Speed control of brushless dc motor using Ant Colony Optimization

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Abstract. DC motor has as a key aspect of industrial applications. Thus, due to their high performance, BLDC motors are preferred as a small horsepower motor. However, it is hard to acquire the good controlling performance with traditional tuning approaches in order to solve the speed control. This paper provides an approach of determining the optimum control parameters of PID for the BLDC speed control using the Ant Colony Optimization (ACO), which is an intelligent algorithm based on feeding behavior of the swarm. The efficiency and validity of the design method based on ACO are shown in the Simulation outcomes.

1. Introduction
There is a lengthy history of using general dc motors. A dc motor offers easy ways of controlling and accurate. It also has high efficiency and a strong starting torque compared to dropping speeds, which helps to avoid a sudden load rise [1]. However, the dc motors with such features have certain deficiencies to deal with that resulted in some other alternate kinds of dc motors being designed [2]. So, developing brushless direct current (BLDC) motors, which are alternatives to the conventional dc motor types, become an interest for researchers. BLDC has a lot of benefits, such as greater velocity versus dynamic response, high effectiveness, high ranges of velocity, low maintenance, etc [3]. In addition, the ratio of torque yielded to the size of the motor is higher, and this abets to its convenience in terms of space and weight perception. Commonly, BLDC contain sensors to achieve the position of the rotor and the speed measurement. These motors have uncertainty in a discrete time example and have many hardships to design speed regulators. However, to reach the desired performance, the motor requires proper speed controllers. Then, the speed control is usually performed by using the proportional-integral (PI) controller based on traditional approaches such as Ziegler and Nichols [4]. Nevertheless, that approaches required long time and effort for the controller parameters tuning, as well its produce a surge and important overshoot. To overcome these tuning inconveniences, more and more approaches based on clever algorithms are now used in order to optimize PID parameters [5], [6].

The Ant Colony Algorithm (ACO) is a metaheuristic behavior, which based on the swarm intelligence generated by the cooperation in a colony, particularly by pheromone communication between ants on a good path from the colony to a potential food source in an environment [7]. The ACO algorithm is applied to find the good parameters of the PID controller amid a stability area. The PID controller parameters are set with the Ant Colony Optimization algorithm in this research [8].
This paper is arranged as follows: the second section explains briefly the BLDC Motor. The third section explains the PID tuning approach. The fourth section is about the Ant Colony Optimization
(ACO) technique. Section five provides some results of simulations on Matlab/Simulink to show the performance of ACO. Finally, section six gives the conclusion of the research.

2. Mathematical approach of BLDC motor

As shown in fig.1 below, the circuits illustrated a typical dc motor equivalent circuit.

\[ L \frac{di(t)}{dt} = v_i(t) - K_e \Omega_m(t) - r_i(t) \]  
\[ J \frac{d\Omega_m(t)}{dt} = K_i i(t) - b \Omega_m(t) - T_L \]

Where \( v_i(t) \) is the voltage driven by the source, \( i(t) \) is the armature current; \( L \) is the armature inductance; \( r \) is armature resistance, \( K_e \) denotes the back electromotive force constant, \( K_i \) denotes the torque constant, \( J \) denotes the inertia moment of the rotor, \( b \) denotes the mechanical system damping, \( T_L \) denotes the load torque and \( \Omega_m(t) \) denotes the shaft angular velocity.

By applying the Laplace law to both eq.1 and eq.2 (considering no load \( T_L \approx 0 \)), the motor speed transfer function \( G_M(t) \) is given by:

\[ G_M(s) = \frac{\Omega_m(s)}{V_i(s)} = \frac{K_i}{L_1 J s^2 + (r_1 J + L_1 b) s + r_1 b + K_e K_i} \]

where:

\[ \tau = \frac{1}{J}, \quad \tau_\alpha = \frac{1}{r_1} \]

\[ G_M(s) = \frac{K_0}{\tau \tau_\alpha s^2 + (\tau + \alpha \tau_\alpha) s + 1} \]

Figure 1. A typical model of DC motor schematic.

Figure 2. A typical Block diagram of DC motor speed control.
with $\tau$ the time constant and $\tau_e$ the electromechanical time constant.

Usually, $K_r i(t) > b \Omega_m(t)$ and $K_e \Omega_m(t) >> r i(t)$ then eq.4 can be rewritten as follows with some approximation:

$$G_M(s) = \frac{K_0}{\tau_\epsilon \tau_s s^2 + (\tau + \tau_\epsilon) s + 1}$$

(6)

$$G_M(s) = \frac{K_0}{(1 + \tau_s s)(1 + \tau_\epsilon s)}$$

(7)

Eq.7 is in accordance with a closed-loop block diagram shown in fig.2. However, for the continuation of the operations, some approximations will be considered ($K_r, K_e >> r b$ and $\tau >> \tau_\epsilon$), so from the transfer function described by eq.6, it yields:

$$G_M(s) = \frac{K_0}{\tau_\epsilon \tau_s s^2 + \tau_s + 1}$$

(8)

Finally, the transfer function $G_M(t)$ that described the conventional dc motor speed control is given by eq.8. Conventionally, the mathematical model of BLCD motor has some particularities. The phases especially influence the resistive and the inductive of the BLDC setting. So, with symmetrical arrangement, the electromechanical time constant $\tau_\epsilon$ and the time constant $\tau$ are given as follows:

$$\begin{aligned}
\tau & = J \sum_{i=1}^{3} r_i \\
\tau_\epsilon & = L \sum_{i=1}^{3} \frac{1}{r_i}
\end{aligned}$$

(9)

3. Model of PID Controller

PID controller is a device that essentially depends on past and actual error values as well as a premedication of the future control errors. In fact, the integral part acts on the average of past errors; the proportional part takes effect on the present error value; and the derived part acts as a forecast of future errors founded on a linear extrapolation. PID computes continually the error value $err(t)$ as the difference between the needed process variable (output) and the required input (reference) as shown in fig.3 [9].

$$err(t) = reference - output$$

(10)

By adjusting the control variable $err(t)$, the control attempts to minimize the failure over time.

Generally, the time description of a PID is given as follows:

$$u(t) = K_p err(t) + K_i \int_0^t err(t) dt + K_d \frac{derr(t)}{dt}$$

(11)
With $K_p$ proportional parameter, $K_i$ integral parameter and $K_d$ derivative parameter of the PID controller.

![PID controller diagram](image)

**Figure 3.** PID parameters optimization based on intelligent algorithms block diagram.

The tuning parameters are usually based on the performance of the controller described by the objective function [10]. That typical criteria for PID tuning, can be such as the absolute error, the time-weighted absolute error, the time-weighted square error and the square error. These different evaluated errors have distinct judgments on the system great performance, but this has no essential repercussion on the designing of robust PID [11], [12].

4. **The Ant Colony Optimization algorithm**

Intelligent swarm is a paradigm that sees collective cleverness as a behavior that emerges through the interaction and cooperation of large numbers of lesser clever agents. The paradigm is inspired by the swarms foraging and flocking behavior. These algorithms are probabilistic investigations [13]. The Ant Colony Optimization (ACO) is a new population-based technology for problem solving optimization [14]. It is an intelligent swarm based on feeding behavior of ants, particularly pheromone communication between ants on a good path betwixt the colony and an energy source in an environment as seen in fig. 4. That mechanism is called stigmergy.

![Stigmergy between ants nest and food location](image)

**Figure 4.** Stigmergy between ants nest and food location.

As shown in fig.4, the ants which take the shortest route are those that take the minimum time on the way back and forth between the nest and the food. This path has a higher pheromone concentration and is more attractive for ants, so it is more likely to be borrowed. This path will be further strengthened, and the vast majority of the ants will ultimately choose this path.

The ACO provides the main pseudo-code list to minimize a cost function [15]. The process of updating pheromones is described by a unique equation that combines the contributions of all candidate solutions with a decline coefficient to determine the new pheromone value. Fig.5 shows the flowchart of PID tuning based on Ant Colony Optimization.
The fundamental algorithm has three main phases:

- **Initialization**: The problem is finding a chart with the shortest cycle and let denote \( r_{ij} \) the distance between location \( i \) and location \( j \). Each ant crosses the graph and creates a path. The amount of pheromone on the edges is initialized \( \lambda_{ij} \).

- **Shaping ant solution**: In each phase of the solution construction, the ant needs to settle when it is going to move. This decision is taken probabilistic based on pheromone values and statistical information that enables it to find a good solution, in particular. So, the likelihood that an ant \( k \) will move from \( i \) to \( j \), which includes some vertices not yet visited by ant denoted by \( L_k \), is defined as:

\[
P_{ij}^k = \frac{\lambda_{ij}(t) \cdot \eta_{ij}^\sigma}{\sum_{l \in L_k} \lambda_{il}(t) \cdot \eta_{il}^\sigma}
\]

(12)

\( \delta \) and \( \sigma \) are two parameters that involve the abundance of the pheromone intensity \( \lambda_{ij} \) and \( \eta_{ij} \) the visibility (statistical information) given by \( \eta_{ij} = \frac{1}{r_{ij}} \).

- **Pheromone updating**: All the ants have built a solution, when each ant \( k \) has deposited a certain amount of pheromone \( \Delta \lambda_{ij}^k \) on its path. For every iteration \( t \), the quantities of pheromones deposited on the path \((i, j)\) are in the round of ant \( k \), given by:

\[
\Delta \lambda_{ij}^k (t) = \frac{q}{D^k(t)}
\]

(13)
where \( D^k(t) \) is the length of the ant \( k \) path, and \( q \) is a constant.

The concept of pheromone tracer evaporation is simulated by an evaporation rate \( \varphi \) parameter to avoid the negligence of the worst solutions obtained and therefore, the convergence to low-end local vision:

\[
\lambda_{ij}(t + 1) \leftarrow (1 - \varphi).\lambda_{ij}(t) + \sum_{\alpha=1}^{N} \Delta \lambda_{ij}^{\alpha}(t)
\]

where \( \varphi \in [0,1] \).

The ACO algorithm is robust and flexible because of its resemblance to natural ant colonies. Many issues that require optimization can be targeted by self-adaptability.

5. Simulation and discussion

In this section, a mathematical model of a DC motor described by fig. 6, is used for simulation. The model is used for building Simulink transfer functions, which makes simulation easier.

In this section, the BLDC motor is a Maxon EC 45 flat \( \Phi 42.9 \) mm, 30 Watt (order number: 200142). The parameters used, are given in table 1. As well, Table 2 gives the ACO algorithm parameters used.

### Table 1. DC motor specification.

| DC motor parameters         | value   |
|-----------------------------|---------|
| Terminal resistance         | 1.2 Ohms|
| Terminal inductance         | 0.56 mH |
| Torque constant             | 25.5 rpm/A |
| Speed constant              | 374 rpm/V |
| Speed/torque gradient       | 17.6 rpm/mNm |
| Mechanical time constant    | 17.1 ms |
| Rotor inertia               | 92.5 gcm² |
| *Number of pole pairs       | 8       |
| *Number of phases           | 3       |

### Table 2. ACO parameters.

| Parameters            | Values |
|-----------------------|--------|
| Number of ants        | 20     |
| number of iteration   | 20     |
| Evaporation rate \( \varphi \) | 0.95 |
| Number of parameters  | 3      |
| Delta \( \delta \)    | 0.2    |
| Sigma \( \sigma \)    | 0.8    |
| Number of nodes       | 100    |

From table 1, it follows that:

\[
\begin{align*}
\tau_e &= \frac{L}{3r} = 1.556.10^{-4} \\
K_0 &= \frac{1}{K_e} = \frac{\tau.K_e}{3r.J} = 13.095
\end{align*}
\]

Then eq.8 derives by the BLDC motor parameters becomes:

\[
G_m(s) = \frac{13.095}{2.66.10^{-6}.s^2 + 1.71.10^{-2}s + 1}
\]
Figure 6. Matlab/Simulink diagram-bloc model of the BLDC motor.

Figure 7. BLDC open loop step Root-Locus and bode diagram.

Figure 8. Closed-loop step response and cost function curve.

The open-loop analysis gives the step root-locus and Bode diagram as shown in fig.7. However, the performances of the ACO are shown in fig.8. As seen, the step response from ACO has good setting parameters (zero overshoot and less settling time) than Ziegler-Nichols tuning parameters as given in table 3.
Table 3. ACO and Ziegler-Nichols PID tuning parameters.

| PID parameters | $K_p$ | $K_i$ | $K_d$ | $O_p$(%) | $t_i$(s) | $t_r$(s) |
|----------------|-------|-------|-------|----------|----------|----------|
| Ziegler-Nichols| 11.327| 1381.34| 0.0232| 0.405   | 2.10$^2$ | 2.45$^2$ |
| ACO            | 6.8718| 4.8536| 0.5146| 0 | 9.82$^6$ | 8.02$^6$ |

where $t_s$ denotes the settling time, $t_r$ denotes the rise time, and $O_p$ denote the overshoot.

6. Conclusion
The Ant Colony Optimization algorithm is used to adjust the optimal controller for best system performance. It is used to ensure the proper tuning of the PID controller, by eliminating the steady-state error between the BLDC motor speed measured and the reference speed to be tracked. The control goal is to ensure that the speed of the motor follows the input shift by developing a suitable controller.

Simulation results show the achievement and efficiency of using ACO algorithm for the speed control of BLDC motor. This algorithm guarantees the system, its stability and a faster response.

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