Application of Flower Pollination Algorithm to Parameter Identification of DC Motor Model

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***Abstract*—Flower pollination algorithm (FPA) is one of the most efficient population-based nature-inspired metaheuristic optimization algorithms based on the flower pollination process of flowering plants. With Lévy distribution, the FPA can control the balance of exploration and exploitation properties with a proposed switch probability. This leads the FPA efficiently escape from local entrapment and reach global optimal rapidly. In this paper, the application of FPA to parameter identification of a direct current (DC) motor model is proposed. Under testing, the DC motor system was excited by the step input to generate the specific level of the motor speed considered as the output of the system. As results of parameter identification and validation, it was found that the FPA can provide the optimal parameters of DC motor model representing system dynamics accurately. Very good agreement between actual system dynamics behavior and model parameters obtained by the FPA is completely confirmed.**

Keywords—Flower pollination algorithm; metaheuristic optimization; DC motor parameter identification

I. Introduction

In 2012, flower pollination algorithm (FPA) was firstly proposed by Yang [1] as the metaheuristic optimization algorithm for solving the optimization problems. The algorithm of FPA is based on the flower pollination process of flowering plants. Naturally, the main purpose of a flower is ultimately reproduction via pollination, while the objective of the flower pollination is the survival of the fittest and the optimal reproduction of plants depended on pollinators. In the FPA algorithm, the Lévy flight behavior is used for efficiently movement by pollinators. By literatures, the performance evaluation of the FPA against many standard single-objective test functions was proposed [1],[2],[3]. It was found that the FPA is more efficient than both genetic algorithm (GA) and particle swarm optimization (PSO) [1],[2] and more powerful than bat algorithm (BA) [3]. To perform its higher level of search performance, the FPA was also evaluated against several standard multi-objective test functions [4]. From this performance test, it was found that the FPA could find the optimal Pareto fronts for a set of multi-objective test functions superior to existed popular algorithms, i.e. vector evaluated genetic algorithm (VEGA), non-dominated sorting genetic algorithm II (NSGA-II), multi-objective differential evolution (MODE), differential evolution for multi-objective optimization (DEMO), multi-objective bees algorithms (Bees) and strength Pareto evolutionary algorithm (SPEA) [4]. In addition, the FPA was applied to solve many real-world optimization problems, for examples, pressure vessels design [1], disc break design [4], PID controller design [5] and structural design problems [6]. In this paper, the FPA is applied to parameter identification of DC motor model. The proposed identification approach can be considered as a class of metaheuristic optimization problems. The accuracy and efficiency of the proposed FPA-based parameter identification approach will be evaluated via the quality of agreement between actual dynamics behavior from tests and model parameters obtained by the FPA.

II. Flower Pollination Algorithm

In nature, the objective of the flower pollination is the survival of the fittest and optimal reproduction of flowering plants. Pollination in flowering plants can take two major forms, i.e. biotic and abiotic [7]. About 90% of flowering plants belong to biotic pollination. Pollen is transferred by a pollinator such as bees, birds, insects and animals. About 10% remaining of pollination takes abiotic such as wind and diffusion in water. Pollination can be achieved by self-pollination or cross-pollination as visualized in Fig. 1 [8],[9]. Self-pollination is the fertilization of one flower from pollen of the same flower (Autogamy) or different flowers of the same plant (Geitonogamy). They occur when a flower contains both male and female gametes. Self-pollination usually occurs at short distance without pollinators. It is regarded as the local pollination. Cross-pollination, Allogamy, occurs when pollen grains are moved to a flower from another plant. The process happens with the help of biotic or abiotic agents as pollinators. Biotic, cross-pollination may occur at long distance with biotic pollinators. It is regarded as the global pollination. Bees and birds as biotic pollinators behave

Lévy flight behavior [9] with jump or fly distance steps obeying a Lévy distribution.

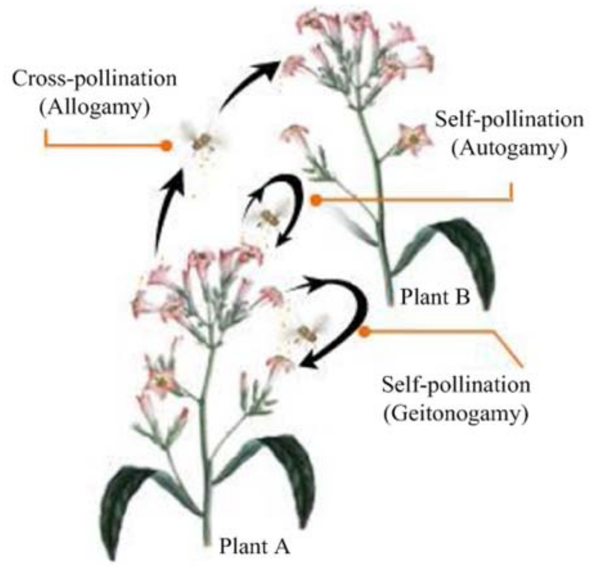

Fig. 1. Flower pollination.

- Objective $f(\boldsymbol{x})$, $\boldsymbol{x} = (x_1, x_2,..., x_d)$
- Initialize a population of n flowers/pollen gametes with random solutions
- Find the best solution $\boldsymbol{g}^*$ in the initial population
- Define a switch probability $p \in [0, 1]$

while ($t < MaxGeneration$)
  for $i = 1 : n$ (all n flowers in the population)
    if $rand < p$,
      - Draw vector L via Lévy flight in (2)
      - Activate global pollination in (1)
    else
      - Draw ε from uniform distribution in [0,1]
      - Randomly choose j and k solutions
      - Invoke local pollination in (3)
    end if
    - Evaluate new solutions
    - If new solutions are better, update solutions
  end for
  - Find the current best solution $\boldsymbol{g}^*$
end while

Fig. 2. Pseudo code of FPA algorithm.

From above characteristics of flower pollination, the FPA algorithm proposed by Yang [1] is based on four particular rules as follows:

- Biotic and cross-pollination are global pollination process via Lévy flight (Rule-1).
- Abiotic and self-pollination are local pollination process with random walk (Rule-2).
- Pollinators such as insects can develop flower constancy, which is equivalent to a reproduction probability that is proportional to the similarity of two flowers involved (Rule-3).
- Local pollination and global pollination can be controlled by a switch probability $p \in [0, 1]$ (Rule-4).

In FPA algorithm, a solution $\boldsymbol{x}_i$ is equivalent to a flower and/or a pollen gamete. For global pollination, flower pollens are carried by pollinators. With Lévy flight, pollens can travel over a long distance. Therefore, Rule-1 and flower constancy in Rule-3 can be expressed in (1), where $\boldsymbol{g}^*$ is the current best solution found among all solutions at the current generation/iteration t, and L stands for the Lévy flight that can be approximated by (2), while $\Gamma(\lambda)$ is the standard gamma function.

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + L(\boldsymbol{x}_i^t - \boldsymbol{g}^*) \tag{1}$$

$$L \approx \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}}, \quad (s >> s_0 > 0) \tag{2}$$

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + \varepsilon(\boldsymbol{x}_j^t - \boldsymbol{x}_k^t) \tag{3}$$

For local pollination, Rule-2 and Rule-3 can be represented by (3), where $\boldsymbol{x}_j$ and $\boldsymbol{x}_k$ are pollens from the different flowers of the same plant species, while ε stands for random walk by using uniform distribution in [0,1]. Flower pollination activities can occur at all scales, both local and global pollination. In this case, a switch probability or proximity probability p in Rule-4 is used to switch between common global pollination to intensive local pollination. The FPA algorithm can be summarized by the pseudo code shown in Fig. 2. From Yang's research reports [1], the number of pollens n = 25, proximity probability p = 0.8 and λ = 1.5 works better for most applications and are recommended parameter set based on preliminary parametric studies.

III. DC Motor Model Identification

DC motor driven by power-amplifier is represented by the block diagram in Fig. 3, where R_a is an armature-winding resistance, L_a is an armature-winding inductance, J is a moment of inertia, B is a viscous-friction coefficient, K_t is a torque constant, K_b is a back b.m.f. constant, K_A is an amplifier constant and τ_A is an amplifier time constant, respectively. $E_a(s)$ is an armature voltage, $E_b(s)$ is a back b.m.f. voltage, $I_a(s)$ is an armature current and $T(s)$ is an induced torque. The $E_i(s)$ is an applied voltage considered as the system input, while $\Omega(s)$ is the motor speed standing for the system output. Mathematical model in transfer function form of DC motor driven by power-amplifier can be expressed in (4) [10],[11].

The proposed FPA-based parameter identification of the DC motor model can be represented by Fig. 4, where $\omega(t)$ and $\omega^*(t)$ stand for motor speed from tests and one from model, respectively. The objective function J, sum-squared error between $\omega(t)$ and $\omega^*(t)$, is set for minimization purpose as

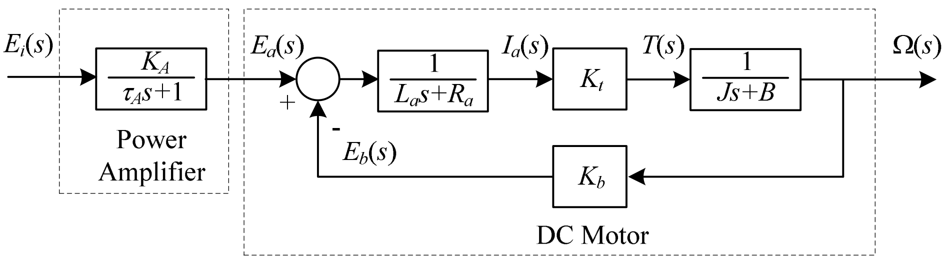

Fig. 3. Block diagram of DC motor driven by power-amplifier.

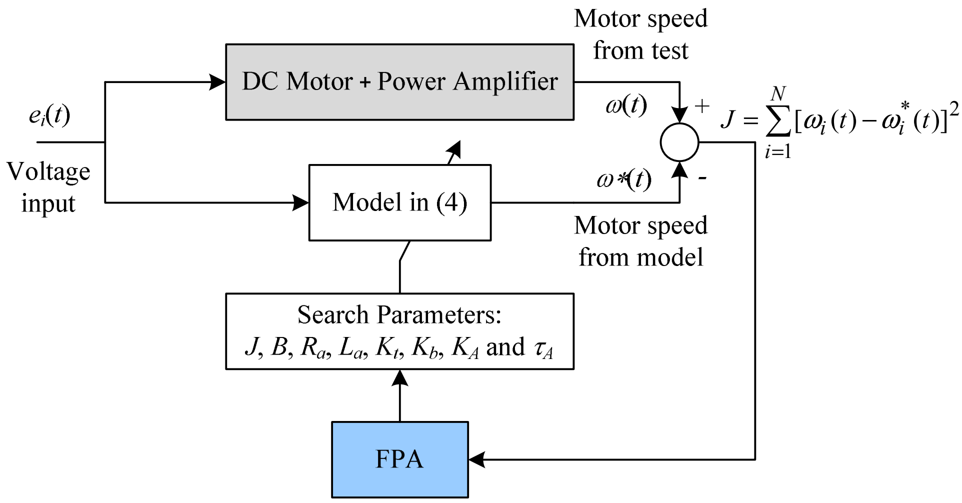

Fig. 4. FPA-based parameter identification of DC motor model.

expressed in (5). The J will be fed back to the FPA in order to minimize and obtain an appropriate eight model parameters, i.e. J, B, R_a, L_a, K_t, K_b, K_A and τ_A, for best fitting the motor speed from tests. Boundaries of eight model parameters are practically set as inequality constraints stated also in (5).

$$\frac{\Omega(s)}{E_i(s)}=\frac{K_A K_t}{(\tau_A s+1)[JL_a s^2+(BL_a+JR_a)s+(BR_a+K_t K_b)]} \tag{4}$$

$$\left.\begin{aligned} &\textbf{Minimize} \quad J=\sum_{i=1}^{N}[\omega_i(t)-\omega_i^*(t)]^2 \\ &\text{Subject to} \quad \left.\begin{aligned} &0\le R_a\le 60,\ \ 0\le L_a\le 2,\\ &0\le J\le 50,\ \ 0\le B\le 1,\\ &0\le K_t\le 10,\ \ 0\le K_b\le 5,\\ &0\le K_A\le 10,\ \ 0\le \tau_A\le 1 \end{aligned}\right\} \end{aligned}\right\} \tag{5}$$

The testing rig of the DC motor identification is depicted in Fig. 5 consisting of DC motor (LEYBOLD-DIDACTIC GMBH, Type 731-91, 0.3 kW, 220 V, 2.2 A, 2,000 rpm), power-amplifier (SCR full-bridge rectifier), a speed sensor (tachogenerator LEYBOLD, Type 731-09) and a digital storage oscilloscope (GW-INSTEK, GDS-2104, 100 MHz). Under testing, the DC motor was excited by the two step input voltages to generate two levels of the motor speed: 1,000 and 1,100 rpm. Data of 1,000 rpm are used for parameter identification process, while those of 1,100 rpm are conducted for parameter validation process.

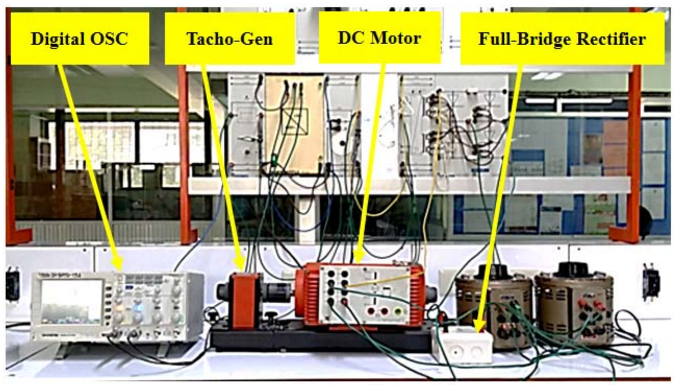

Fig. 5. DC motor testing rig.

IV. Results and Discussion

In this work, the FPA algorithm was coded by MATLAB for parameter identification purpose. The search parameters of the FPA are set along Yang's recommendation [1], i.e. $n = 25$, $p = 0.8$ and $\lambda = 1.5$. *MaxGeneration* = 500 is set as the termination criteria (TC). The proposed identification approach processes 20 trials to obtain the optimal parameters of DC motor model. Once the search process stopped, eight model parameters of DC motor are successfully obtained as follows: J = 36.4277 Kg-m^2, B = 0.0988 N-m-s/rad, R_a = 54.7280 Ω, L_a = 1.5104 H, K_t = 2.7761 N-m/A, K_b = 1.6046 V-s/rad, K_A = 3.4449 and τ_A =0.3350 s. By using data of 1,000 rpm for parameter identification and 1,100 rpm for parameter validation, the sum-squared error, SSE = 515.9506, between $\omega(t)$ and $\omega^*(t)$ is also reported. It was found that the FPA can provide optimal parameters of the DC motor model with high accuracy. This can be observed by results of parameter identification in Fig. 6 and those of parameter validation in Fig. 7, respectively. Both Fig. 6 and Fig. 7 show very good quality of agreement between actual system dynamics behavior of DC motor from tests and model parameters obtained by the FPA from model simulation. In addition, the convergent rate of the proposed objective function in (5) for searching parameters is visualized in Fig. 8. It is confirmed that the optimal solutions (model parameters of DC motor) are completely found by the FPA.

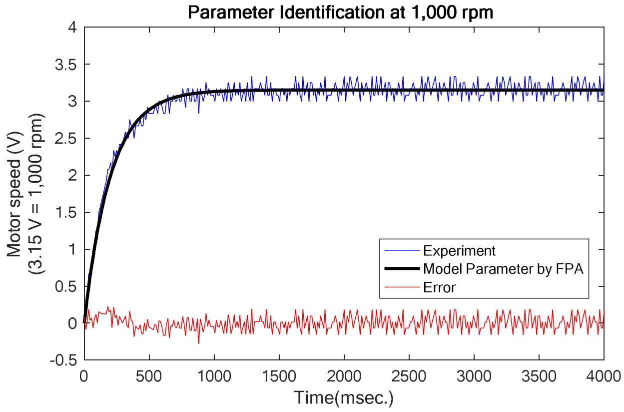

Fig. 6. Results of parameter identification.

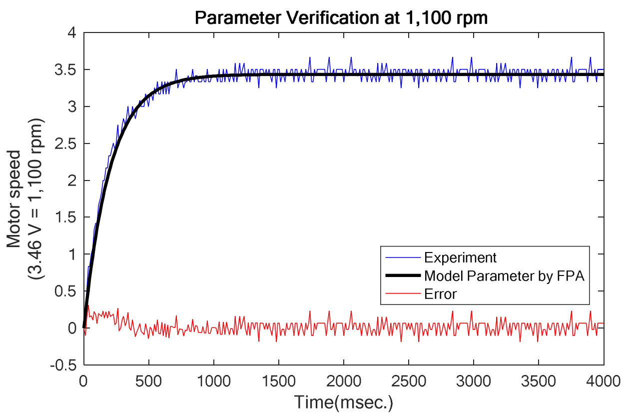

Fig. 7. Results of parameter validation.

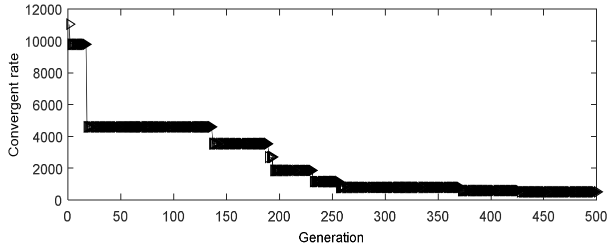

Fig. 8. Convergent rate of search process by FPA.

V. Conclusions

Application of the flower pollination algorithm (FPA) to parameter identification of a direct current (DC) motor model has been proposed in this paper. The proposed identification approach can be considered as the constrained optimization problem. In this work, the FPA has been applied as the optimizer for model parameter identification. As results, it was found that, the FPA can provide eight optimal parameters of DC motor model representing system dynamics with high accuracy. Very good quality of agreement between actual system dynamics behavior of DC motor from tests and model parameters obtained by the FPA from model simulation has been completely confirmed. This can be concluded that the FPA is one of the most efficient optimizers for parameter identification problems and other real-world applications.

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