Speed Control Analysis of BLDC motor using Modified Queen Bee Evolution Based Genetic Algorithm Tuned Fuzzy Knowledge Base Controller.

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 examines the ease and effectiveness of genetically tuned fuzzy controller and demonstrates the performance of a Brushless DC motor under different speed conditions. The effectiveness of Genetically Tuned Fuzzy controller has been proved in terms of BLDC parameter like rise time, peak overshoot and settling time by developing the Brushless DC motor drive model using MATLAB/SIMULINK Environment.

Keywords--- Brushless DC (BLDC) motor; Genetic Algorithm (GA); Back EMF (BEMF); Fuzzy knowledge base controller (FKBC)

I. 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.

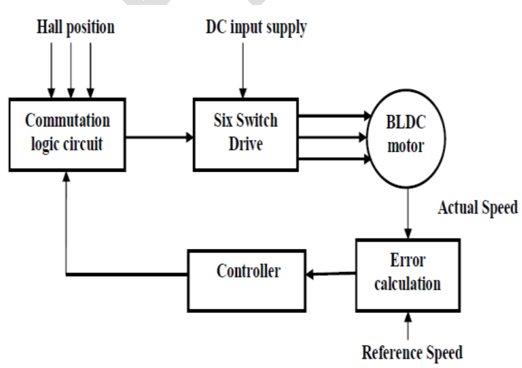


Fig. 1 schematic of BLDC motor drive

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 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 a expert human operator, which is quite tedious and unreliable.

Artificial neural networks can learn from a given set of data while it's not a case of fuzzy systems, and hence numerous techniques have been suggested to obtain fuzzy rules from training data set gathered from inspection of the various control strategies [4].

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

II. 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]

$$\begin{pmatrix} V_a \\ V_b \\ Vc \end{pmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{pmatrix} i_a \\ i_b \\ i_c \end{pmatrix} + p \begin{bmatrix} L_a & L_{ba} & L_{ca} \\ L_{ba} & L_b & L_{cb} \\ L_{ca} & L_{cb} & L_c \end{bmatrix} \begin{pmatrix} i_a \\ i_b \\ i_c \end{pmatrix} + \begin{pmatrix} e_a \\ e_b \\ e_c \end{pmatrix} \tag{1}$$

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

ω_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 [7] in shape & resistance value are same for three phases, above equation will reduce to.

$$\begin{pmatrix} V_a \\ V_b \\ Vc \end{pmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{pmatrix} i_a \\ i_b \\ i_c \end{pmatrix} + p \begin{bmatrix} L & M & M \\ M & L & M \\ M & M & L \end{bmatrix} \begin{pmatrix} i_a \\ i_b \\ i_c \end{pmatrix} + \begin{pmatrix} e_a \\ e_b \\ e_c \end{pmatrix} \tag{2}$$

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

$$\begin{pmatrix} V_a \\ V_b \\ Vc \end{pmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{pmatrix} i_a \\ i_b \\ i_c \end{pmatrix} + p \begin{bmatrix} L-M & 0 & 0 \\ 0 & L-M & 0 \\ 0 & 0 & L-M \end{bmatrix} \begin{pmatrix} i_a \\ i_b \\ i_c \end{pmatrix} + \begin{pmatrix} e_a \\ e_b \\ e_c \end{pmatrix} \tag{3}$$

$$=> \quad P\begin{pmatrix} i_a \\ i_b \\ i_c \end{pmatrix} = \begin{bmatrix} 1/L-M & 0 & 0 \\ 0 & 1/L-M & 0 \\ 0 & 0 & 1/L-M \end{bmatrix}\begin{pmatrix} V_a \\ V_b \\ Vc \end{pmatrix} - \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix}\begin{pmatrix} i_a \\ i_b \\ i_c \end{pmatrix} - \begin{pmatrix} e_a \\ e_b \\ e_c \end{pmatrix} \tag{4}$$

and $$\omega_r \times T_e = e_a i_a + e_b i_b + e_c i_c \tag{5}$$

Where,

T_e = Electric torque in N-m

ω_r = Rotor speed in rad./sec.

Total mechanical torque transferred to brushless DC motor shaft

$$T_e - T_l = J \times p\omega_r + B\omega_r \tag{6}$$

Where,

T_l = mechanical torque in N-m

J = inertia in kg-m^2

Equations (4), (5), and (6) represents the current drawn, generated electric torque & overall mechanical torque delivered to shaft of the brushless DC motor and, hence the dynamic model of the brushless DC motor drive [8].

III. 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 Figure 2 represents FKBC. Tuning of scaling factors K_e, K_{ce}, and K_{du} is done by modified queens bee based genetic algorithm, During the process of tuning controlled process act like a black box to the controller.

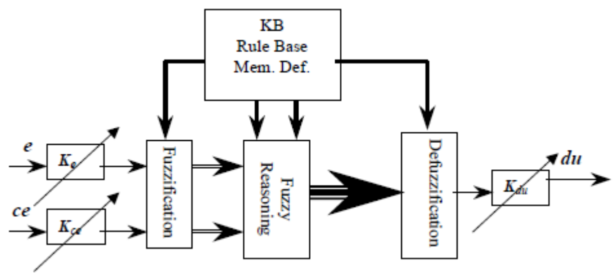


Fig. 2. Components of FKBC

IV. 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 (10) and equation (11) respectively. Global optima are more likely to be achieved by GA's, as it works with population of points, on contrary to point by point approach of traditional optimization techniques.

$$\textbf{Fitness} = \frac{\mathbf{1}}{\mathbf{ITAE}} \qquad (10)$$

$$\textbf{ITAE} = \int_0^t \mathbf{t|e|dt} \qquad (11)$$

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], 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 [11] 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 proposed modified queen bee algorithm. Figure 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 figure 3, it clearly shows that the least fit, pool 1 & pool 7 are omitted from the scheme.

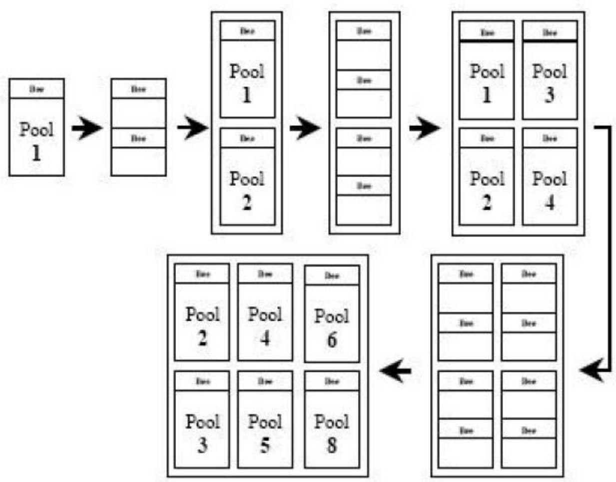


Fig. 3. Schematic of pool splitting generation by generation in modified Queen bee evolution

(ii) Weighted 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 weighted 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 Figure 4. Table I below shows the rules for Weight based crossover operator.

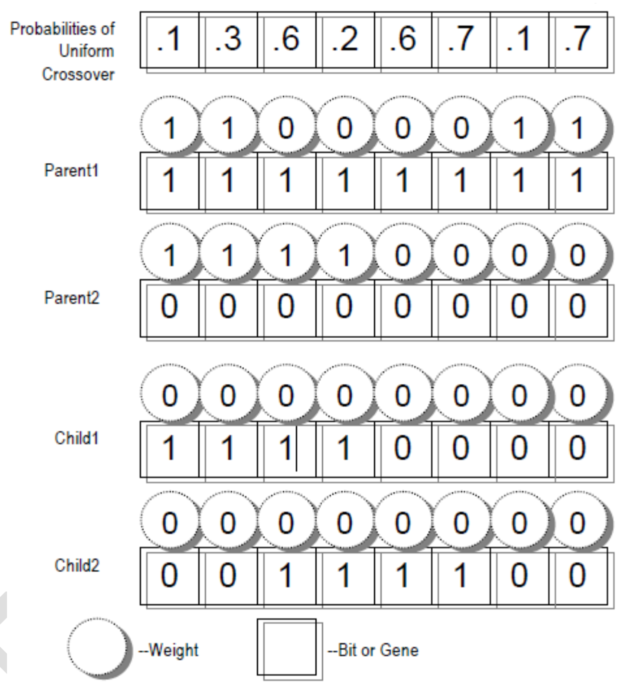


Fig. 4. Schematic representation of weight based uniform crossover.

TABLE I

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 below displays modified queen bee evolution based Genetic Algorithm.

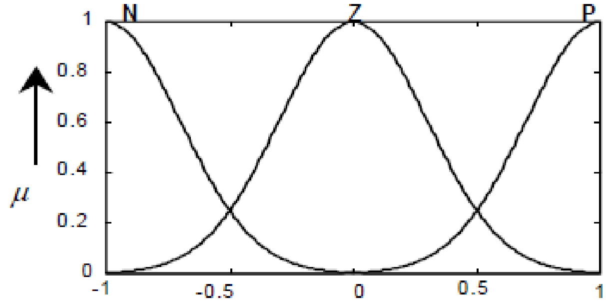
Algorithm 1:

//t: generation//, //n: population size in a pool//,
//pl: number of pools//, //P: populations//,
//pl_{max}: maximum number of pools//
//ξ: normal mutation rate//,
//p_m: normal mutation probability//,
//p'_m: strong mutation probability//,
//I_q: a queen bee//, //I_m: selected bee//

$t \leftarrow 0$: $pl(t) \leftarrow 1$; initialize $P\{pl(t)\}$; evaluate $P\{pl(t)\}$
while 1 (not terminate condition)
do
    $t \leftarrow t+1$
    while 2 $[pl(t)]$
    do 2
        select $P\{pl(t)\}$ from $P\{pl(t\text{-}1)(*)\}$
        $P\{pl(t)\}=[\, I_q\{pl(t\text{-}1)\}\ ,\ I_m\{pl(t\text{-}1)\}\ ]$
        recombine $P\{pl(t)\}$; do crossover; do mutation (*)
        for i=1 to n
            if $i \le (\xi \times n)$
                do mutation with p_m
            else
                do mutation with p'_m
            end if
        end for
        evaluate $P\{pl(t)\}$; search for $new\_I_q\{pl(t)\}$
        if ($new\_I_q\{pl(t)\}$ found)
            split the pool and $new\_pl(t) \leftarrow pl(t)+1$
        else
            $new\_pl(t) \leftarrow pl(t)$
        end if
        if $(new\_pl(t) > pl_{max})$
            $pl(t) \leftarrow pl_{max}$ (oldest pool deleted)
        end if
    end while2
end while1

V. 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 figure 5, membership function used is of Gaussian shape, with a variance of 0.424. Table II shows controlling rules of FKBC. For 'and' and implication operation 'min' operator is used while 'max' operator for 'or' and aggregation operation. Defuzzification is done by centroid method. The designed FKBC is applied to BLDC motor as shown in figure 6.



e, ce, du

Fig. 5 Gaussian membership function for e, ce and du

TABLE II
Fuzzy knowledge base rules

ce e	N	Z	P
N	N	N	Z
Z	N	Z	P
P	Z	P	P

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 III. 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.

TABLE III
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

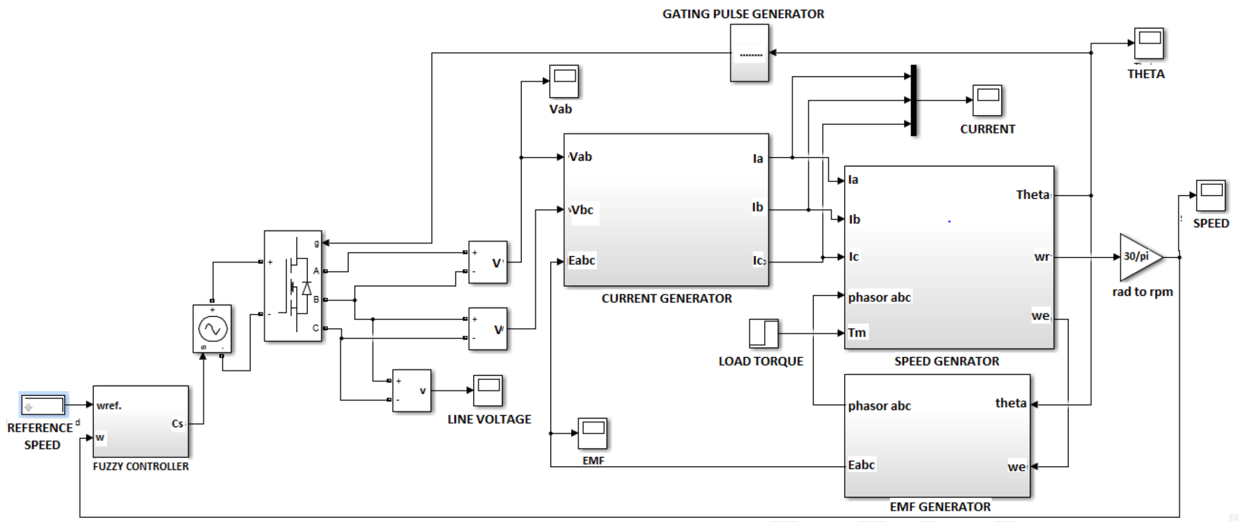


Fig. 6 BLDC motor drive simulation

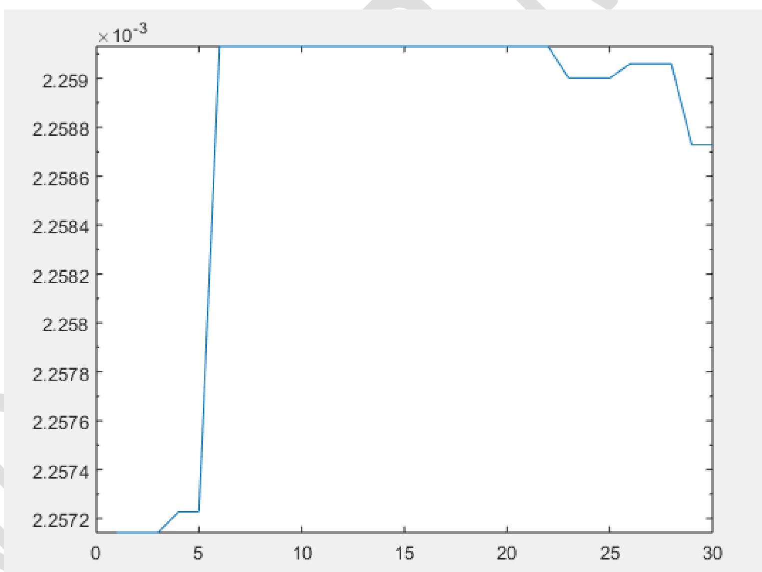


Fig. 7 generation vs. fitness

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

Results

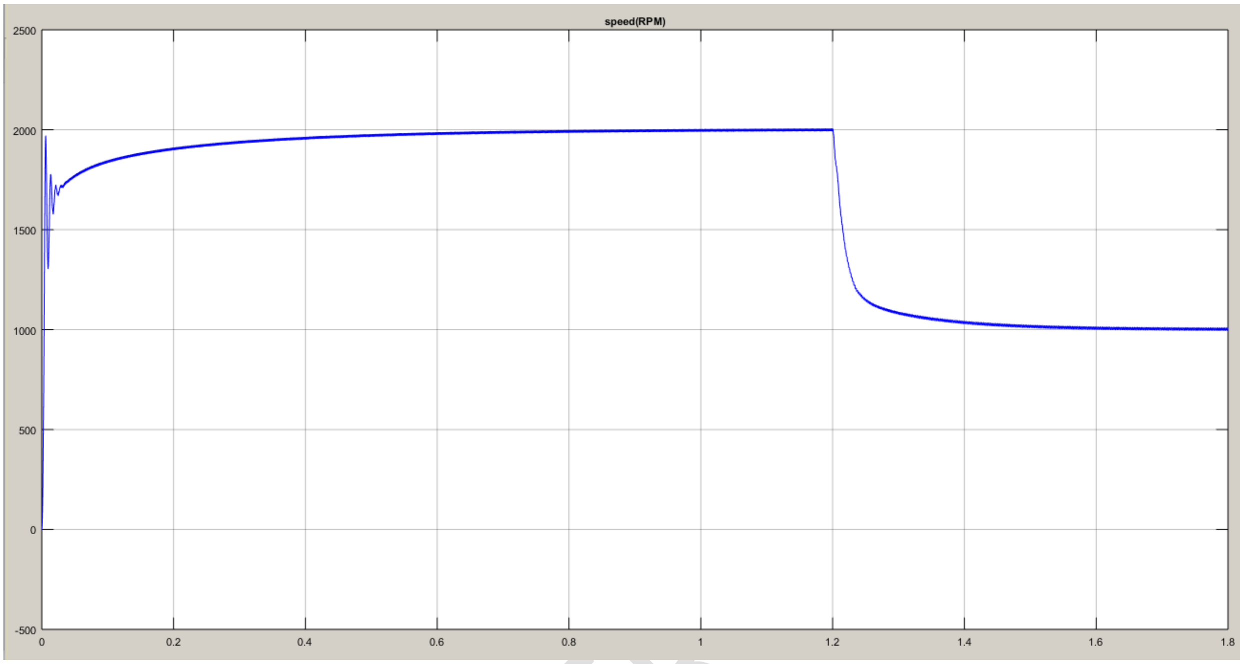


Fig. 8 speed in rpm versus time

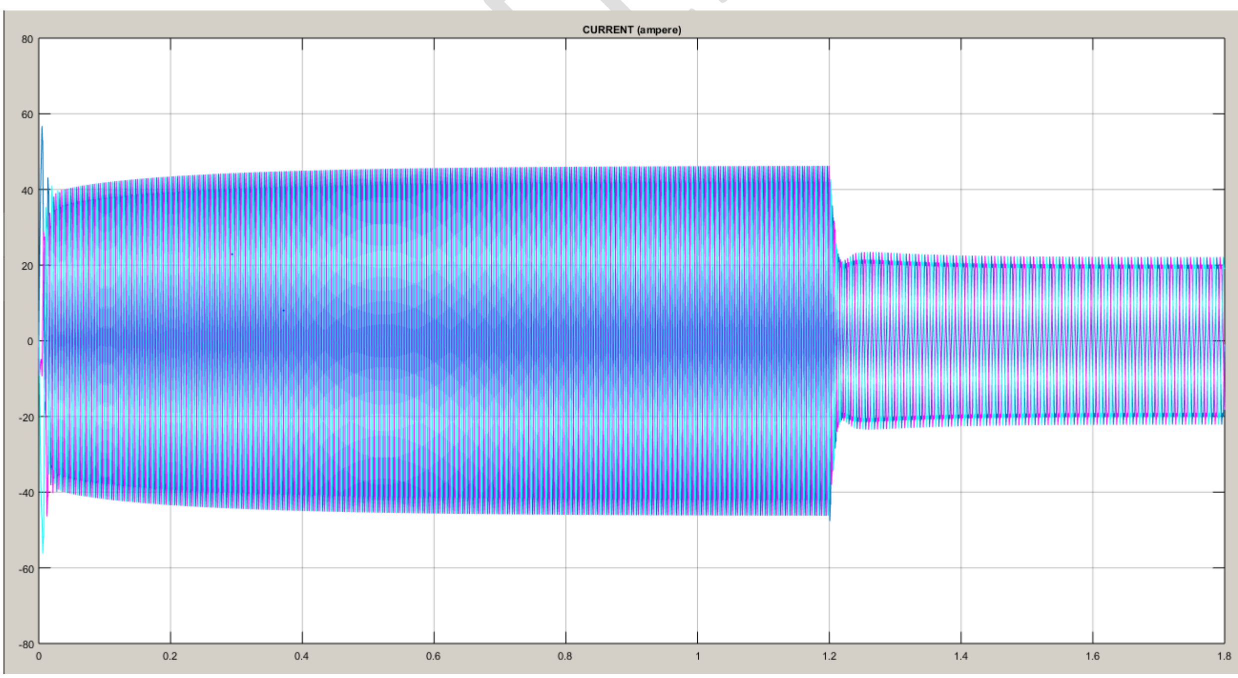


Fig 9 Current in amps. Versus time

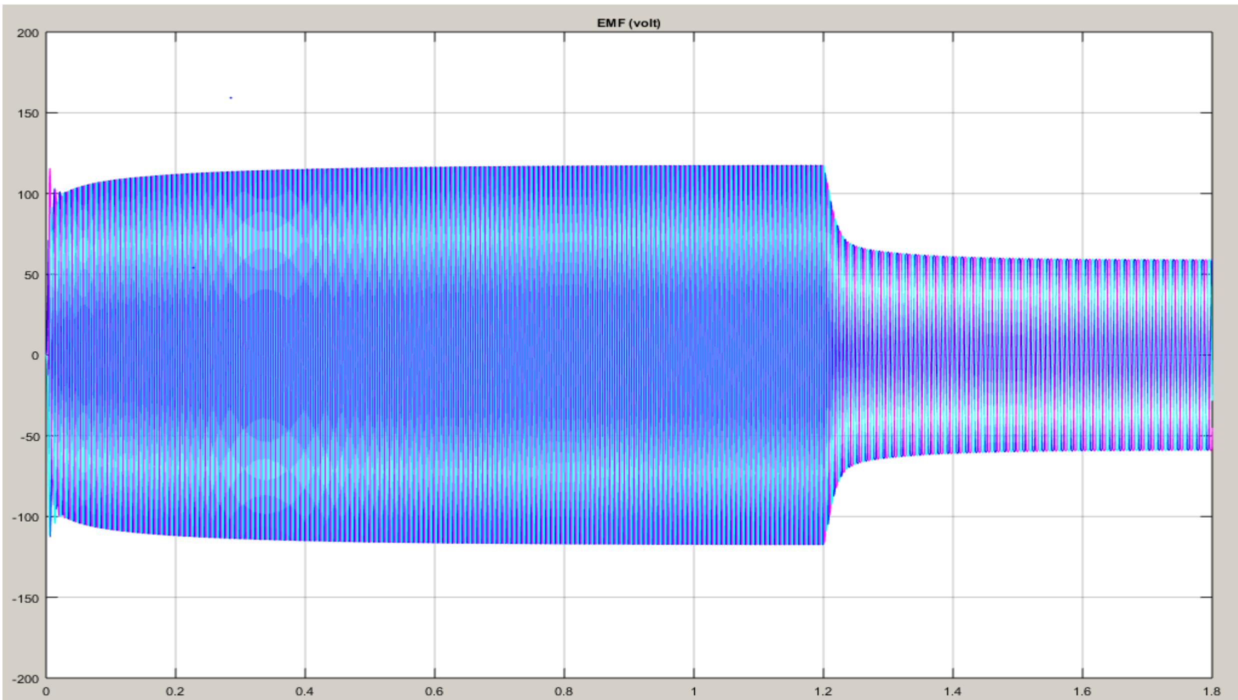


Fig. 10 EMF in volts versus time

VI. RESULTS AND DISCUSSION

The learning patterns in figure 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 2.25924x10^{-3}. Figure 10, shows speed response characteristic of brushless DC motor after utilizing scaled parameters values to the motor simulation. Simulation period for BLDC motor is around 1.8 second. Machine is loaded initially with a load of 5N, and speed reference of 2000 rpm. Settling time for GA based fuzzy controller is around 0.8 sec. On abruptly changing motor reference speed from 2000 rpm to 1000 rpm, after 1.2 sec from starting. Controller takes 0.4 sec to settle at final value. Overshoot remains absent in the response.

VII CONCLUSION

MATLAB/SIMULINK environment is used to developed model of Brushless DC motor and the performance characteristics are analyzed by using modified queen bee based tuned fuzzy controller. During speed control analysis, the motor is in loaded condition and subjected to various operating speeds. Simulation results clearly shows that under dynamic operating conditions, modified queen bee based tuned fuzzy controller performs satisfactory in terms of rise time, settling time and Peak overshoot. All the simulation results are of theoretical aspects and can be utilized for practical implementation

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