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SPEED CONTROL OF SENSORLESS BRUSHLESS DC MOTOR USING RANDOM DRIFT PARTICLE SWARM OPTIMIZATION TECHNIQUE

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***ABSTRACT* - PMBLDC (Permanent Magnet Brushless DC motors) find wide applications in industries due to their high power density and ease of control. Traditionally, BLDC motors are commutated in six-step pattern with commutation controlled by position sensors. To reduce the cost and complexity of the drive system, sensorless drive is preferred. The existing sensorless control scheme with conventional back EMF sensing based on motor neutral voltage for BLDC Motor has certain drawbacks, which limits its applications. In this paper, a novel back EMF sensing scheme, direct back EMF detection, for sensorless BLDC drives is presented. The motor neutral voltage is not needed to measure back EMFs. The true back EMF of motor winding can be detected during turn off time of PWM because the motor is directly proportional to the terminal voltage of the phase back EMF during this interval. This Project reviews the research and development in speed control of PMBLDC motor drives with an emphasis on sensorless control Microcontroller based PI controller are Simulated.**

Keywords: BLDC, back-EMF, sensorless control, position, speed, estimator, Hall-effect sensors, electronic processors

1.INTRODUCTION

1.1 GENERAL

Brushless DC motors are becoming more common in a variety of motor applications such as fans, pumps, automation, and automotive drive. The reasons for their increased popularity are better speed versus torque characteristics, higher efficiency, long operating life, and noiseless operation. In addition to these advantages, the ratio of the torque delivered to the motor is higher, making it useful in applications where space and weight are of critical factors.

The stator of a BLDC motor is similar to that of an induction machine but the windings are distributed quite different. The stator windings can be seen on the outside ring. The two different windings are distributed and sinusoidal. A distributed winding will have a trapezoidal back EMF while a sinusoidal winding will have a sinusoidal back EMF. The rotor of a brushless DC motor is different in the fact that the rotor contains permanent magnets. This is represented by the north and south poles.

Unlike a brushed DC motor, the commutation of a Brushless DC motor is controlled electronically. To rotate the BLDC motor, the stator windings should be energized in sequence. In order to make sure the motor controller is energizing coils in the correct sequence; The position of the rotor is detected by using the Hall

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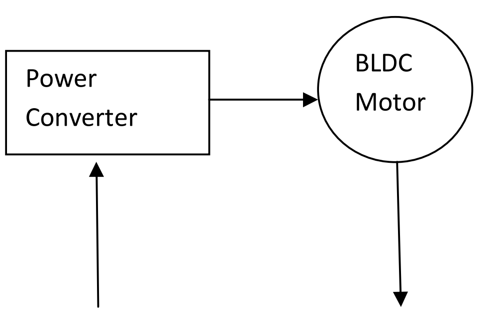
effect sensors. When the rotor is spinning inside the motor either the North or South Pole pass by the Hall Effect sensors which will cause the sensor to output which section of the rotor is passed.

In effect, a Brushless DC is a modified PMSM motor with the modification being that the back-emf is trapezoidal instead of being sinusoidal as in the case of Permanent magnet synchronous Motor. The “commutation region” of the back-emf of a BLDC motor should be as small as possible.The flat constant portion of the backemf should be 120° for smooth torque production.

The position of the rotor can be sensed using an optical position sensors and its associated logic. Optical position sensors consist of photo transistors (sensitive to light), revolving shutters, and a light source. The output of an optical position sensor are usually a Logical signal.

1.2. PRINCIPLE OPERATION OF BLDC MOTOR

A brush less dc motor is defined as the permanent magnet synchronous machine with rotor position feedback. The brushless motors are generally controlled using a three phase semiconductor bridge. The motor requires a rotor position sensor for starting and for providing proper commutating sequence to turn on the power devices in the inverter bridge. Based on the rotor position, the power devices commutated sequentially at every 60 degrees. Instead of commutating the armature current using brushes, the electronic commutation is used for this reason it is an electronic motor. This eliminates the problems associated with the brushes and the commutator arrangement, for example, sparking and wearing out of the commutator brush arrangement, thereby, making a Brushless DC more rugged as compared to a dc motor.



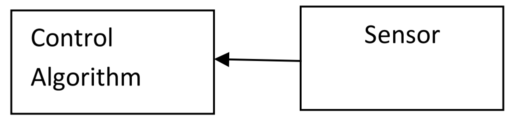


Fig.1.1. Basic Operational diagram of BLDC motor

The basic operational block diagram brushless dc motor as shown Fig.1.1.The brush less dc motor consist of four main parts of power converter, (permanent magnet-synchronous machine) PMSM sensors, and control algorithm. The power converter transforms power from the source to the Permanent magnet synchronous motor which inturns converts electrical energy into mechanical energy. One of the salient features of the brushless dc motor is rotor position sensors ,based on the rotor position and the command signals which may be a torque ,voltage and the speed command and so on the control algorithms which determines the gate signal to each semiconductor in the power electronic converter.

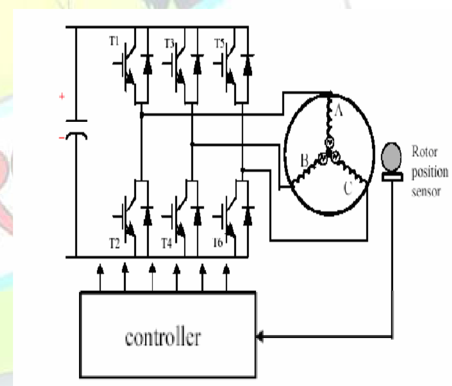


Fig 1.2 Typical BLDC Motor Control System

The structure of the control algorithms determines the type of the brush less dc motor of which there are two main classes voltage source based drives and current source based drives. Both voltage source and current source based drive used with permanent magnet synchronous machine with either sinusoidal or non-sinusoidal back emf waveforms .Machine with sinusoidal back emf may be controlled so as to achieve nearly constant torque. However, machine with a non sinusoidal back emf offer reduces inverter sizes and reduces losses for the same power level.

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1.3 BLDC MOTOR WITH SENSORLESS DRIVES

Typically, a Brushless dc motor is driven by a three-phase inverter with, what is called, six-step commutation. The conducting interval for each phase is 120o by electrical angle. The commutation phase sequence is like AB-AC-BC-BA-CA-CB. Each conducting stage is called one step. Therefore, only two phases conduct current at any time, leaving the third phase floating. In order to produce maximum torque, the inverter should be commutated every 60o so that current is in phase with the back EMF. The commutation timing is determined by the rotor position, which can be detected by Hall sensors or estimated from motor parameters, i.e., the back EMF on the floating coil of the motor if it is sensorless system.

Basically, two types of sensorless control technique can be found. The first type is the position sensing using back EMF of the motor, and the second one is position estimation using motor parameters, terminal voltages, and currents. The second type scheme usually needs DSPs to do the complicated computation, and the cost of the system is relatively high. So the back EMF sensing type of sensorless scheme is the most commonly used method, which is the topic of this thesis.

In brushless dc motor, only two out of three phases are excited at one time, leaving the third winding floating. The back EMF voltage in the floating winding can be measured to establish a switching sequence for commutation of power devices in the three-phase inverter.The method of sensing back EMF (will be referred to the conventional back EMF detection method in this thesis) to build a virtual neutral point that will, in theory, be at the same potential as the center of a Y wound motor and then to sense the difference between the virtual neutral and the voltage at the floating terminal. However, when using a chopping drive,the neutral is not a standstill point. The neutral potential is jumping from zero up to near dc bus voltage, creating large common mode voltage since the neutral is the reference point. Meanwhile, the PWM signal is superimposed on the neutral voltage as well, inducing a large amount of electrical noise on the sensed signal. To sense the back EMF properly, it requires a lot of attenuation and filtering. The attenuation is required to bring the signal down to the allowable common mode range of the sensing circuit, and the low pass filtering is to smooth the high switching frequency noise. Filtering causes unwanted delay in the signal. The result is a poor signal to noise ratio of a very small signal, especially at start-up where it is needed most. Consequently, this method tends to have a narrow speed range and poor start up characteristics. To reduce the switching noise, the back EMF integration and third harmonic voltage integration were introduced. The integration approach has the advantage of reduced switching noise sensitivity. However, they still have the problem of high common voltage in the neutral.

2.METHODOLOGY

2.1 INTRODUCTION

The random drift particle swarm optimization (RDPSO) algorithm, inspired by the free electron model in metal conductors placed in an external electric field, is presented, systematically analyzed and empirically studied in this paper. The free electron model considers that electrons have both a thermal and a drift motion in a conductor that is placed in an external electric field. The motivation of the RDPSO algorithm is described first, and the velocity equation of the particle is designed by simulating the thermal motion as well as the drift motion of the electrons, both of which lead the electrons to a location with minimum potential energy in the external electric field. Then, a comprehensive analysis of the algorithm is made, in order to provide a deep insight into how the RDPSO algorithm works.

It involves a theoretical analysis and the simulation of the stochastic dynamical behavior of a single particle in the RDPSO algorithm. The search behavior of the algorithm itself is also investigated in detail, by analyzing the interaction between the particles. Some variants of the RDPSO algorithm are proposed by incorporating different random velocity components with different neighbourhood topologies. Finally, empirical studies on the RDPSO algorithm are performed by

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using a set of benchmark functions from the CEC2005 benchmark suite.

Based on the theoretical analysis of the particle's behavior, two methods of controlling the algorithmic parameters are employed, followed by an experimental analysis on how to select the parameter values, in order to obtain a good overall performance of the RDPSO algorithm and its variants in real-world applications. A further performance comparison between the RDPSO algorithms and other variants of PSO is made to prove the efficiency of the RDPSO algorithms.

2.2 PARTICLE SWARM OPTIMIZATION

In a PSO with M individuals, each individual is treated as a volume-less particle in the N-dimensional space, with the current position vector and the velocity vector of particle i at the nth iteration represented as

for $i = 1,2,\mathrm{L}M$; $j = 1,2\mathrm{L},N$, where $c1$ and $c2$ are known as the acceleration coefficients. The vector

Pi n = Pi n Pi n L Pi n is the best previous position (the position giving the best objective function value or fitness value) of particle *i,* called the personal best **(pbest)** position, and the vector (1 , 2 , , N)

Gn = Gn Gn L Gn is

the position of the best particle among all the particles in the population and called the global best **(gbest)** position. Without loss of generality, we consider the following minimization problem:

Minimize $f(X)$ **,** $s.t.\ X \in S \subseteq RN$ **, (3)**

where $f(X)$ is an objective function and S is the feasible space. Accordingly, ***Pi n*** , can be updated by Generally, the value of ***j Vi n*** , is restricted within the interval **[−*V*max ,*V*max]** . The original PSO algorithm with equation appears to have a weak local search ability. It should be noted that the tradeoff between the local search (exploitation) and the global search (exploration) is vital for the performance of the algorithm. Therefore, the original PSO needs to accelerate the convergence speed of the particles in order to achieve a better balance between exploitation and exploration. Work in this area involves introducing an inertia weight into equation and the resulting update equation for velocities becomes:

where w is the inertia weight. The PSO algorithm with equation replacing equation is known as the PSO with inertia weight (PSO-In). The inertia weight w can be a positive value chosen according to experience or from a linear or nonlinear function of the iteration number. When w is 1, the PSO-In is equivalent to the original PSO. The values of $c1$ and $c2$ in equation are generally set to be 2 as originally which implies that the 'social' and 'cognition' parts have the same influence on the velocity update. another acceleration method by adding a constriction factor in the velocity update equation in order to ensure the convergence of the PSO without imposing any restriction on velocities, as given below.

2.3 RANDOM DRIFT PARTICLE SWARM OPTIMIZATION (RDPSO):

3.3.1 The Motivation And Procedure Of RDPSO

In fact, as the particles are converging to their own local attractors, their current positions, **pbest** positions, local focuses and the **gbest** position are all converging to one point.This way, the canonical PSO algorithm is said to be convergent. Since **pin** , is a random point uniformly distributed within the hyper-rectangle with **Pi,n** and **Gn** being the two ends of its diagonal, the particle's directional movement towards **pi n** , makes the particle search around this hyper-rectangle and improves its fitness value locally. Hence, this directional movement essentially reflects the local search of the particle. In equation there are three parts on the right side. The last two ones are known as the 'cognition' part and the 'social' part, the superimposition of which results in the directional motion of the particle toward **pin** , . The first part on the right side of each equation is the 'inertia part', which may lead the particle to fly away from **pi n** , or **Gn** and provide necessary momentum for the particle to search globally in the search space. The 'inertia part' is deterministic and reflects the global search of the particle.

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The motivation of the proposed RDPSO algorithm comes from the above trajectory analysis of the canonical PSO and the free electron model in metal conductors placed in an external electric field. According to this model, the movement of an electron is the superimposition of the thermal motion, which appears to be a random movement, and the drift motion (i.e., the directional motion) caused by the electric field. That is, the velocity of the electron can be expressed by $V = VR + VD$, where VR and VD are called the random velocity and the drift velocity, respectively. The random motion (i.e., the thermal motion) exists even in the absence of the external electric field, while the drift motion is a directional movement in the opposite direction of the external electric field.

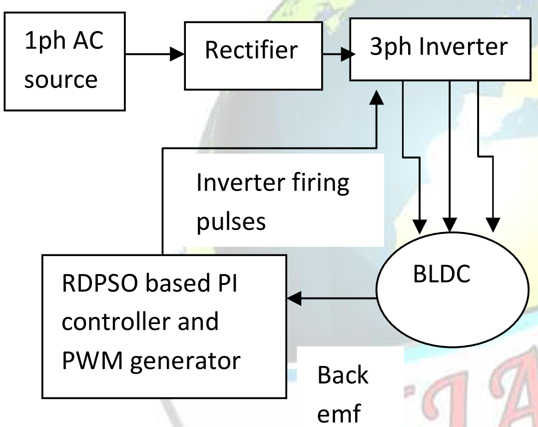

Fig:2.1 Block Diagram Of BLDC Motor Using RDPSO Algorithm

The overall physical effect of the electron's movement is that the electron careens towards the location of the minimum potential energy. In a non-convex-shaped metal conductor in an external electric field, there may be many locations of local minimum potential energies, which the drift motion generated by the electric force may drive the electron to. If the electron only had the drift motion, it might stick into a point of local minimum potential energy, just as a local optimization method converges to a local minimum of an optimization problem. The thermal motion can make the electron more volatile and, consequently, helps the electron to escape the trap of local minimum potential energy, just as a certain random search strategy is introduced into the local search technique to lead the algorithm to search globally.

Therefore, the movement of the electron is a process of minimizing its potential energy. The goal of this process is essentially to find out the minimum solution of the minimization problem, with the position of the electron represented as a candidate solution and the potential energy function as the objective function of the problem. Inspired by the above facts, we assume that the particle in the RDPSO behaves like an electron moving in a metal conductor in an external electric field. The movement of the particle is thus the superposition of the thermal and the drift motions, which implement the global search and the local search of the particle, respectively.

The trajectory analysis, as described in the first paragraph of this subsection, indicates that, in the canonical PSO, the particle's directional movement toward its local attractor *pi n* , reflects the local search of the particle. In the proposed RDPSO, the drift motion of the particle is also defined as the directional movement toward *pi n* , , which is the main inheritance of the RDPSO from the canonical PSO. However, in the RDPSO, the 'inertia part' in the velocity equation of the canonical PSO is replaced by the random velocity component.

This is the main difference between the RDPSO and the canonical PSO. Christo Ananth et al. [4] discussed about Improved Particle Swarm Optimization. The fuzzy filter based on particle swarm optimization is used to remove the high density image impulse noise, which occur during the transmission, data acquisition and processing. The proposed system has a fuzzy filter which has the parallel fuzzy inference mechanism, fuzzy mean process, and a fuzzy composition process. In particular, by using no-reference Q metric, the particle swarm optimization learning is sufficient to optimize the parameter necessitated by the particle swarm optimization based fuzzy filter, therefore the proposed fuzzy filter can cope with particle situation where the assumption of existence of "ground-truth" reference does not hold. The merging of the particle swarm optimization with the fuzzy filter helps to build an auto tuning mechanism for the fuzzy filter without any prior

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knowledge regarding the noise and the true image. Thus the reference measures are not need for removing the noise and in restoring the image. The final output image (Restored image) confirm that the fuzzy filter based on particle swarm optimization attain the excellent quality of restored images in term of peak signal-to-noise ratio, mean absolute error and mean square error even when the noise rate is above 0.5 and without having any reference measures.

It is unnecessary and impossible to depict the exact change of the particle's velocity with time. Therefore, there is no 'inertia part' in the velocity equation of the RDPSO algorithm anymore. From an algorithm design point of view, the role of the 'inertia part' in the global search is assumed by the random velocity component in the RDPSO, so that there is no need of an 'inertia part' in the RDPSO. Therefore, the velocity of the particle in the RDPSO algorithm has two components, i.e., the thermal component and the drift component. Mathematically, the velocity of particle i in the jth dimension can be expressed by j velocity component and the drift velocity component, respectively.

```
%-----RDPSO ALGORITHM---------------------------------------------

c1=1.4962;
c2=1.4962;          %initial velocity
w=0.7298;           %initial acceleration
MaxDT=100;          %Maximum duty

D=30;               %Minimum duty
N=50;               %Iteration
eps=10^(-6);        %Absolute value

for i=1:N
  for j=1:D
    x(i,j)=randn;  %   initial random values
    v(i,j)=randn;
  end
end

for i=1:N
  p(i)=fitness(x(i,:),D);
  y(i,:)=x(i,:);
end
pg=x(1,:);          %Initial the current position
for i=2:N
  if fitness(x(i,:),D)<fitness(pg,D)
    pg=x(i,:);
  end
end

for t=1:MaxDT
  for i=1:N
    v(i,:)=w*v(i,:)+c1*rand*(y(i,:)-x(i,:))+c2*rand*(pg-x(i,:));
    x(i,:)=x(i,:)+v(i,:);
    if fitness(x(i,:),D)<p(i)
      p(i)=fitness(x(i,:),D);
      y(i,:)=x(i,:);
    end
    if p(i)<fitness(pg,D)
```

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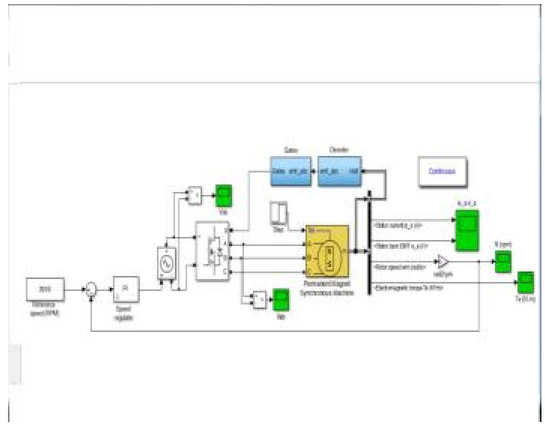
```
            pg=y(i,:);
        end
    end
    Pbest(t)=fitness(pg,D);

end
Solution=pg'
Result=fitness(pg,D)
P1 = Result;
I1 = sqrt(Result);
sim('SENSORLESSD');
```

3.SIMULATION RESULT

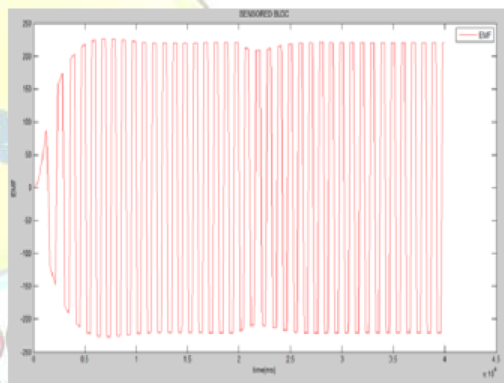
3.1 EXISTING SYSTEM

In the Existing system, The PSO method is a simple and effective meta-heuristic approach that can be applied to a multivariable function optimization having many local optimal points. The PSO uses several cooperative agents and each agent shares the information attained by each individual during the search process. Here PSO initializes the variables randomly in a given space. The number of decision variables determines the dimension of space. Each optimization problem is to search the solution space of a particle, each particle runs at a certain speed in the search space, the speed of particles is in accordance with its own flight experience and flight experience of other examples with dynamic adjustments.

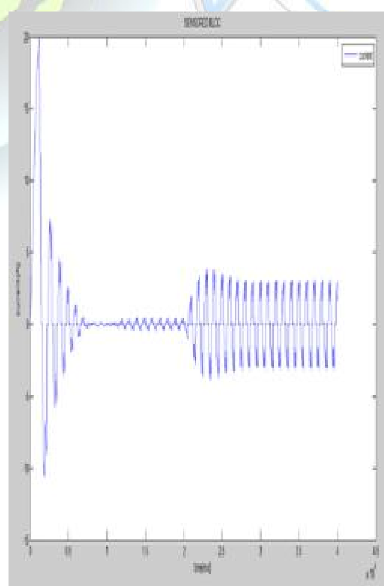
3.1.1 SIMULINK MODEL OF EXISTING SYSTEM



3.1.2 OUTPUT WAVEFORM OF EXISTING SYSTEM



(a)Emf vs time



(b)Speed vs time

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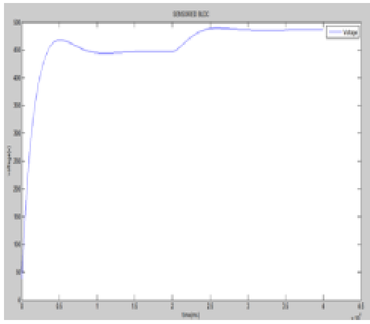

(c)voltage vs time

3.2 PROPOSED SYSTEM

In the Proposed system, The Random drift particle swarm optimization (RDPSO) algorithm, inspired by the free electron model in metal conductors placed in an external electric field, is presented, systematically analyzed and empirically studied in this paper. The free electron model considers that electrons have both a thermal and a drift motio in a conductor that is placed in an external electric field.

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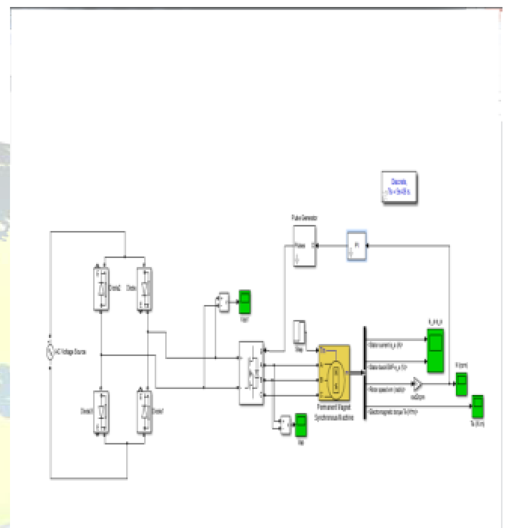
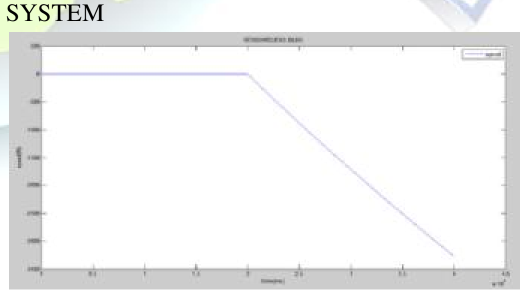
Based on the theoretical analysis of the particle's behavior, two methods of controlling the algorithmic parameters are employed, followed by an experimental analysis on how to select the parameter values, in order to obtain a good overall performance of the RDPSO algorithm and its variants in real-world applications. A further performance comparison between the RDPSO algorithms and other variants of RDPSO is made to prove the efficiency of the RDPSO algorithms.

3.2.1 SIMULINK MODEL OF PROPOSED SYSTEM



3.2.2 OUTPUT WAVWFORM OF PROPOSED SYSTEM



(a)Speed vs time

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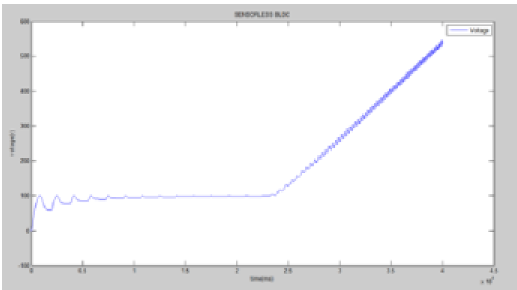
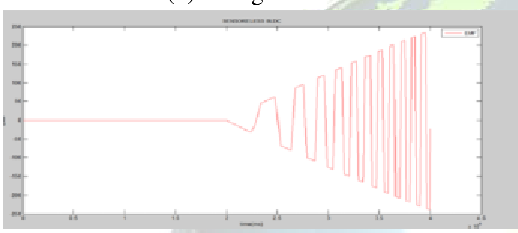


(b)Voltage vs time



(c)EMF vs time

4.CONCLUSION

The applications of brushless DC (BLDC) motors and drives have grown significantly in recent years in the appliance industry and the automotive industry. Sensorless BLDC drive are very preferable for compact, low cost, low maintenance, and high reliability system. The speed control for BLDC using PI controller with RDPSO algorithm has been designed. The dynamic performance of BLDC is analysed by simulation in MATLAB/simulink environment. The PI controller provides a better performance in terms of low ripples, high efficiency and low RMSE value. In this thesis, a novel back EMF sensing technique, direct back EMF sensing, without motor neutral voltage for BLDC drives is proposed, analyzed, and extended, overcoming the drawbacks of the conventional scheme.

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