Speed Control of Brushless DC Motor Using Modified Genetic Algorithm Tuned Fuzzy Controller

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Authors' contributions

This work was carried out in collaboration between both authors. Author AR proposed, designed the study, managed the literature searches, performed the simulation, analysis and wrote the first draft of manuscript. Author MFZ supervised every stage of the work. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/CJAST/2020/v39i930606

Editor(s):
(1) Dr. Chien-Jen Wang, National University of Tainan, Taiwan.
(2) Dr. Jerzy Nowacki, West Pomeranian University of Technology, Poland.

Reviewer(s):
(1) Trinh Trong Chuong, Hanoi University of Industry, Vietnam.
(2) János Ladvánszky, Hungary.

Complete Peer review History: http://www.sdiarticle4.com/review-history/57107

Received 01 March 2020
Accepted 08 May 2020
Published 11 May 2020

ABSTRACT

In the last decade with increasing motor application domain, need towards usage of precisely controlled, noise free, highly efficient and high starting torque motors also increases, as a result dedicated applications has fascinated the researcher toward brushless DC motor. Brushless DC motors can act as suitable alternative to the traditional Brushed direct current motor, Induction Motor etc. This research paper inspects the ease and effectiveness of modified queen bee based GA tuned fuzzy controller and shows the performance of a proposed controller under diverse speed settings. A comparative study with conventional PI controller shows effectiveness of modified queen bee based GA Tuned Fuzzy controller, in terms of parameter like peak overshoot and settling time. MATLAB/SIMULINK Environment is used for optimization and modeling of Brushless DC motor drive.

Keywords: Brushless DC motor; genetic algorithm; back EMF; fuzzy knowledge base controller.

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1. INTRODUCTION

The Brushless Direct Current (BLDC) motor is rapidly attaining popularity due to its ease of controllability & widespread application in industries, such as Domestic Appliances, Automobile sectors, industrial robotics, defense etc. As the name suggests, brushless DC motor is free from mechanical brushes & do not require brushes for process of commutation; instead, BLDCM utilizes sensor technique to perform electronic commutation. The BLDC motors have lots of advantages over conventional motors [1,2]. Schematic diagram of six switch BLDC motor is as shown in Fig. 1.

![Fig. 1. Schematic of BLDC motor drive](image)

Brushless DC motors are gaining more popularity as fractional horsepower control motors due to its greater reliability, higher efficiency, noise free working, relatively smaller size and less wear & tear. BLDC motor starting and its control are quite complex due to its wide dynamic range of operation.

This paper utilizes genetic Fuzzy Logic Control [3], fuzzy logic is a non-analytical approach opposite to classical control, which requires meticulous mathematical analysis. Fuzzy control systems work with mode of approximate reasoning which is similar to decision making process of humans. Intuitive linguistic rules are used to express the knowledge in a Fuzzy Knowledge Base Controller; as a result human expert can quite easily understand operation of FKBC. It can overcome the problems of non-fuzzy expert systems that cannot deal with the linguistic, imprecise and fuzzy structure of human perception and judgments.

Trial and error approach is used to obtain the fuzzy knowledge base from an expert human operator, which is quite tedious and unreliable, hence numerous techniques have been suggested to extract fuzzy rules [4] for the controller.

Fuzzy Knowledge Base Controller scaling factors are optimally tuned by utilizing modified queen bee evolution for weighted crossover based GA [5].

2. MATHEMATICAL MODEL OF THE BLDC MOTOR

The BLDC motor comprises three windings, connected to the stator & a permanent magnet rotor made up of rare earth alloy. Rotor magnet has high resistivity and low reluctance, as a result currents induced in rotor is negligible and hence modeling of damper windings isn’t necessary. The resultant equations in terms of the circuit variables are [6].

\[
\begin{align*}
V_a & = R_0 I_a + p L_a E_a \\
V_b & = R_0 I_b + p L_b E_b \\
V_c & = R_0 I_c + p L_c E_c \\
\end{align*}
\]

Where,

\( E_a, E_b, \) and \( E_c = \) back emf of three phases in volts

\( p = \) derivative operator

\( I_a, I_b, \) and \( I_c = \) motor currents of three phase in amperes

\( R = \) stator resistance per phase in ohm

\( V_a, V_b, \) and \( V_c = \) terminal voltages of three phases in volts

\( \omega_s = \) Synchronous speed in rad./ sec.

On taking the assumptions that variation in reluctance of rotor with rotor position is negligible, also assuming that back EMF is trapezoidal [1] in shape & resistance value are same for three phases, above equation will reduce to.

\[
\begin{align*}
V_a & = R_0 I_a + p L M E_a \\
V_b & = R_0 I_b + p L M E_b \\
V_c & = R_0 I_c + p L M E_c \\
\end{align*}
\]

Stator is star connected & algebraic sum of three currents is zero, therefore equation will further reduce to

\[
\begin{align*}
V_a & = R_0 I_a + p L M M E_a \\
V_b & = R_0 I_b + p L M M E_b \\
V_c & = R_0 I_c + p L M M E_c \\
\end{align*}
\]
\[
\begin{bmatrix}
V_a \\
V_b \\
V_{\beta}
\end{bmatrix} =
\begin{bmatrix}
R & 0 & 0 \\
0 & R & 0 \\
0 & 0 & R
\end{bmatrix}
\begin{bmatrix}
l_a \\
l_b \\
l_{\beta}
\end{bmatrix}
+ \begin{bmatrix}
0 & R & 0 \\
0 & 0 & R \\
0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
I_a \\
I_b \\
I_{\beta}
\end{bmatrix}
+ \begin{bmatrix}
0 \\
0 \\
0
\end{bmatrix}
\begin{bmatrix}
E_a \\
E_b \\
E_{\beta}
\end{bmatrix}
\] (3)

and

\[p \begin{bmatrix}
l_a \\
l_b \\
l_{\beta}
\end{bmatrix} = \begin{bmatrix}
1/L - M & 0 & 0 \\
0 & 1/L - M & 0 \\
0 & 0 & 1/L - M
\end{bmatrix}
\begin{bmatrix}
V_a \\
V_b \\
V_{\beta}
\end{bmatrix}
- \begin{bmatrix}
R & 0 & 0 \\
0 & R & 0 \\
0 & 0 & R
\end{bmatrix}
\begin{bmatrix}
l_a \\
l_b \\
l_{\beta}
\end{bmatrix}
- \begin{bmatrix}
E_a \\
E_b \\
E_{\beta}
\end{bmatrix}
\] (4)

\[
\text{Where,}
\]

\[\omega r \times \tau e = E_a I_a + E_b I_b + E_{\beta} I_{\beta}
\] (5)

\[Y(t) = K_p e(t) + K_i \int e(t)dt
\]

Where,

\[K_p = \text{proportional gain}
\]
\[K_i = \text{Integral gain.}
\]

Trial and error method is used to obtain values of gain parameter \(K_p\) and \(K_i\) [8] for various reference speeds. Manual controller tuning, results in the following gain constant values.

| parameter values | \(K_p\) | \(K_i\) |
|------------------|--------|--------|
|                   | 0.7    | 11     |

3. BRUSHLESS DC MOTOR CONTROL

Performance analysis of brushless DC motor is investigated by using manually tuned conventional PI controller and modified queen bee based genetic algorithm tuned fuzzy controller.

a) PI controller

Conventional PI controller generates a control signal in response of the error between the reference value and actual value. In the proposed work motor speed is the parameter need to be controlled, hence reference speed and motor speed are used to generate necessary error signal for PI controller. Once this error is fed to the controller, controller generates the necessary correcting signal based on the tuning of \(K_p\) & \(K_i\). Due to simplicity of design and ease of application it is one of the most popular controllers in industries, its algorithm is expressed as follow:-

\[\omega r \times \tau e = E_a I_a + E_b I_b + E_{\beta} I_{\beta}
\] (5)

\[Y(t) = K_p e(t) + K_i \int e(t)dt
\]

b) Fuzzy knowledge base controller

Inspiration for Fuzzy logic control (FKBC) was taken from Zadehs's work on fuzzy set & Mamdani [9] was the first to introduce fuzzy logic control. Experiment shows that FKBC yields results superior to those obtained by conventional control algorithms in the complex situations, where the system model or parameters are difficult to obtain. FKBC Design comprises two essential steps, design of knowledge base and tuning of Fuzzy knowledge base controller. Main component of FKBC is fuzzy knowledge base. This knowledge base comprises rule to operate in fuzzy space. Rules of fuzzy knowledge base is characterized with an IF part called antecedent and with a THEN part called consequent. If the conditions of antecedents are satisfied, then conclusions of consequents are applied. More precisely input and output of FKBC are states of a controlled system, thus FKBC is a kind of state variable controller governed by a family of rules and fuzzy inference mechanism.

The block diagram shown in Fig. 2 represents FKBC. Tuning of scaling factors \(K_v\), \(K_a\), and \(K_u\) is done by modified queens bee based genetic algorithm. During the process of tuning controlled process act like a black box to the controller.
3.1 Genetic Algorithm

Genetic Algorithm is an optimization technique inspired by the mechanics of genetic evolution. Genetic Algorithm perform arbitrary search with the help of an objective function, called fitness. In the proposed work Integral Time Absolute Error (ITAE) of the obtained solution is reciprocal to the fitness. This fitness function enables genetic algorithm to search for best possible solution as generation progresses. Fitness & ITAE are expressed by equation (7) and equation (8) respectively. Global optima are more likely to be achieved by GAs, as it works with population of points, on contrary to point by point approach of traditional optimization techniques.

\[
\text{Fitness} = \frac{1}{\text{ITAE}} \quad (7)
\]

\[
\text{ITAE} = \int_0^t |e| \, dt \quad (8)
\]

Genetic algorithm comprises three basic operators called reproduction operator, crossover operator and mutation operator. Initially GA works with randomly created group of solutions, known as population. As the algorithm progresses further this existing set of solutions help to create a new set of solutions through evolutionary process. Reproduction operator helps in selection of good chromosomes from the existing population to form the mating pool. Chromosome selection process for parenthood can range from a completely random process to one that is guided by fitness of chromosome. Subsection (i) deals with the modified Queen bee evolution. Crossover operator is used to obtain better chromosomes by exchanging genetic materials between the parents. Two parent chromosomes are randomly picked from the population and the probability of new chromosome creation, from the parents is determined by crossover rate. Numerous crossover operators are explained in various literatures [10,11], but the weight based crossover operator utilized in this work is explained in subsection (ii), at final step mutation operator is applied. The mutation operator randomly changes some genes of each child chromosome with a pre-defined mutation probability. Flipping a bit, of binary coded child chromosome, result in mutation.

(i) Modified queen bee evolution

Queen bee algorithm [12] is conventionally restricted to a single pool. This restriction is somewhat less practical; in a more practical approach the modified queen bee algorithm [5] is not restricted to a single pool. In nature honeycombs grow around queen bee, and on birth of new queen bee in a honeycomb. This new queen bee shares the members from her parent honeycomb & builds her own honeycomb. This similar strategy is adopted in utilized modified queen bee algorithm. Fig. 3 below shows the scheme of pool splitting generation by generation with the birth of new queen bee. During crossover each solution (bee) exchanges genetic information with fittest solution (queen bee) of the pool. On the birth of new queen the initial pool splits between the queens and the pool population size is specified by the mating process. Recognition of the new queen in a pool is a function of fitness and this new queen must have fitness very close or above that of mother queen to get recognized. In reality only few bee hives survive & other beehive get destroyed due to random events like attack of bear, death of queen, attack of harvester, hail storms etc. This loss of least fit beehives is also mimicked in the proposed work and is shown in the schematic shown in Fig. 3, it clearly shows that the least fit, pool 1 & pool 7 are omitted from the scheme.

(ii) Weight-based crossover operator

In case of uniform crossover the selection of gene is done arbitrarily. Typically each bit in a chromosome is exchanged with a probability of one half. An arbitrary value R is generated for every gene in the chromosome. If R is less than the probability, the corresponding bit of parent 1 is assigned to child 1 & the corresponding bit in parent 2 is assigned to child 2 otherwise the corresponding bit in parent 1 is assigned to child 2 & the corresponding bit in parent 2 is assigned to child 1.

In weight-based crossover operator, crossover operation of genes is based on the weight assigned to the gene. Uniform crossover is a
special case of weighted uniform crossover. In weighted uniform crossover, weights are assigned to each bit/gene in the chromosome according to the similarity of the test patterns in the population and weighted uniform crossover is performed which is based on some probability that depends on the weights of the parent bits. For example, two parents P1 and P2 are selected to create two child chromosomes C1 and C2. Each gene Gi,1 in parent P1 contests against the corresponding gene Gi,2 of parent P2. If weight Wi,1 is equal to Wi,2, the bits are crossed with a given probability as in uniform crossover. If Wi,1 and Wi,2 are different, both the child chromosomes are assigned the value of the lighter bit, i.e., bit with weight 0 as shown in Fig. 4. Table 2 shows the rules for Weight based crossover operator.

![Fig. 3. Schematic of pool splitting generation by generation in modified Queen bee evolution](image.png)

![Fig. 4. Schematic representation of weight based uniform crossover](image.png)
Table 2. Rules for weight based crossover operator

| Action performed                  | Weight of Bit/gene in parent 1 | Weight of Bit/gene in parent 2 |
|-----------------------------------|---------------------------------|---------------------------------|
| Similar as uniform cross over     | 0                               | 0                               |
| P1 bits are allotted to C1 & C2  | 0                               | 1                               |
| P2 bits are allotted to C1 & C2  | 1                               | 0                               |
| Similar as uniform cross over     | 1                               | 1                               |

Algorithm 1: Displays modified queen bee evolution based genetic algorithm

4. SIMULATION RESULTS

FKBC is designed by first partitioning the scaling parameter $e$, $ce$ and $du$ in Fuzzy sets of $N$, $Z$ and $P$ as shown in Fig. 5, membership function used is of Gaussian shape, with a variance of 0.424. Table 3 shows controlling rules of FKBC. For ‘and’ and implication operation ‘min’ operator is used while ‘or’ and aggregation operation. Defuzzification is done by centroid method. The designed FKBC is applied to BLDC motor as shown in Fig. 6.
Fig. 5. Gaussian membership function for e, ce and du

Table 3. Fuzzy knowledge base rules

| e    | ce | N | Z | P |
|------|----|---|---|---|
| N    | N  | N | Z |   |
| Z    | N  | Z | P |   |
| P    | Z  |   | P |   |

Fig. 6. BLDC motor drive simulation

Table 4. Genetic algorithm parameters

| Parameter                              | Values       |
|----------------------------------------|--------------|
| Population Size                        | 15*9=135     |
| Maximum Number of Pools                | 9            |
| Individual Bit Length                  | 10           |
| Crossover Probability                  | 0.8          |
| Strong Mutation Probability (pm')      | 0.4          |
| Normal Mutation Probability (pm)       | 0.01         |
| Normal Mutation Rate (ξ)               | 0.6          |
During the scaling of controller parameters BLDC motor model acts like a black box to the FKBC. A genetic algorithm, based on proposed modified queen bee evolution and weight base crossover, tunes the scaling factors. Fitness of solution is obtained by reciprocal of ITAE, and hence this improved solution guides the algorithm generation by generation. Parameter values for GA are as shown in Table 4. Size of population per pool for modified queen bee genetic algorithm is fifteen and since the no. of maximum pool is restricted to nine, therefore on reaching ninth pool the no. of solution would be one hundred thirty five.

Genetically tuned pi controller results

![Fig. 7. Generation (x-axis) vs. fitness (y-axis)](image)

**Fig. 7. Generation (x-axis) vs. fitness (y-axis)**

*Final values of scaling factor are Ke = 0.4059, Kce = 659.2742 & Kdu = 0.0968*

![Fig. 8. Speed (y-axis) vs. time (x-axis)](image)

**Fig. 8. Speed (y-axis) vs. time (x-axis)**
Fig. 9. Current (y-axis) vs. time (x-axis)

Fig. 10. Current (y-axis) vs. time (zoom along x-axis)

Manually tuned pi controller results

Fig. 11. Speed (y-axis) vs. time (x-axis)
RESULTS AND DISCUSSION

The learning pattern in Fig. 7 shows how fitness changes generation by generation. Fitness pattern shows that modified queen bee evolution based GA takes 7 generation to achieve ITAE=442.6267 and hence a maximum fitness value of $2.25924 \times 10^{-3}$. Fig. 8 shows speed response characteristic of brushless DC motor using GA tuned fuzzy controller, similarly Fig. 11 shows speed response characteristic using PI controller. Simulation period for BLDC motor is around 1.8 sec. Machine is loaded initially with a load of 5N, and speed reference of 2000 rpm. Settling time for GA tuned fuzzy controller is around 0.8 sec. while in case of PI controller settling time is around 0.76 sec. overshoot is absent in case of fuzzy controller while overshoot for PI controller is 15%. On abruptly changing motor reference speed from 2000 rpm to 1000 rpm after 1.2 sec from starting. Genetically tuned fuzzy controller takes 0.4 sec to settle at final value on the other hand PI controller takes 0.55 sec. to settle at reference speed. Figs. 9 & 12

Table 5. BLDC motor parameters

| No. of poles | 8  |
|--------------|----|
| No. of phases| 3  |
| Types of connection | Star |
| Resistance/phase | 2.875Ω |
| Stator inductance | 0.0085H |
| Moment of inertia, J | 0.0008kg-m/s² |
| Damping constant, B | 0.001N-m/rad/s |
| Mechanical Load | 5Nm |

Fig. 12. Current (y-axis) vs. time (x-axis)

Fig. 13. Current (y-axis) vs. time (zoom along x-axis)
shows the 3 phase current characteristics. In case of PI controller current overshoot is much higher compared to GA tuned fuzzy controller.

6. CONCLUSION

MATLAB/SIMULINK environment is used to developed model of Brushless DC motor. Analysis of performance characteristics are done for modified queen bee based GA tuned fuzzy controller and manually tuned PI controller. During speed control analysis, BLDC motor is in loaded condition and subjected to various operating speeds. Simulation results shows that speed overshoot in case of PI controller is high, while speed overshoot is absent in case modified queen bee based GA tuned fuzzy controller. Settling time is also satisfactory for modified queen bee based GA tuned fuzzy controller; hence proposed controller results are encouraging and simulation results can be utilized for practical implementation.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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Peer-review history:
The peer review history for this paper can be accessed here: http://www.sdiarticle4.com/review-history/57107