NI USB-6221 DAQ is shown in Fig. 7. The PMDC wheelchair motor is operated with two 12 V battery. The signals are acquired at a sampling rate of 100 Hz. The instantaneous armature current and voltage variation from no load to full load and to no load are shown in Fig. 8.

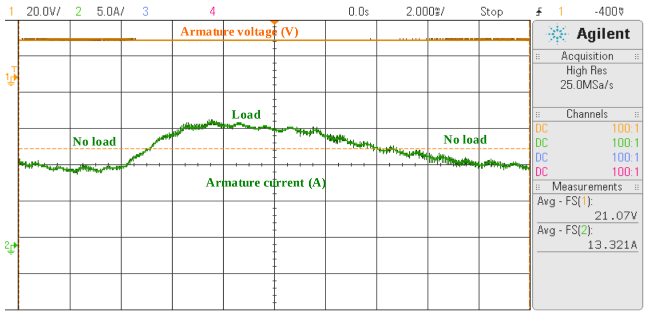

Fig. 8. Instantaneous armature current and voltage waveforms

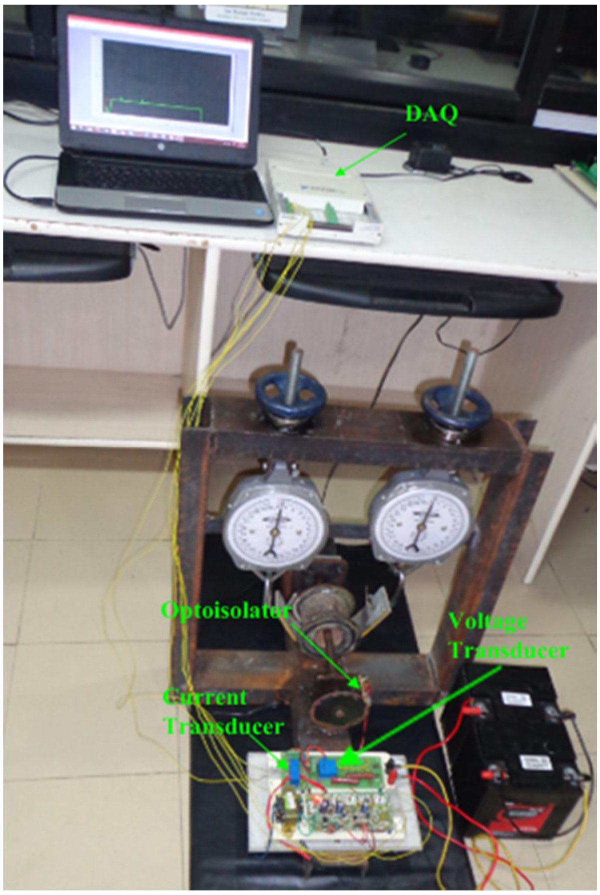

Fig. 7. Experimental setup

In Matlab/Simulink angular speed and current are obtained using estimated parameter for various loading conditions from different techniques. It has been found that experimental test gives more than 5% of armature current error and more than 1% of speed error compared with bio-inspired optimization techniques. Further, standard PSO, dynamic PSO with constant inertia weight and ant colony optimization algorithm gives current error more than 1% and less than 2%. However, dynamic PSO with varying inertia weight and artificial bee colony gives speed as well as current error less than 0.5%. Figure 9 shows the percentage errors of angular speed and armature current from estimated parameters.

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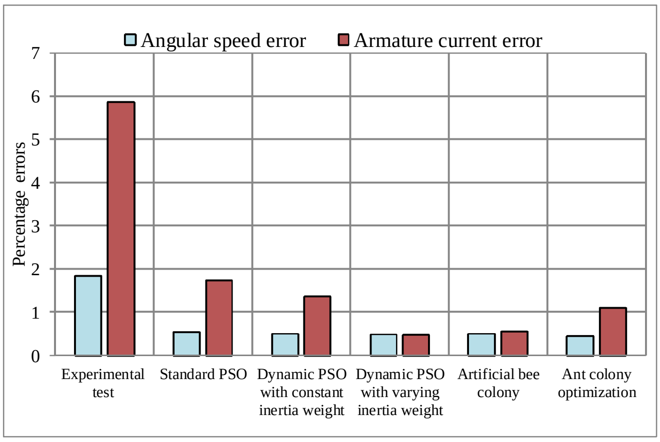

Fig. 9. Percentage error of angular speed and armature current

In order to test the significance of speed and current performance, ANOVA test was applied with significance level of 0.05. The ANOVA test shows the significant difference in speed as well as current performance between experimental and bio-inspired optimization techniques. However, there is no significant difference in speed performance among bio-inspired optimization algorithms. The dynamic PSO with varying inertia weight and artificial bee colony have no significant difference with current error. However, dynamic PSO with varying inertia weight and artificial bee colony shows significant difference with current performance compared to other techniques.

The ant colony optimization algorithm needs a less number of iterations compared to other methods. However, current error is high. Dynamic PSO with constant inertia weight as well as standard PSO takes a number of iterations for convergence. However, dynamic PSO with varying inertia weight needs less iteration compared to other PSO techniques considered. Further, it is clear artificial bee colony algorithms takes less number of iteration for convergence and performance is significantly closed to dynamic PSO with varying inertia weight algorithms. Therefore, artificial bee colony algorithm may be considered for less computation and less error in the estimation of PMDC motor parameter estimation.

V. Conclusion

The parameter estimated from experimental tests under steady-state conditions show less accuracy with the experimental load test data. This is due to the fact that the experimental tests are unable to capture the non-linear dynamics in a motor parameter due to various influences. In this paper, applications of the standard PSO, dynamic PSO with constant inertia weight and dynamic PSO with varying inertia weight algorithms, ABC, and ACO algorithms have been studied for parameter estimation of a PMDC motor along with experimental tests. The dynamic PSO algorithm a variant of standard PSO, modifying parameter iteratively improves the parameter estimation accuracy. It is evident that the dynamic PSO with varying inertia and artificial bee colony algorithms may be used to obtain motor parameter with more accuracy without being trapped in local minima. The artificial bee colony algorithm may be preferred for estimation of PMDC motor parameters used in a wheelchair due to faster convergence as well as relatively less current error except for dynamic PSO with varying inertia. The dynamic PSO with varying inertia weight may be used for more accurate PMDC motor parameter estimation.

Appendix

Specification of wheelchair PMDC motor, 24 V, 3 A, 320 W and 4600 rpm, Motion Technology Electric & Machinery Co., Ltd., Taiwan.

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NOMENCLATURE

A	torque present at the stand-still condition of the motor
a	weight to mean square current error
c_1, c_2	cognitive and social parameters between 0 and 2
c_{1Iv}, c_{1Fv}	initial and final values of cognitive parameter
c_{2Iv}, c_{2Fv}	initial and final values of social parameter
d	number of motor parameters to be optimized
e_b	back emf in Volts
f	viscous friction coefficient in Nm/(rad/sec)
f_{best}	best objective function value for ant
$gbest_j^k$	global best position from a swarm in j^{th} dimension
H	number of ants
i_{arm}	armature current in Amps
i	particle of the swarm
J	moment of inertia in kg-m^2
j	dimension of a particle in parameter space
K_b	back-emf constant in V/(rad/sec)
K_t	torque constant in Nm/A
k	current iteration of the algorithm
L_{arm}	armature inductance in Henry
M	swarm size
N	number of measured samples
$pbest_{ij}^k$	best position of the particle i in j^{th} dimension from own behavior
p_{qs}	probability among the H ants travels to a particular q^{th} node at the s^{th} level
Q	quantity of the pheromone placed by the ant for each iteration
q	number of nodes
R_{arm}	armature resistance in Ohms
$rand_1$, $rand_2$	two independent random sequences between 0 and 1
S_p	number of food sources
s	number of levels
T_e	electromagnetic torque in Nm
T_l	load torque in Nm
t	time in seconds
u	input vector
v_{arm}	armature voltage in Volts
v_{ij}^k	velocity of an i^{th} particle in j^{th} dimension parameter space at iteration k
w_1, w_2	initial and final values of the inertia weight
w	weighting function also known as inertia parameter
x_{ij}^k	position of an i^{th} particle in j^{th} dimension parameter space at iteration k
y	output vector
$\hat{y}$	estimated output vector
z	parameter vector
$\hat{z}$	estimated parameter vector
α	control the relative importance of the pheromone
ρ	evaporation rate
τ_{qs}	amount of pheromone at a q^{th} node for s^{th} level
ω	angular speed in rad/sec
$d\omega/dt$	slope of retardation curve

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