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Full Length Research Paper

Brain emotional learning based intelligent controller for stepper motor trajectory tracking

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Excellent attributes of permanent magnet stepper motor (PMSM) make it prominent in robotic, aerospace, and numerical machine applications. However, the problem of nonlinearity and presence of mechanical configuration changes, particularly in precision reference trajectory tracking, must be put into perspective. In this paper, a novel cognitive strategy based on the emotional learning in limbic system of mammalian's brain is employed to establish an intelligent controller in order to provide the necessary control actions as to achieve trajectory tracking of the rotor speed in different circumstances. Brain emotional learning based intelligent controller (BELBIC) is a model free controller, independent of model dynamic and variations that occurs in system, can be taken in to account as an outstanding option for the nonlinear applications. Fast response, high accuracy, and the ability of disturbance rejection introduce BELBIC as an eminent controller. To verify these attributes, different test beds have been simulated in Matlab Simulink environment and the performance of BELBIC is investigated. For further illumination, a classic controller called static proportional-integral-derivative (PID) is also applied on the model and then a comprehensive comparison, both in certain and uncertain condition, between the results of the proposed controllers is done. Uncertain situation is provided by applying load torque disturbance and variation in parameters of PMSM. The results of simulations clearly indicate the outstanding ability of BELBIC in speed tracking with high accuracy for the arbitrary reference signals and conspicuous robustness of this controller in presence of uncertainties.

Key words: Permanent magnet stepper motor, limbic system, emotional learning, speed tracking, uncertainty, robustness.

INTRODUCTION

Utilizing reliable and efficacious electrical motors in high precision motion control is of the paramount importance. Due to the characteristics of high accuracy, quick response, small size and mechanical structure, stepper motors are recognized as the expedient options. They are nonlinear incremental motion actuators compatible with digital electronic circuits. In simple point-to-point position applications, they produce an acceptable response based on the open loop control. In this configuration, stepper motor receives a rectangular train of pulse, and then, rotates its shaft without using any information on the motor shaft position or speed (Ghafari and Behzad, 2005a, b). Without a doubt, open loop configuration cannot guarantee functionality of stepper motor where it is susceptible to internal and external variations. In other words, feedback is an essential part to obtain the information on losing step or when oscillation occurs in stepper motor. Closed loop configuration was suggested for upgrading the accuracy of trajectory control by decreasing the sensitivity in the presence of variations

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(Fredriksen, 1968; Clarkson and Acarnley, 1988). The linear and nonlinear algorithms were developed by the advancements in power electronic and data processing. Feedback linearization in which the dynamic of stepper motor is linearized around its operating point, offered superior results in comparison with open loop configuration (Zribi and Chanson, 1991). However, this scheme did not present the ability of adaption for different operating points. Concentration of researchers on adaptive algorithms has improved the deficiencies of non-adaptive control schemes (Bodson et al., 1993). Self-tuning regulator (STR) was developed for speed control of stepper motor by obligating the controller to be adapted under motor operation conditions (Betin et al., 1999); but, this approach is not suitable for practical implementations because it requires a large amount of floating point computation which results in increasing of sampling period. In real applications, attention to the mechanical variations, which might be exerted by load torque disturbance and inertia variations, is indispensible. Supporting the robustness property, sliding mode control (SMC) can be taken in to consideration (Utkin, 1992; Zribi et al., 2001). SMC ensures exceptive accuracy and significant robustness in dealing with plant's parameter changes. It is remarkable that SMC offers the robustness property for a group of uncertainties matched within its bound of variations whereas the load torque and variation of the moment of inertia are considered as the unmatched disturbances. Employing the observer to estimating the load torque is a common strategy to eliminate the load torque influences (Nollet et al., 2008).

In recent decades, artificial intelligence (AI) has attracted a large group of researchers who has been trying to find a new alternative for solving complex problems. The significant capability of artificial neural network (ANN) in handling the nonlinearity, has been vastly used in high performance control of stepper motor (Rubaai and Kotaru, 2001; Rubaai et al., 2007). However, in using ANN, long training process and long recovery time are counted as a substantial issue. Further-more, there are several attempts in applying fuzzy logic in controlling various electrical drives (Betin et al., 2000). Fuzzy logic is a solution when mathematical description of the complex system is not possible. Even though fuzzy logic offers a simple computation for nonlinear applications, however, designing the membership functions and arranging the inference rules do not follow a systematic approach.

Recently, a structural model based on emotional learning algorithm in the limbic system of mammalian brain has been proposed (Balkenius and Moren, 1998 a, b; Moren and Balkenius, 2000; Moren, 2002). This model was developed, and then, shared for control engineering applications (Lucas et al., 2004).

The proposed structure is known as a powerful controller for fast decision making particularly in blurred environments. BELBIC is increasingly being utilized in control engineering tasks (Mehrabian and Lucas, 2006; Arami et al., 2008a, b), robotic designing and navigations (Sharbafi et al., 2010; Mehrabian, and Lucas 2009), system identification and prediction (Kharaajoo, 2004), adaptive learning based on the critics (Arami et al., 2011), and finally, intelligent devices (Milasi et al., 2007) and yielding excellent results. In the area of electrical motor control, it has been employed for speed control of interior permanent magnet synchronous motor in field-weakening region (Dehkordi et al., 2011a, b), sensorless speed control of switched reluctance motor (Dehkordi et al., 2011a, b) and speed and flux control of induction motor (Markadeh et al., 2011). The results clearly express satisfactory performance of BELBIC in controlling the nonlinear dynamic systems.

Pertaining to the preceding discussion, BELBIC in this paper has been utilized to cope on the problem of speed trajectory tracking in PMSM. Although, adaptive tracking in highly nonlinear and time varying systems has been considered to some extent in the literature, however, even today the problem of high precision speed tracking in PMSM still sparks controversy amongst the researchers. The main objective of this paper is to increase the accuracy of speed tracking in the certain condition and also offers an appropriate control strategy in order to enhance the performance of PMSM particularly when the dynamic model is experiencing different kinds of uncertainties. In other words, a trial was made by the proposed BELBIC model to exert disturbances rejection on the system in such a way that the response of the system is closely like the one achieved in an ideal condition. This remarkable improvement in system performance, in comparison with previous works could be described based on the model free structure and quick auto learning of BELBIC which constitute proper tracking of the reference speed independent of the variations occurred on the system parameters.

To prove the aforementioned statements, the functionality of BELBIC is investigated on certain and uncertain condition. Mechanical configuration changes such as variations of load inertia and also load torque disturbance are applied on the system to examine the robustness property of BELBIC. The achieved results are compared with those obtained based on the static PID. The system also was tested under the condition of set point variations. Different classes of reference signals, which incorporate random disturbances, provide a proper test bed for evaluation of the behavior of BELBIC in trajectory tracking. Numerical comparison based on different performance indices was also carried out between static PID and BELBIC. The results are provided by the simulation of PMSM dynamic model and aforementioned controllers in Matlab Simulink to illuminate the performance of the proposed controllers in different circumstances.

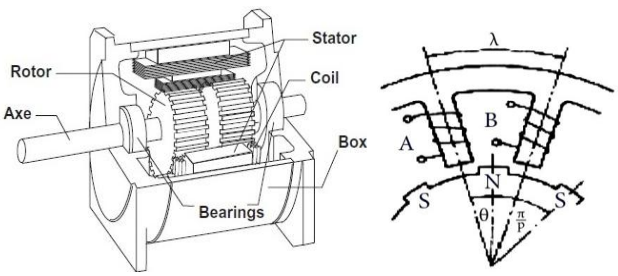

Figure 1. Schematic of two-phase PMSM.

Dynamic modeling of PMSM

Here, physical modeling approach is used to describe the dynamic behavior of PMSM in the form of a set of equations. Fundamental of physical modeling is based on division of the system into the subsystems with comprehensible properties. This is a general approach which results in the construction of mathematical model of the systems.

Basically, the model of PMSM comprises two parts; an electrical and a mechanical part. The structure of the dynamic model is nonlinear originally. Moreover, there are some physical parameters in the model that their values vary with the elapsing of the time. These two directly affect the control objective and make it difficult. Figure 1 depicts the outer and cutaway view of two-phase PMSM. It consists of two phase A and B in the stator. The rotor has (2Nr) magnetic poles, while the stator has a set of identical poles and windings equally arranged at intervals of (λ) (Kenjo, 1984; Marino et al., 1995). In order to constitute a state space representation, the state variables of the model were defined as below:

$$X=[i_a i_b \omega \theta]^T \tag{1}$$

Where, θ represents the angular position of the rotor, ω is angular velocity of the rotor, i_a represents current in winding A and i_b is current in winding B. Then, the state space model of the system can be written as shown in Equation 2 (Marino et al., 1995; Kamalasadan, 2007; Rezeka et al., 2010).

$$\begin{aligned}
\frac{di_a}{dt} &= \frac{1}{L}(V_a - Ri_a + K_m \omega \sin p\theta) \\
\frac{di_b}{dt} &= \frac{1}{L}(V_b - Ri_b + K_m \omega \cos p\theta) \\
\frac{d\omega}{dt} &= \frac{k_m}{J}(-i_a \sin p\theta + i_b \cos p\theta) - \frac{F}{J}\omega - \frac{T_L}{J} \\
\frac{d\theta}{dt} &= \omega
\end{aligned} \tag{2}$$

Where, V_a and V_b are voltages of phase A and B, j is inertia of the motor, F is viscous friction coefficient, K_m is motor torque constant, R is resistance of the phase winding , L is inductance of the phase winding, P is number of rotor teeth, and finally, T_L indicates load torque.

DQ transformation converts the set of equation into a new frame which is called DQ model. It transforms vectors (V) and (i) which are carried in the fixed stator frame (a ,b) into vectors carried in a frame (d ,q) that rotates along the fictitious excitation vector (Marino et al., 1995; Kamalasadan, 2007; Rezeka et al., 2010). Therefore, the phase voltages and currents are transformed in DQ frame based on Equation 3 and 4.

$$\begin{bmatrix} i_d \\ i_q \end{bmatrix} = \begin{bmatrix} \cos(p\theta) & \sin(p\theta) \\ -\sin(p\theta) & \cos(p\theta) \end{bmatrix} \begin{bmatrix} i_a \\ i_b \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} V_d \\ V_q \end{bmatrix} = \begin{bmatrix} \cos(p\theta) & \sin(p\theta) \\ -\sin(p\theta) & \cos(p\theta) \end{bmatrix} \begin{bmatrix} V_a \\ V_b \end{bmatrix} \tag{4}$$

Consequently, a new set of state equations has appeared in Equation 5.

$$\begin{aligned}
\frac{di_d}{dt} &= -\frac{R}{L} i_d + p\omega i_q + \frac{V_d}{L} \\
\frac{di_q}{dt} &= -\frac{R}{L} i_q - p\omega i_d - \frac{K_m}{L}\omega + \frac{V_q}{L} \\
\frac{d\omega}{dt} &= \frac{K_m}{J} i_q - \frac{F}{J}\omega - \frac{T_L}{J} \\
\frac{d\theta}{dt} &= \omega
\end{aligned} \tag{5}$$

Computational model of BELBIC

Brilliant successes achieved by the functional modeling of emotion in control engineering tasks (Rahman et al., 2008; Jamali et al., 2010) motivated the author of this paper to exploit the structural model of limbic system in mammalian's brain and its learning process for the trajectory tracking in PMSM as the main purpose of this study. Generally, emotional learning occurs in specific part of the brain called limbic system (Maren, 1999). Figure 2 shows the limbic system with its peripheral parts. The computational model of emotional learning that mimics Amygdale, Orbitofrontal cortex, Thalamus, sensory inputs, and in general, those parts of the brain thought to be responsible for processing of emotions, has

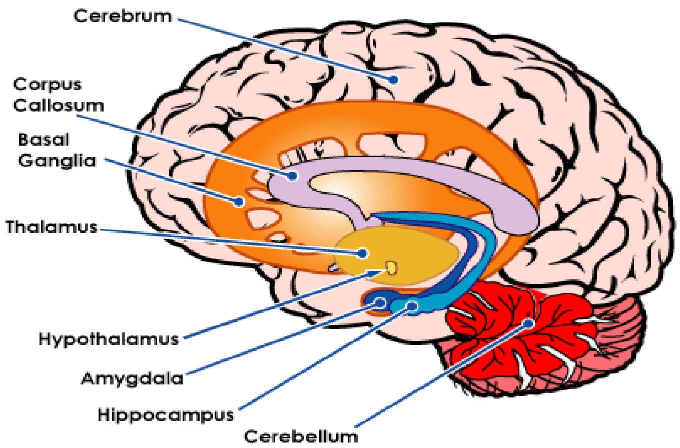

Figure 2. Limbic system in human's brain.

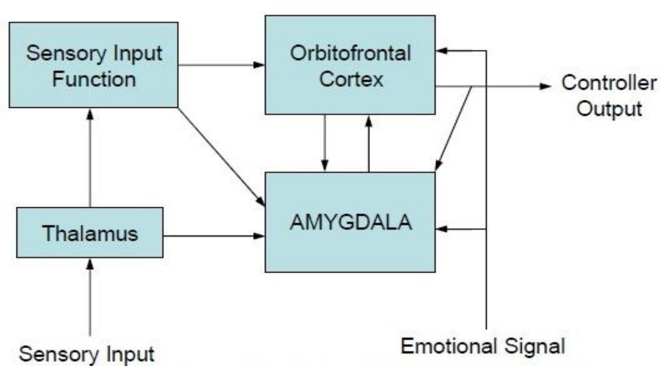

Figure 3. Main blocks structure of emotional learning.

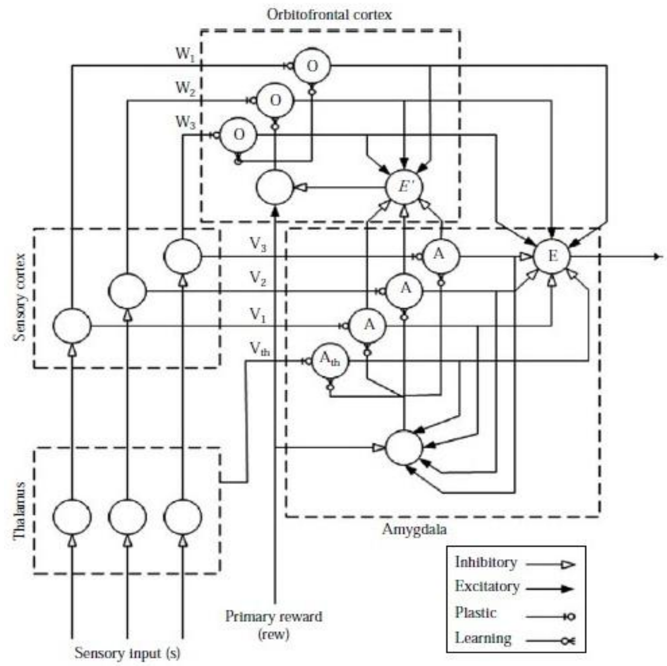

Figure 4. Graphical depiction of BELBC.

been offered (Balkenius and Moren, 1998; Moren and Balkenius, 2000; Moren, 2002). Figure 3 illustrates the basic blocks of this structure. The proposed computational model was then developed in a form of an intelligent controller (Lucas et al., 2004). Fundamentally, BELBIC is an action generation mechanism based on the sensory inputs and emotional cues. As shown in Figure 4, BELBIC receives sensory input signals via Thalamus. After pre-processing in Thalamus, processed input signal will be sent to Amygdala and Sensory cortex. Amygdala and Orbitofrontal cortex are used to compute their outputs based on emotional signal received from the environment. The final output is calculated by subtracting Amygdala and Orbitofrontal cortex outputs. Next, emotional learning process formulation is discussed based on Moren and Balkenius (2000) model.

In general, sensory inputs utter the current situation which the system is dealing with. In the model, there is one node A for each sensory input. It can be in the vector shape as well. A_{th} is a node in Amygdala which directly receives the maximum stimuli signals via a path from Thalamus. This path is called thalamic connection. It is noteworthy that thalamic input is not projected into the Orbitofrontal part and cannot be inhibited by itself.

$$A_{th} = \max(S_i) \tag{6}$$

The output of each node A is calculated based on the multiplication of pre-specified plastic connection weight (V) into the corresponding input. In the Orbitofrontal cortex, each O is similar to A nodes, and the output is calculated by applying connection weight (W) into the input signal.

$$A_i = S_i V_i$$
$$O_i = S_i W_i \tag{7}$$

The difference between the emotional signal (reinforcement signal) and activation of the A nodes determines the updating of the connection weight (V_i) which finally leads to learning process in Amygdala. The rate of learning is specified by the term α.

$$\Delta V_i = \alpha\ [S_i \max(0, ES - \Sigma A_j)] \tag{8}$$

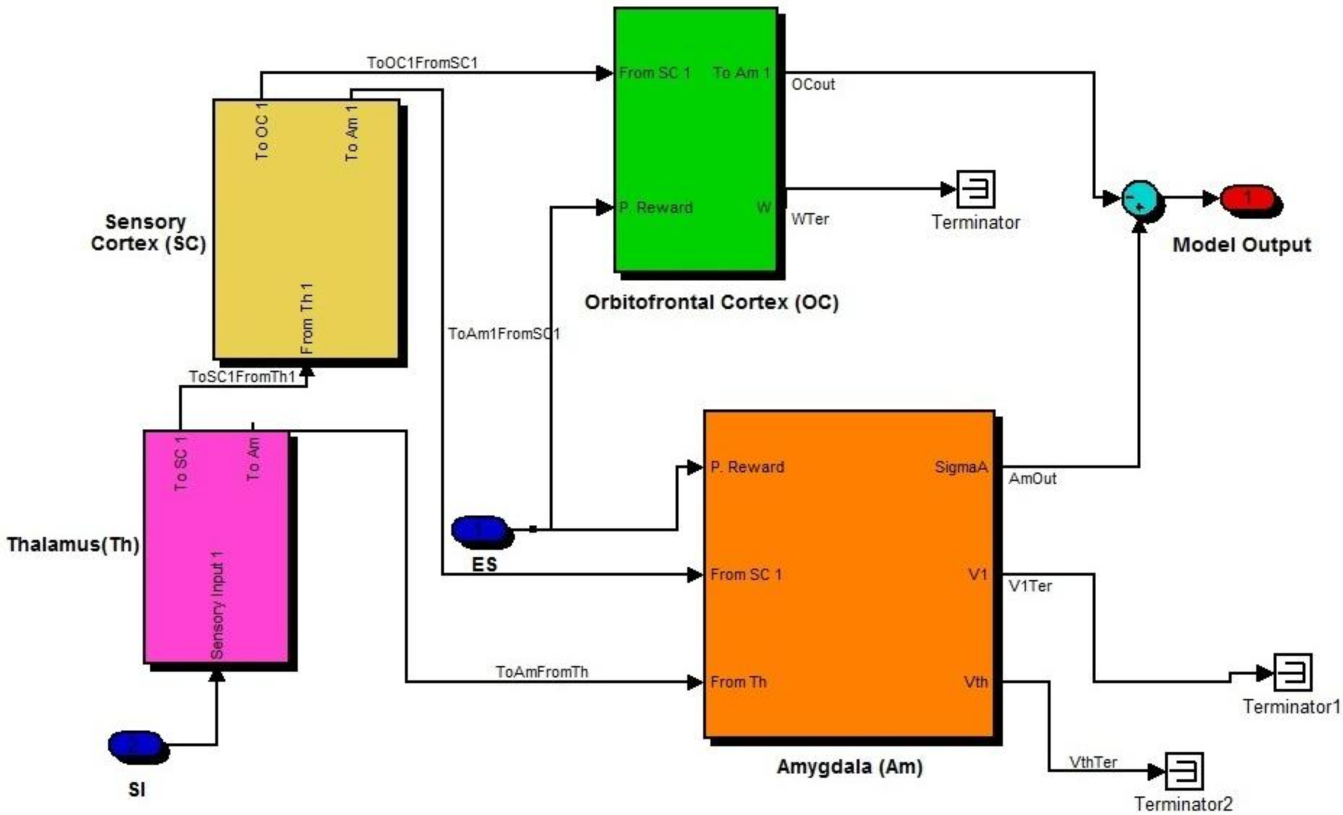

Figure 5. Simulink block diagram of BELBIC.

In Equation 6, the term max expresses that the weight (V_i) cannot be decreased. The striking proof for advantage of this concept is that once the Amygdala learns a particular reaction, it must be kept forever. In other words, Amygdala cannot forget the emotional evaluation. Reciprocally, Orbitofrontal cortex carries the omission of inappropriate reaction. The learning rule in the Orbitofrontal cortex is computed based on the comparison between the expected and received reinforcement signal and inhibits the output of the model if there is a mismatch.

$$\Delta W_i = \beta \ [S_i(\Sigma \ O_i - ES \ )] \tag{9}$$

Updating the adaptive weights in Orbitofrontal cortex is almost similar to the Amygdala rule. The distinguishing point is that for tracking of the inappropriate response from the Amygdala, the Orbitofrontal weights must be decreased and increased. Parameter β is another learning rate constant. The A nodes produce their outputs proportionally to their contribution in predicting the reward or stress, while the O nodes inhibit the output of E if necessary. The model output is, consequently, computed as the difference between the output of Amygdala and Orbitofrontal nodes.

$$E = \Sigma \ A_i - \Sigma \ O_i \tag{10}$$

The computational model of BELBIC was simulated in MATLAB. Figures 5 and 6 illustrate the Simulink framework of the BELBIC and Orbitofrontal cortex respectively.

METHODOLOGY

Three different situations called certain condition, moderate uncertain condition and aggressive uncertain condition are provided for the performance evaluation of the proposed BELBIC and static PID. First, the dynamic model of PMSM is simulated based on the nominal values obtained from the reference (Kamalasadan, 2007). Table 1 depicts the pertinent values for the motor parameters. A trapezoidal signal which covers the characteristics of increasing, constant and decreasing is chosen as an appropriate reference signal. Both static PID and BELBIC controllers are configured in closed loop form as illustrated in Figures 7 and 8 respectively. Static PID generates two control signals (V_d and V_q) under

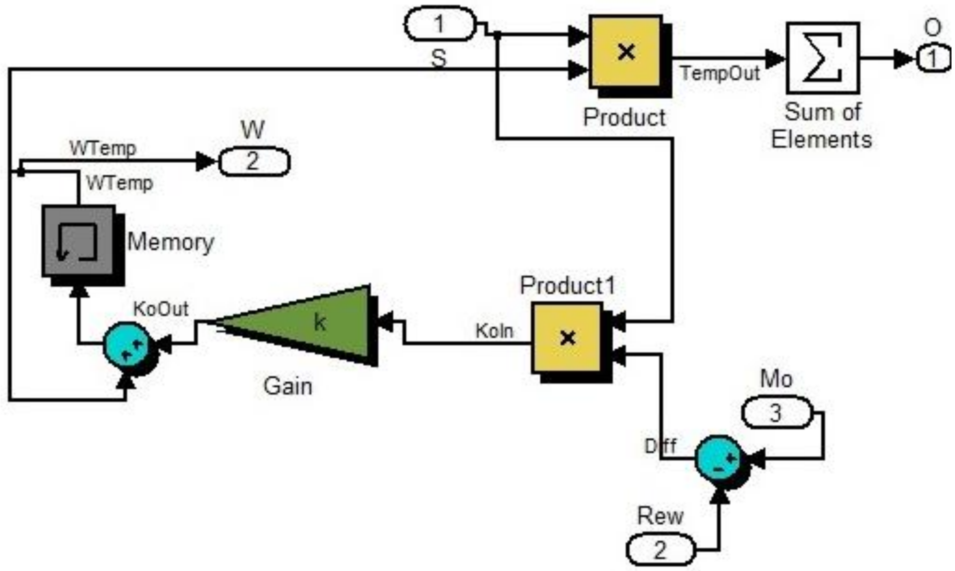

Figure 6. Structure of Orbitofrontal cortex.

Table 1. Parameters of the system and static PID controller.

PMSM parameter	Static PID controller parameter
R Resistance of the phase winding (Ohm) 3	k_1 Proportional gain 80000
L Inductance of the phase winding (Henry) 0.0006	k_2 Integral gain 65* k_1
J Inertia of the motor ($Kg.m^2$) 0.01	k_3 Derivative gain 500
K_m Motor torque constant (Nm/rad) 2	k_4 Gain L/T
F Viscous friction coefficient (Nms/rad) 0.01	k_5 Gain R/T
P Number magnetic poles 6	T Time constant (sec) 0.0005

normal and static system performance described in Equation 11 (Marino et al., 1995).

$$V_d = -pL\omega i_a - k_4(i_d - i_{dr}) - k_5\int_0^t [i_d(\tau) - i_{dr}(\tau)]dr$$

$$V_q = K_m\omega - k_4(i_q - i_{qr}) - k_5\int_0^t [i_q(\tau) - i_{qr}(\tau)]d\tau \qquad (11)$$

With i_{dr} = 0

$$i_{qr} = -\frac{J}{K_m}\{k_1(\theta - \theta_r) + k_2\int_0^t [\theta(\tau) - \theta_r(\tau)]d\tau + k_3(\omega - \omega_r)\}$$

Where ω_r and θ_r denote the reference angular speed and displacement, ω and θ express the actual angular speed and displacement, i_{dr} and i_{qr} are the reference current in rotating set of (d,q) and finally i_d and i_q represent the actual current in rotating set of (d,q) respectively. In addition, k_1, k_2, k_3 are introduced as proportional, integral and derivative gains correspondingly (Marino et al., 1995). The values of the related gains are given in Table 1.

In another perspective, sensory inputs and emotional signals in BELBIC are of the paramount importance in the determination of the proposed controller performance. In other words, these two agents directly affect the functionality of BELBIC and their designations must be put in to perspective. The choice of the sensory inputs (feedback signals) is selected for control judgment, whereas the choice of the emotional signals depends on the performance objectives in PMSM applications. In general, these are vector-valued quantities. For the sake of illustration, one sensory input (SI) and one emotional signal (ES) is considered in this paper. They can be function of several parameters as shown in Equation 12.

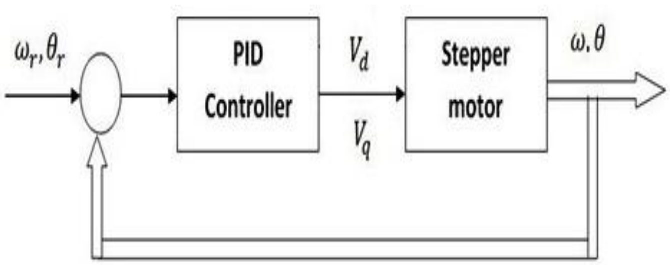

Figure 7. Closed loop block diagram with static PID controller.

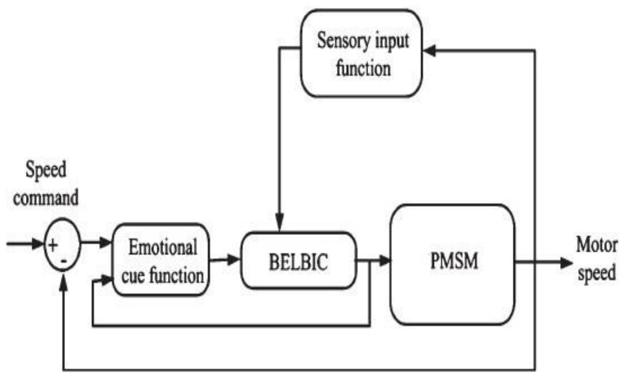

Figure 8. System control configuration using BELBIC.

$$SI = T\left(e, y_p\right) \tag{12}$$

$$ES = Z\left(SI, e, y_p, cs\right)$$

In this paper, the functions of T and Z are given by

$$T = w_1 . e + w_2 . \int e \ dt \tag{13}$$

$$Z = w_3 . e + w_4 . \int e \ dt + w_5 . \left|y_p\right| + w_6 . \left|cs\right| \tag{14}$$

Where e , y_p and cs are system error, system output and control signal respectively. Also, w_1 , w_2 , w_3 , w_4 , w_5 and w_6 are gains like in static PID controller which must be tuned in terms of control objectives for designing a satisfactory controller (Lucas et al., 2004; Arab Markadeh et al., 2011).

It is noteworthy that determination of ES is based on the factors which have the particular sensitivities for designer. These significant factors are regarded as stimuli which cause stress on the system. The effort of the proposed controller is mainly on the way to decreasing the applied stress. As a result, the objectives of control are achieved. In this paper, the recommended fusions for T and Z , are based on the main objective of this paper as mentioned previously. These combinations offer for elimination of overshoot, undershoot and also enhancing the response time under the certain condition and obviation of sudden deviations of speed response from its reference under the uncertain conditions. Providing a proper and smooth control force could be taken into account as well. These objectives all together, are supported based on the meritorious fast auto learning and model free characteristics of BELBIC.

In the following, the aforementioned situations for performance evaluation of the suggested controllers are described in detail. In the first stage, the situation in which there is no destructive disturbance is provided. PMSM is run under completely certain condition. Both static PID and BELBIC controllers are trained based on this condition. Incontrovertibly, absence of load torque disturbance and functional changes of system's parameters in certain condition, affect positively in generating proper command voltages to reach the desired response. However, in real environment the presence of uncertainties in the form of external and internal disturbances is inevitable. The plant to be controlled is often unknown due to its nonlinearity. Its characteristics may change due to aging, wear and tear, etc. Moreover, presence of the different noises in the industrial environment is taken into consideration. To simulate the real circumstances, the issue of uncertainties proceeds by parameter changes in PMSM and applying the random load torque as the external disturbance. The parametric uncertainties are related to the variations of parameters J , K_m , R and L around their nominal values assumed to have slower dynamics than the state dynamics.

In simulating moderate uncertain condition, a step form load torque disturbance, T_L = 4 (N.m), is exerted on the system in t = 0.15 (second) during trajectory control. Model parameter perturbations are described in Equation 15 in which λ_1 , λ_2 , λ_3 and λ_4 are constant parameters and their values are shown in Table 2.

$$\begin{aligned} J_1 &= \lambda_1 . \ J \\ K_{m1} &= \lambda_2 . K_m \\ R_1 &= \lambda_3 . \ R \\ L_1 &= \lambda_4 . \ L \end{aligned} \tag{15}$$

To provide more justifications on the adaptability and ability to disturbance handling of both controllers, an aggressive uncertain condition is simulated as well. It might indeed be true to state that in most of the truly noisy industrial environments, load torque disturbances have the stochastic behaviors. Therefore, simple load modeling might not provide comprehensive atmosphere to examine the performance of the controllers. For this purpose, randomly induced impulsive changes in the load torque are simulated by means of a random Gaussian noise with the zero mean value and variance value equals to 3.6. The functional parameters' changes in this experiment are offered in Equation 15 with respect to this fact that the constant parameters are replaced with different values as depicted in Table 2. Indisputably, these uncertain conditions are counted as an appropriate test bed to evaluate the performance of the controllers. In these situations, robustness criterion is also considered by BELBIC and static PID.

Consequently, several performance indices such as integral absolute error (IAE), absolute maximum value of the direct voltage

Table 2. Coefficients used in model dynamic perturbations tests.

S/N	Test	λ_1	λ_2	λ_3	λ_4
1	Moderate condition	0.1	0.2	0.5	1.5
2	Aggressive condition	0.095	0.5	0.75	2.8

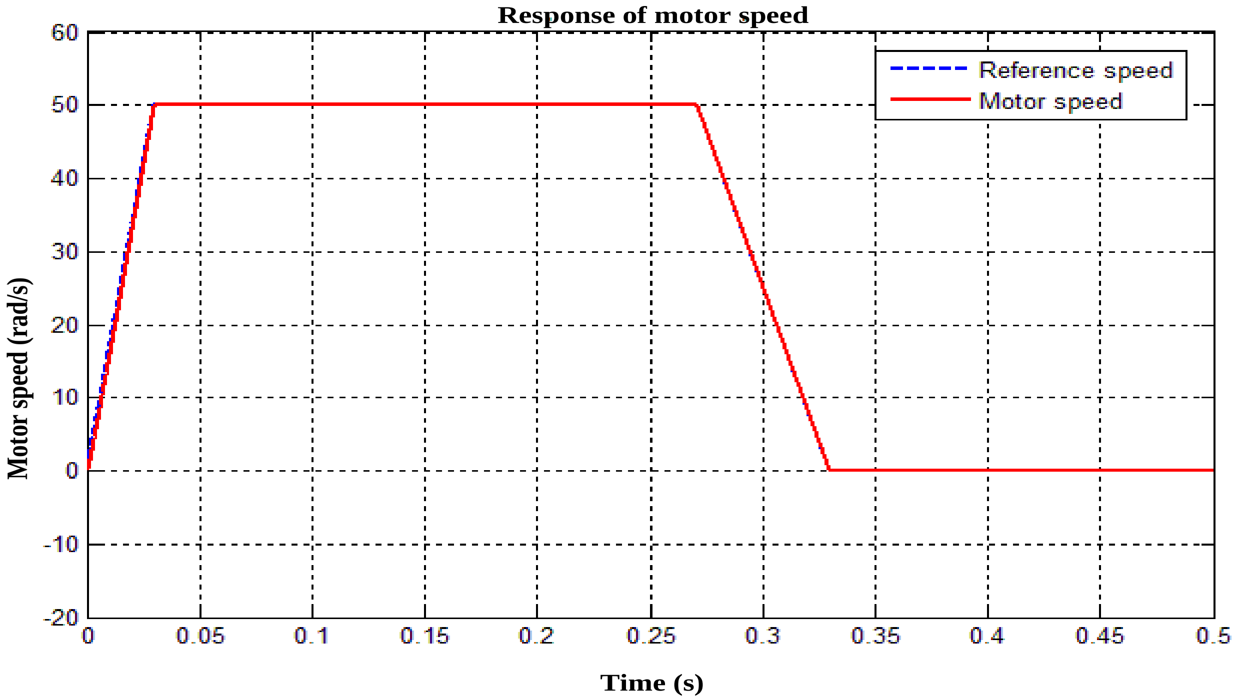

Figure 9. Evaluation of performance of the trajectory tracking in certain condition using BELBIC.

and absolute maximum value of phase current are used to appraise the control performances numerically. Furthermore, insensitivity of BELBIC is examined under the circumstance of set point variations. An incremental step command up to 140 (rad/sec) and sinusoidal signal deteriorated by random external disturbance are applied as set point to the system separately. Evidently enough, in all of the suggested experiments, the comparison between BELBIC and static PID controllers expresses the superiority of BELBIC in dealing with different kinds of environments. The results of simulation are considered in the following part.

RESULTS AND DISCUSSION

Figures 9 and 12 demonstrate the performance of trajectory tracking using BELBIC and static PID, when the PMSM works in an ideal condition, respectively. In other words, a trapezoidal reference signal is tracked by the controllers without presenting any dynamical perturbation and load torque disturbance. As can be seen, BELBIC tracks the reference trajectory with high accuracy and without any deviation while response from static PID suffers from considerable overshoot and undershoots. The fast response which is an outstanding characteristic of BELBIC is clearly observed from the proposed graph. In contrast, static PID needs more time to reach on the set point. As it is observed from Figures 10 and 13, in changing the set point from constant to ramped-shape part and vice versa, the command voltage (V_d) in both controllers shows substantial peaks and this is because of the fast changes in the reference signal in a short period of time. Therefore, the voltages injected to the inputs of PMSM encompass increases in the certain times to support the actual speed in reaching the reference signal. These ranges of increases are acceptable for PMSM drive. Although the peak of phase current (i_d) in static PID (Figure 14) is much less than i_d peak in BELBIC (Figure 11), however, in certain condition, BELBIC shows more exact trajectory tracking with less effort in command voltage in comparison with static PID. Numerical comparisons in this case, based on

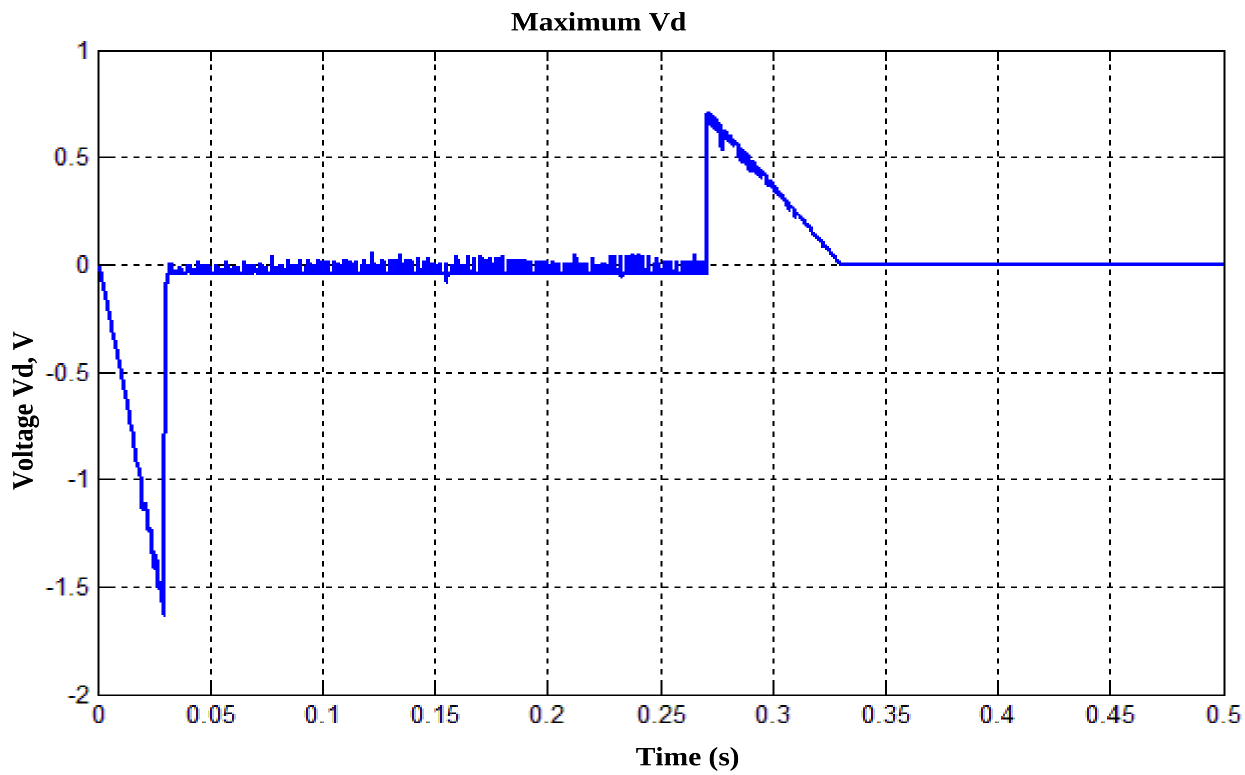

Figure 10. Direct voltage (Vd) based on BELBIC.

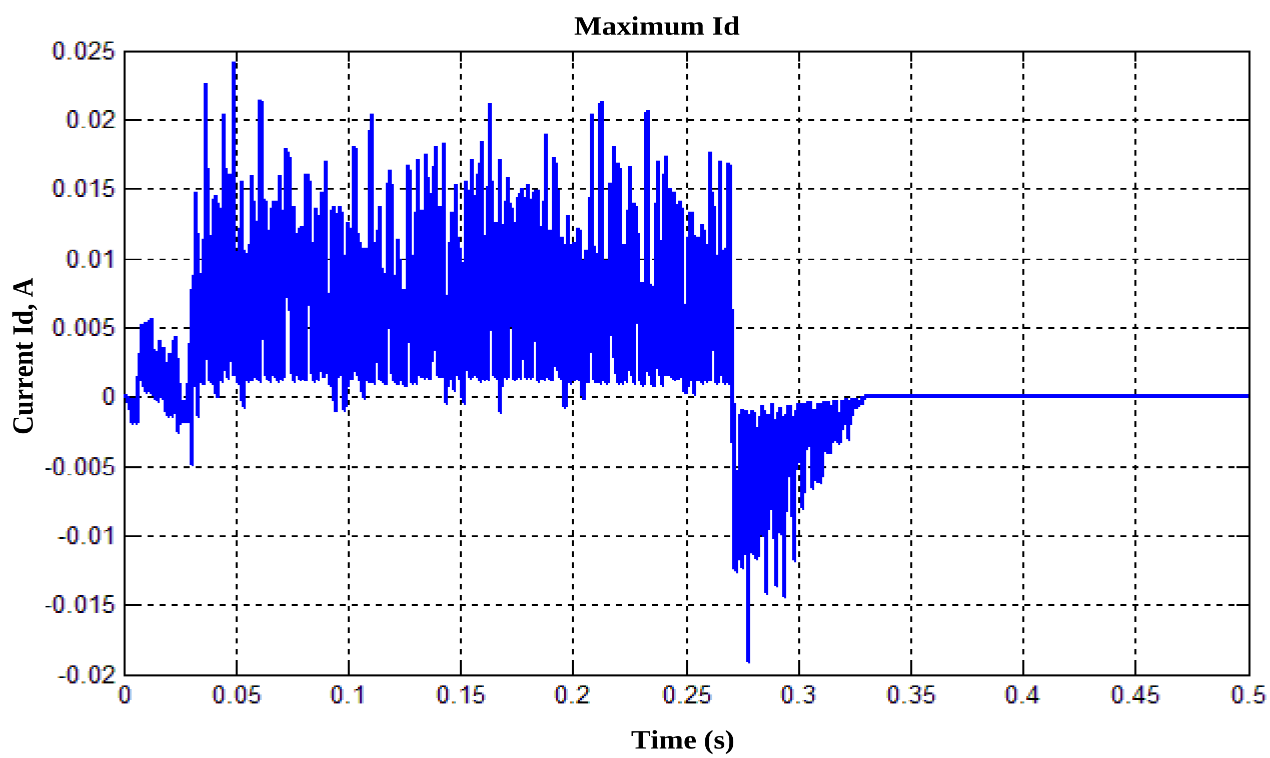

Figure 11. Motor phase current based on the BELBIC.

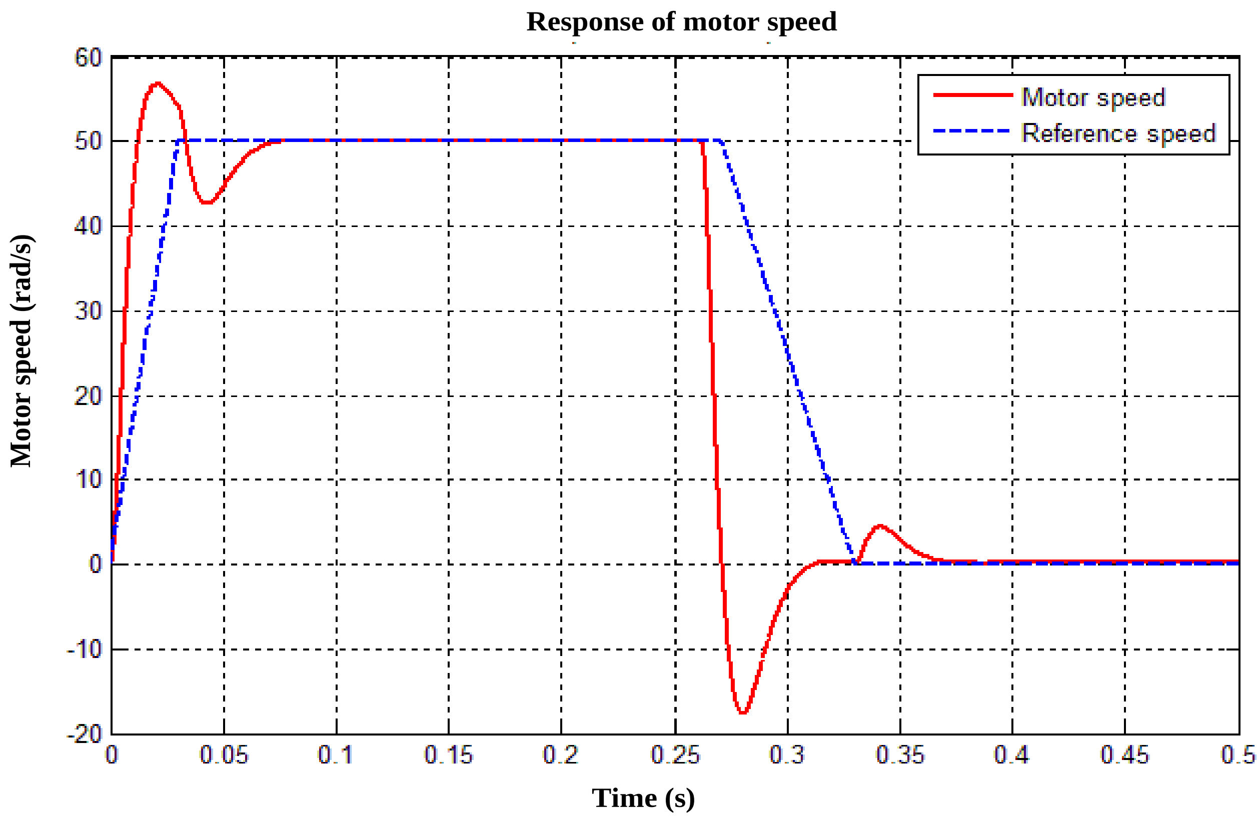

Figure 12. Evaluation of performance of the trajectory tracking in certain condition using static PID.

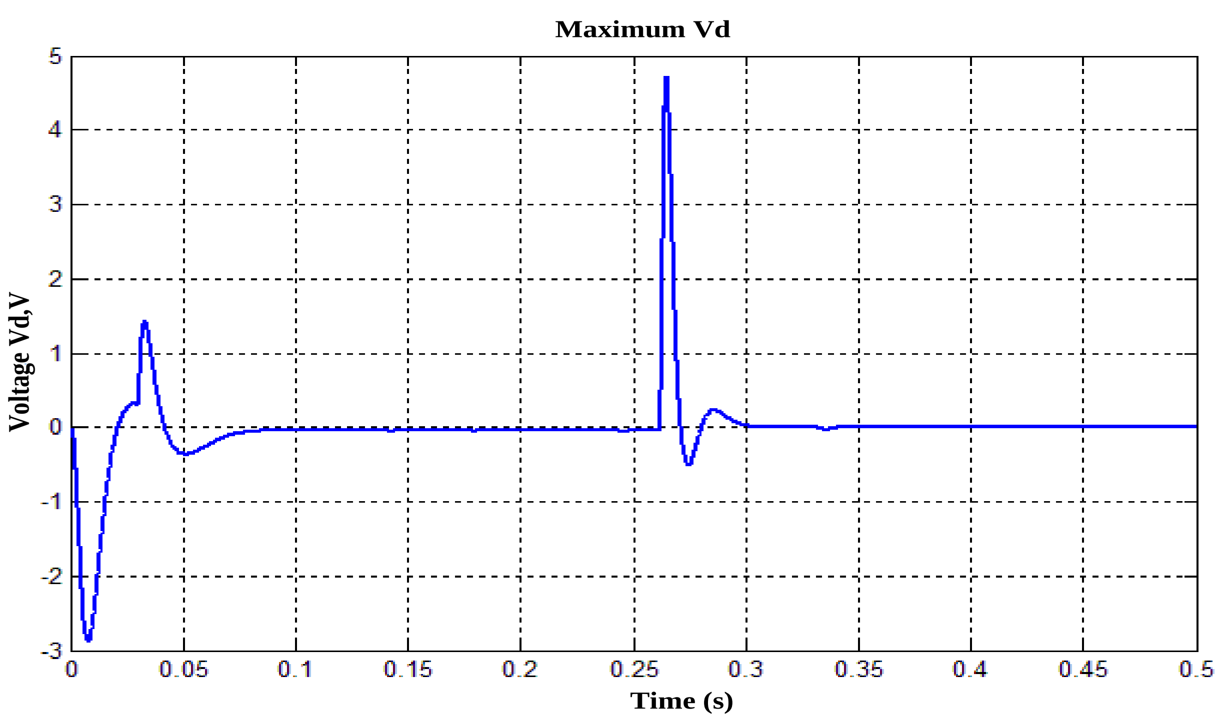

Figure 13. Direct voltage (Vd) based on static PID.

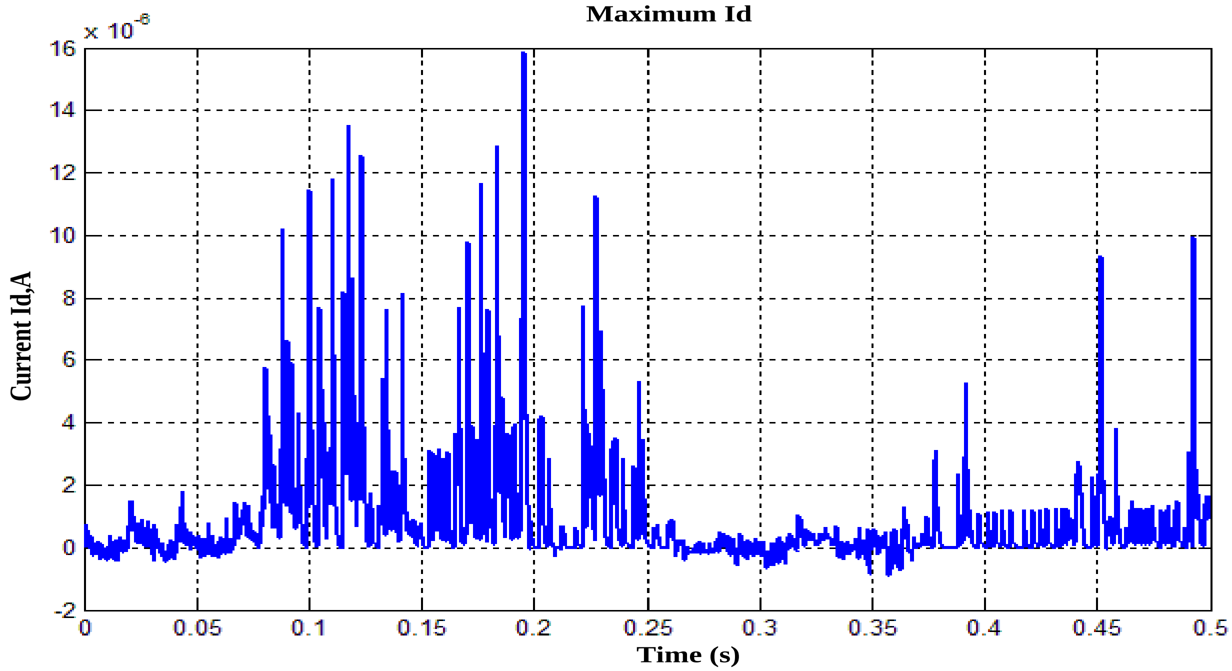

Figure 14. Motor phase current based on static PID.

Table 3. Numerical performance consideration related to the certain, moderate and aggressive uncertain situations.

Controller-Test	Type IAE	Abs Max V_d	Abs Max i_d
BELBIC - certain condition	0.003	1.58	0.023
Static PID - certain condition	2.78	4.73	$1.83*10^{-6}$
BELBIC- moderate uncertain condition	0.024	2.99	0.11
Static PID - moderate uncertain condition	2.86	3.47	$1.38*10^{-5}$
BELBIC- aggressive uncertain condition	0.005	9.46	1.54
Static PID - aggressive uncertain condition	4.96	5.12	$2.61*10^{-6}$

the performance indices, are also shown in Table 3.

Incontrovertibly, the performance of the system in the industrial environments contaminated by various kinds of disturbances and noises is not like an ideal situation and might be deteriorated. The plant to be controlled is often unknown due to its nonlinearity. Its characteristics may change due to aging, wear and tear, etc. To consider these problems, two different uncertain test beds are provided and functionality of both proposed controllers are examined under these situations. In the first place, the performance of controllers are tested in a moderate uncertain condition included bounded changes on system's parameters and exerted load toque. Figures 15 and 16 illustrate the speed response and error of tracking in BELBIC, and also, Figures 19 and 20 present speed response and its error in static PID, respectively. In addition, the variations of the command voltage and phase current under the first uncertain condition depict in Figures 17and 18 for BELBIC and in Figures 21 and 22 for static PID, respectively. As can be seen from Figure 16, there are small variations over the reference in tracking performance of BELBIC corresponding to the model parameter changes and exerted disturbance in t=0.15 (second) whereas the effects of the disturbance and parameters' variations on the performance of static PID are more apparent. In this situation, deviation of rotor speed from its reference signal made by torque load disturbance is about 5 (rad/s) in static PID and it is

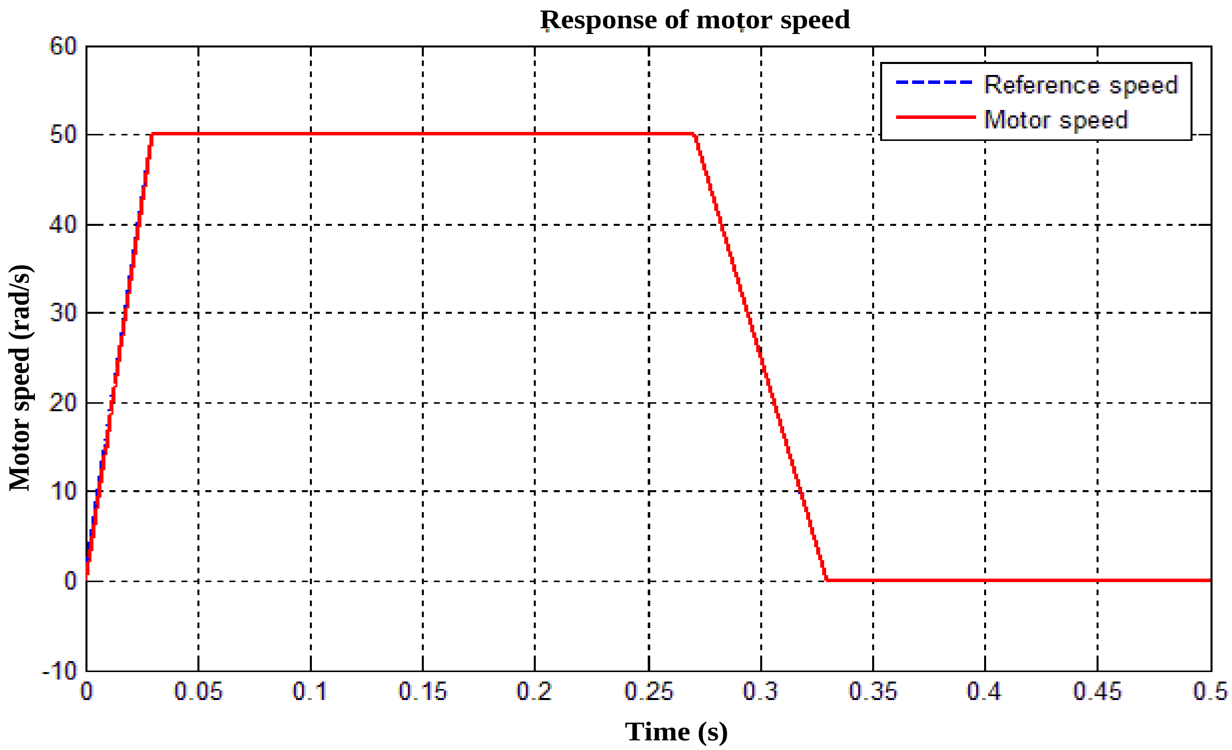

Figure 15. Performance of trajectory tracking with BELBIC under the uncertain condition of test 1.

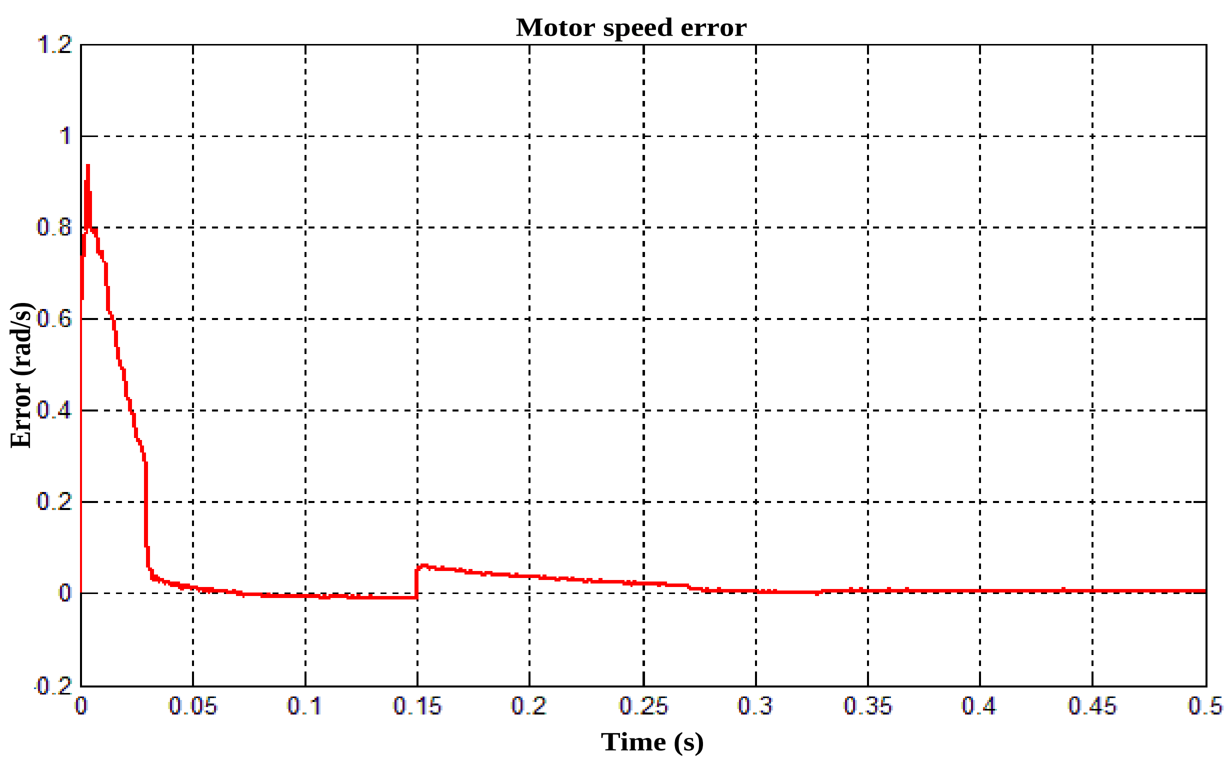

Figure 16. Error of speed tracking with BELBIC in test 1.

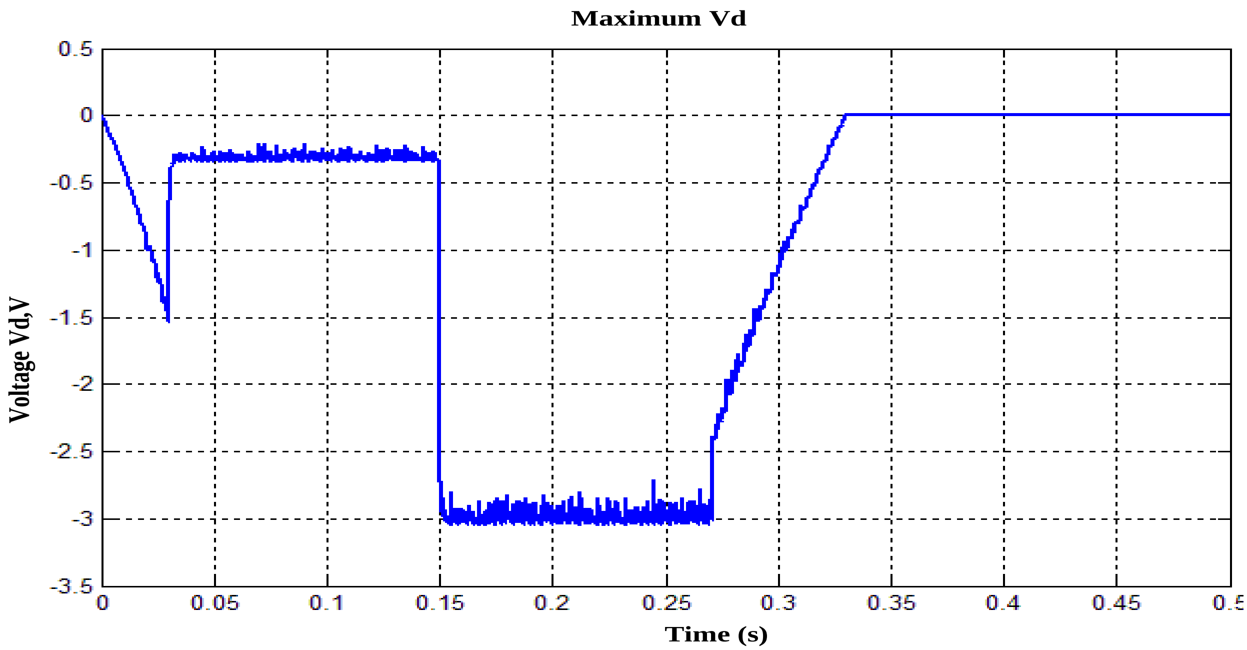

Figure 17. Direct voltage (Vd) based on BELBIC In test 1.

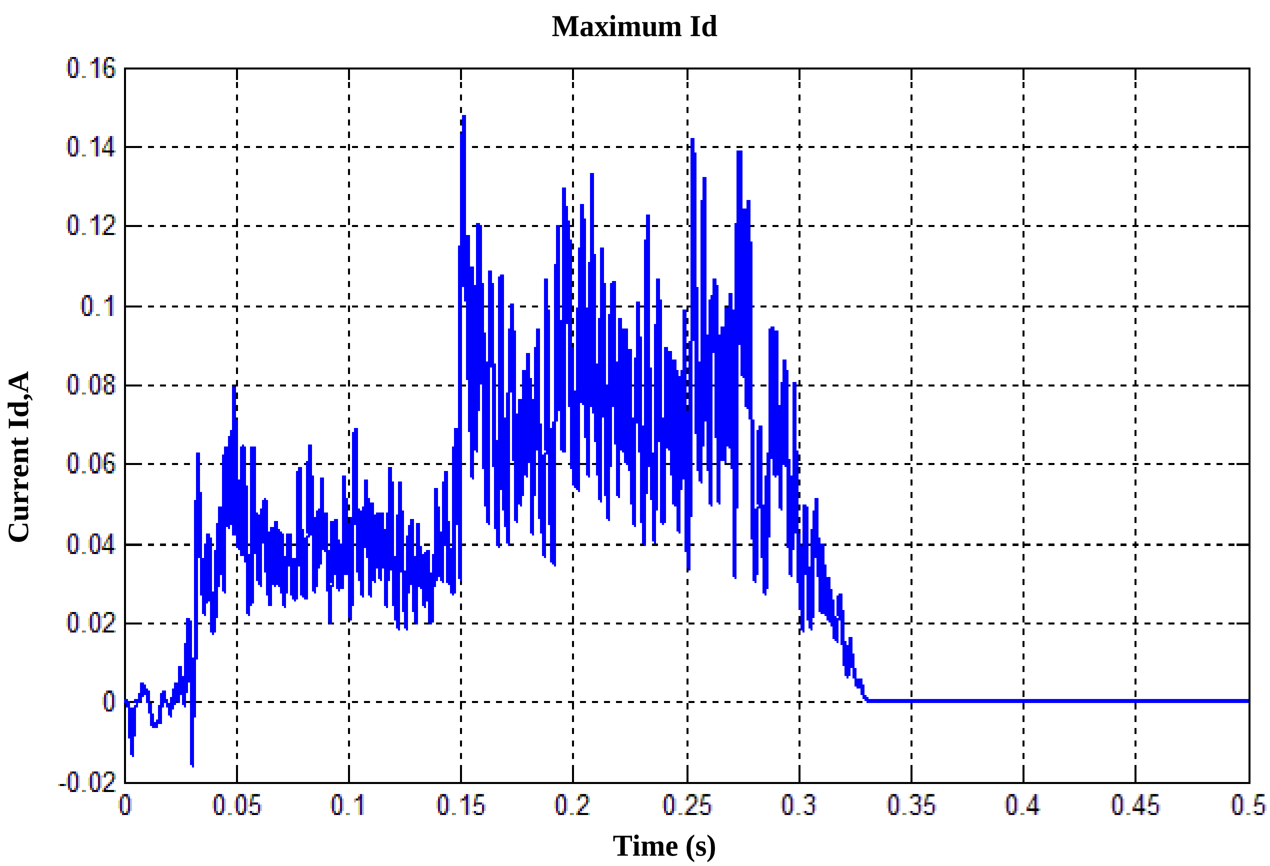

Figure 18. Motor phase current based on BELBIC in test 1.

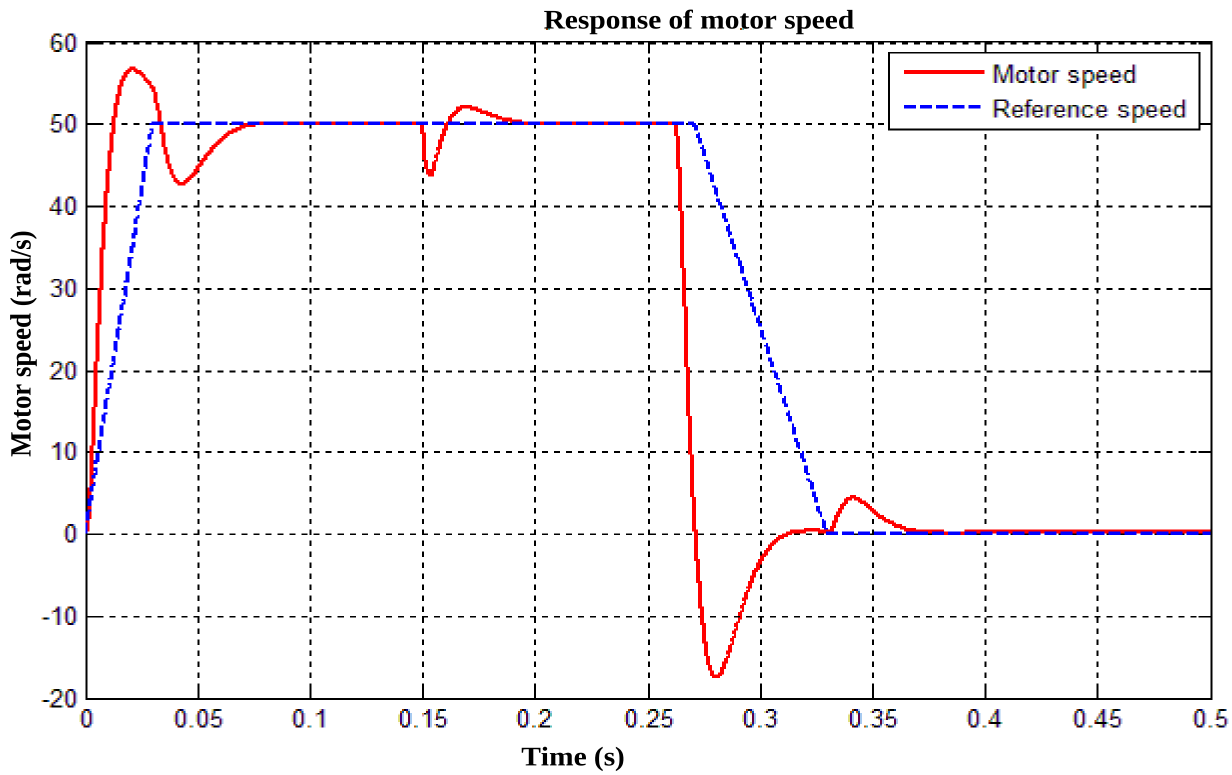

Figure 19. Performance of trajectory tracking with static PID under the uncertain condition of test 1.

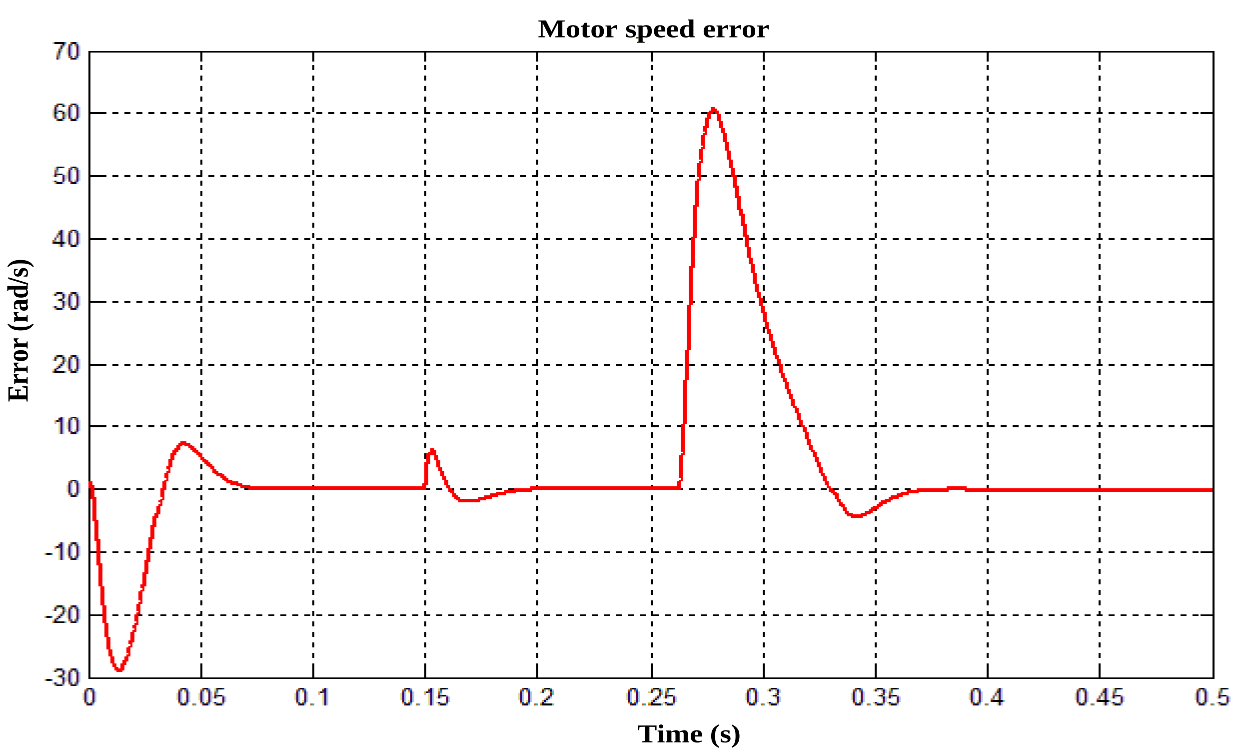

Figure 20. Error of speed tracking with static PID in test 1.

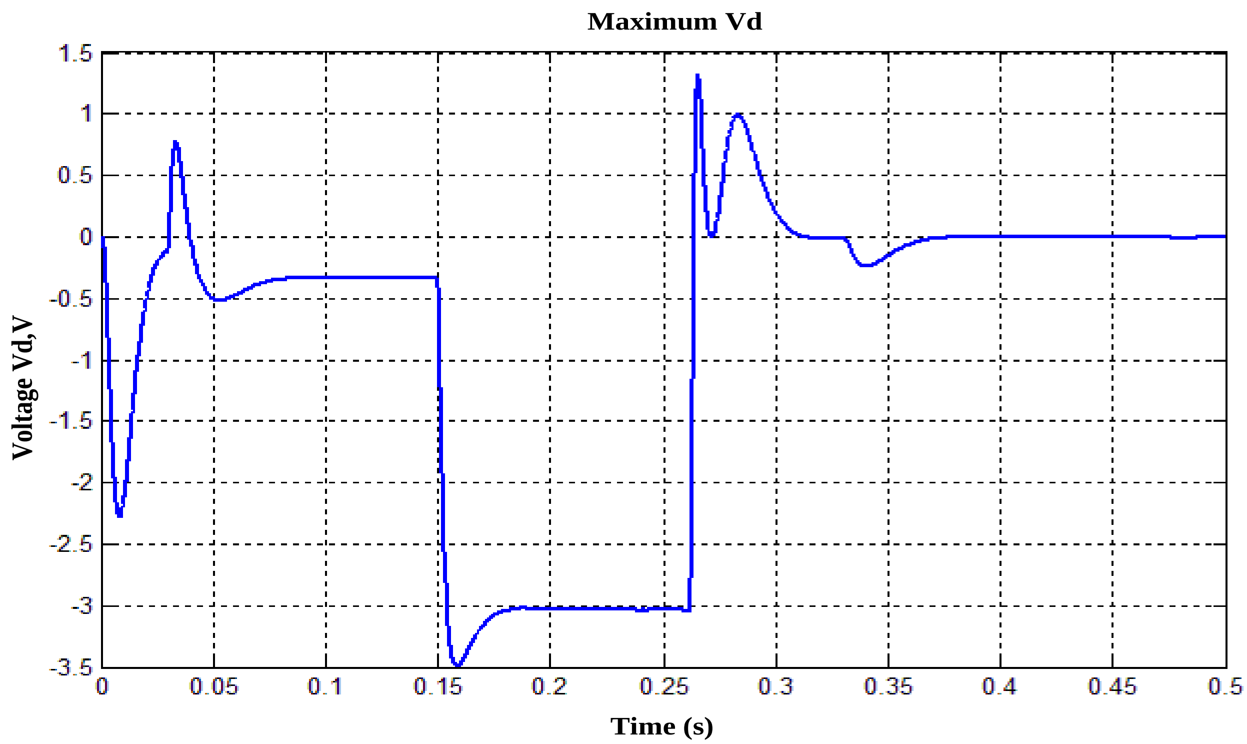

Figure 21. Direct voltage (Vd) based on static PID In test 1.

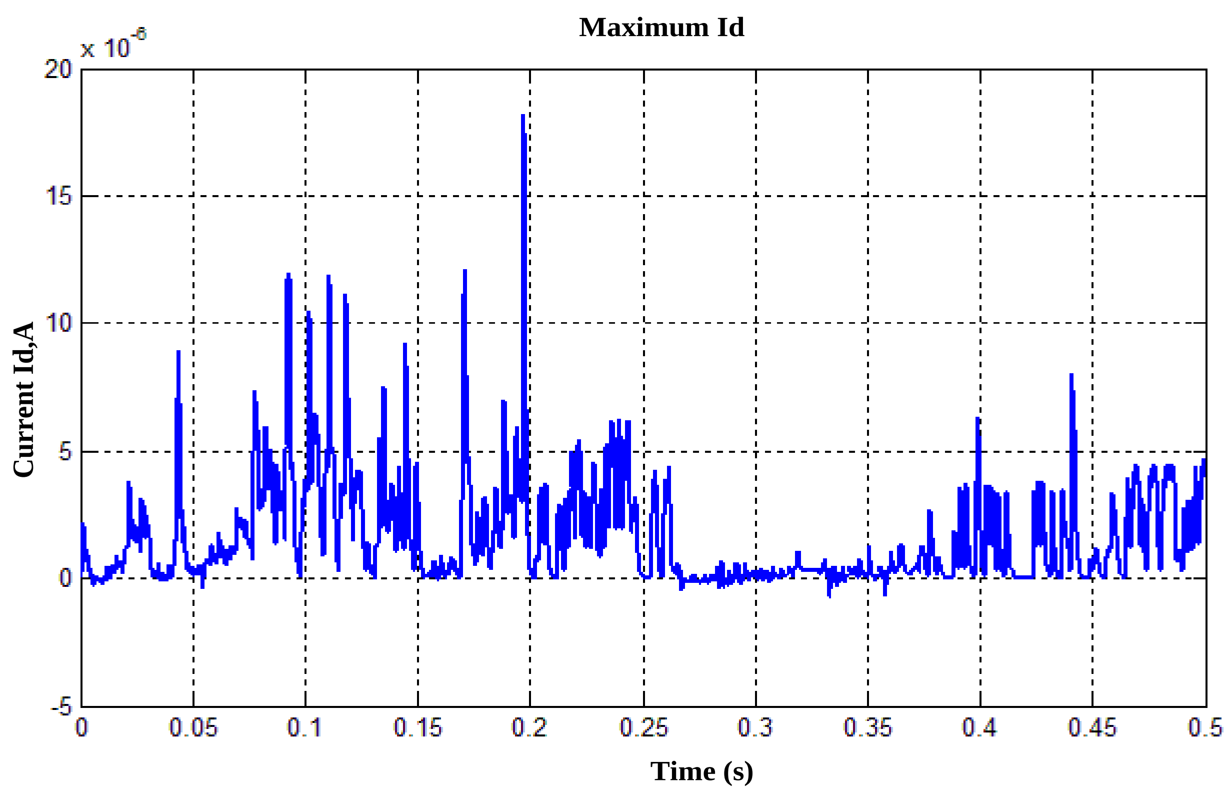

Figure 22. Motor phase current based on static PID in test 1.

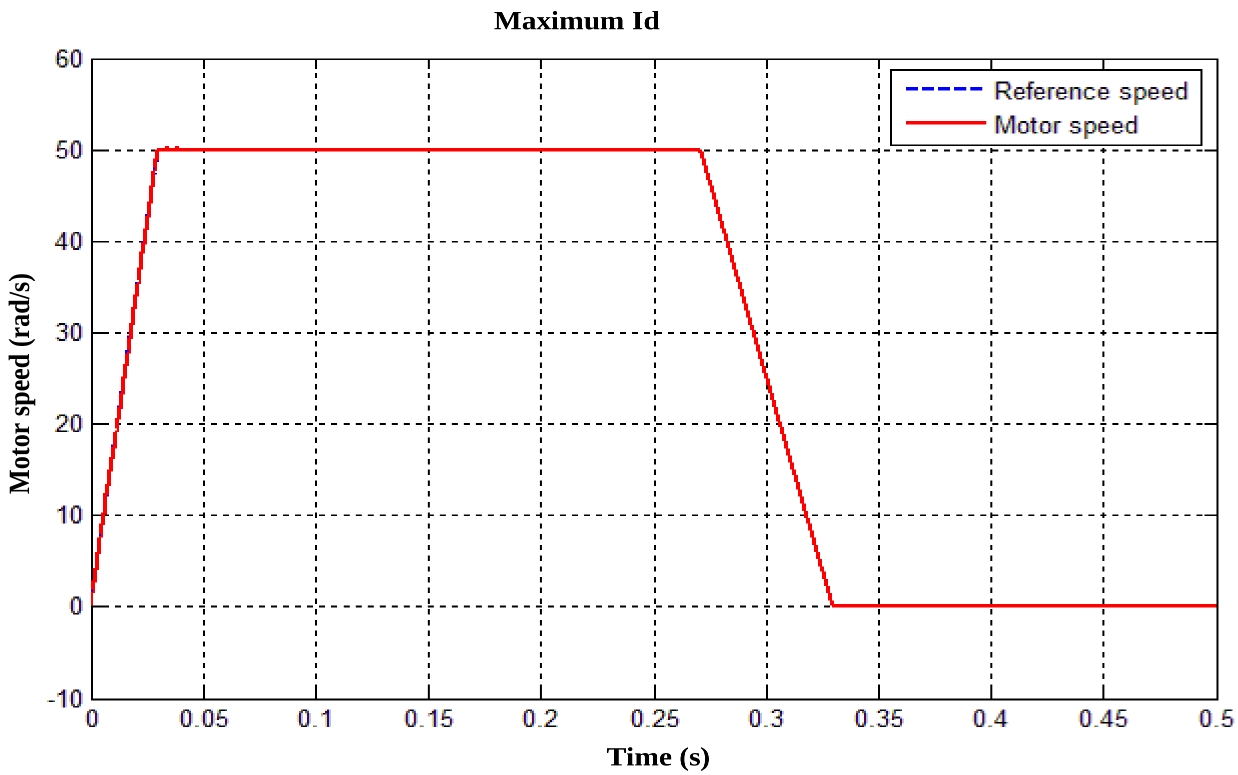

Figure 23. Performance of trajectory tracking with BELBIC under the uncertain condition of test 2.

dramatically reduced just below 0.1 (rad/s) in BELBIC. The preciseness of trajectory tracking can also be evaluated numerically by IAE as a performance criterion. IAE indicates the closeness of the response to the reference signal. In appraising the system's response in tracking of the trapezoidal profile, when the BELBIC plays the role of controller, the quantity of IAE is small and it supports the objective of tracking in a great extent; but, by using static PID this value has significant intensification. In Table 3, these values of IAE along with the quantities of other performance indices are presented. As a matter of fact, command voltage in both controllers becomes immoderate in comparison with certain situation. Even in moderate uncertain condition, maximum variation of V_d in BELBIC is smaller than in static PID.

In the second place, the functionality of the proposed controllers is examined under the more rigorous uncertain environment. Generally, in the purely contaminated noisy situations, the characteristics of load torque extremely follow a stochastic relation. For this purpose, a high frequency random Gaussian noise with zero mean value and 3.6 in variance, including sequences of fast impulsive changes, is replaced instead of previous simple step load torque. Moreover, the per-turbations on model parameters are aggravated. Table 2 shows the values of new coefficients related to parameter changes of the system in the second uncertain condition. Figures 23 and 24 illustrate the speed response and error of tracking in BELBIC, the Direct voltage and Motor phase current based on BELBIC in test 2 is shown in Figures 25 and 26 and also, Figures 27 and 28 represent speed response and its error in static PID, respectively. It is observed from the graphs that speed response with static PID suffers from considerable deviations of reference. Oscillatory response together with the large overshoot, under shoot and sizeable steady state error, are the main drawbacks of static PID controller. Imperfect and chaotic response in the profile tracking of the command speed under the severe uncertain environment, which results in degradation of operating performances, is due to the sensitivity of classic type of controllers to mechanical configuration changes. This weakness, particularly when the fast excitation changes are applied on the motor, affects rotor movement and PMSM might loss its steps, stability and synchronization. The main reason for the explanation of this phenomenon is inflexible structure of classic controller. In other words, fixed gain static PID is tuned for a pre-specified operating point of the system. There-fore, when the system encounters large abrupt changes, the controller cannot guarantee a robust behavior.

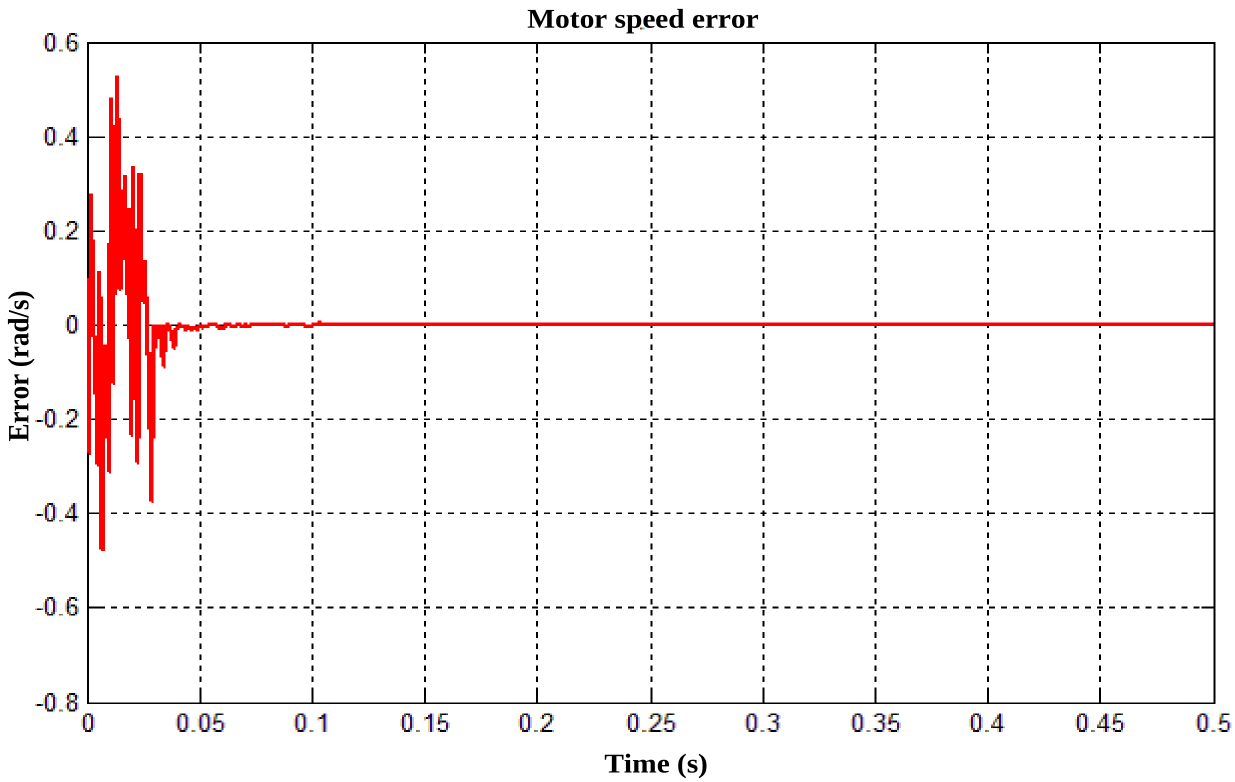

Figure 24. Error of speed tracking with BELBIC in test 2.

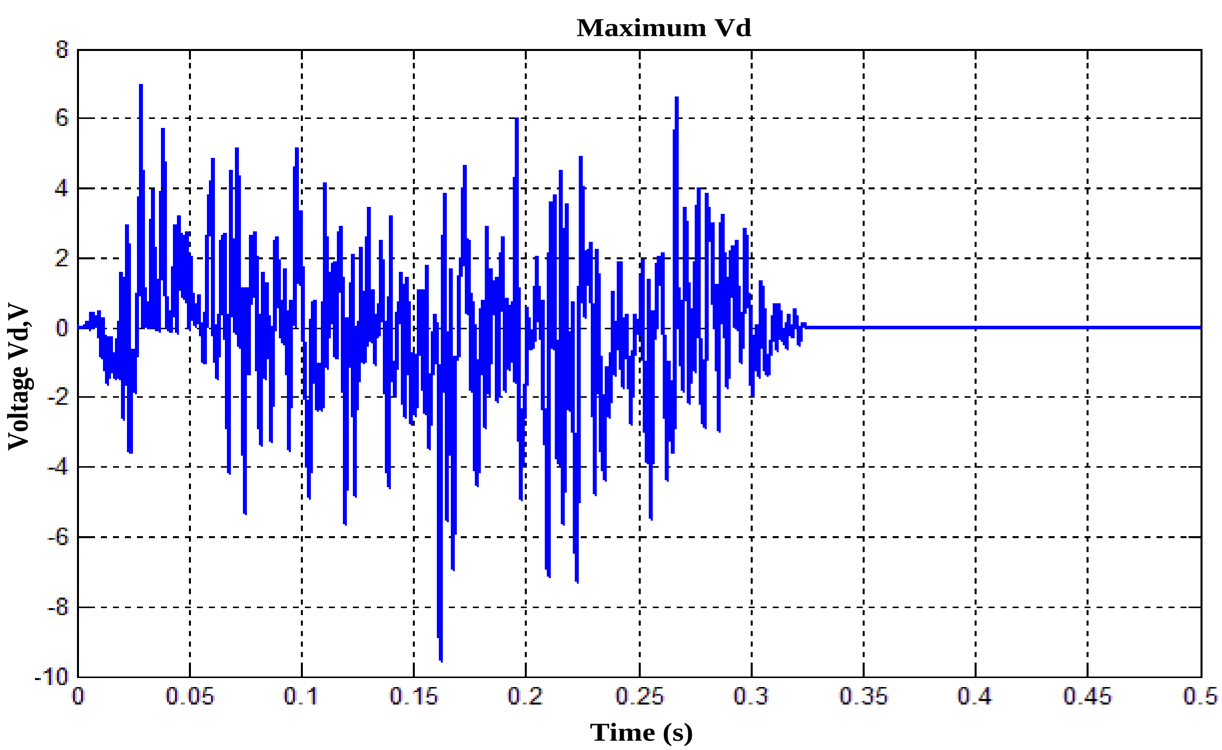

Figure 25. Direct voltage (Vd) based on BELBIC in test 2.

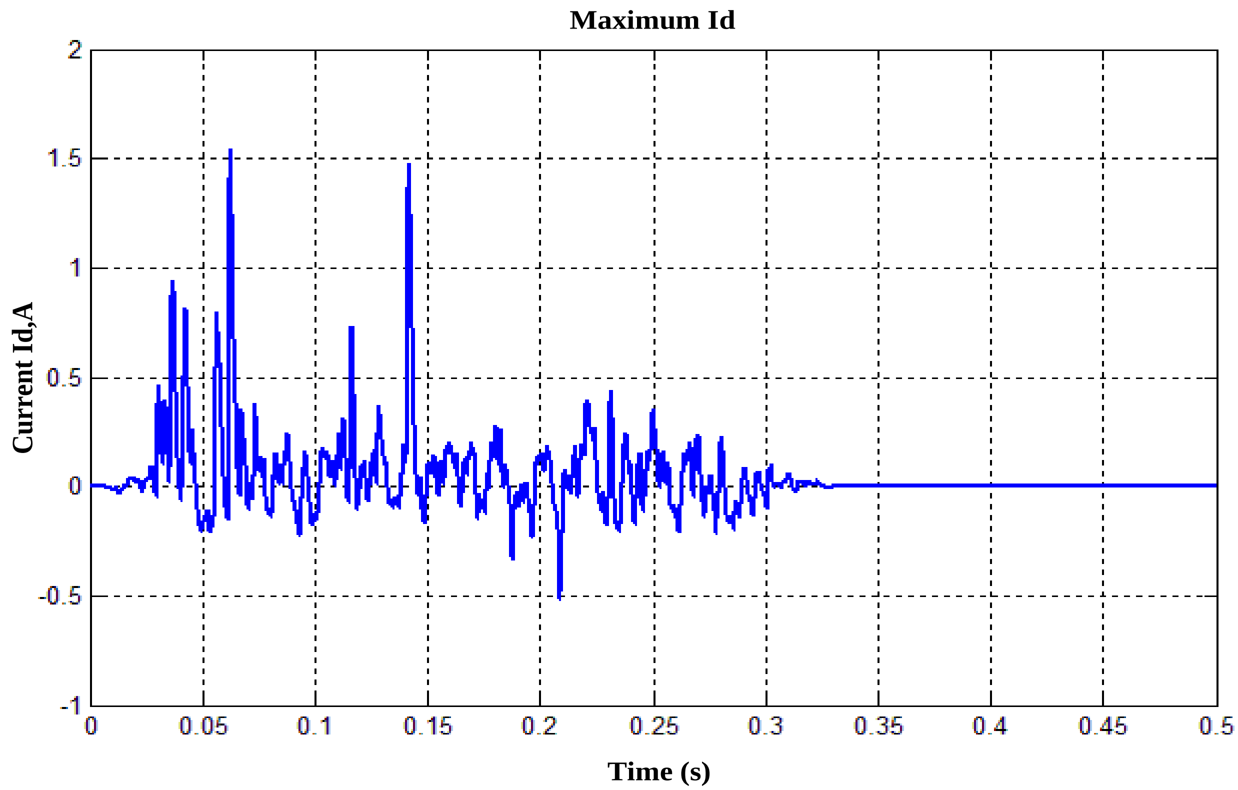

Figure 26. Motor phase current based on BELBIC in test 2.

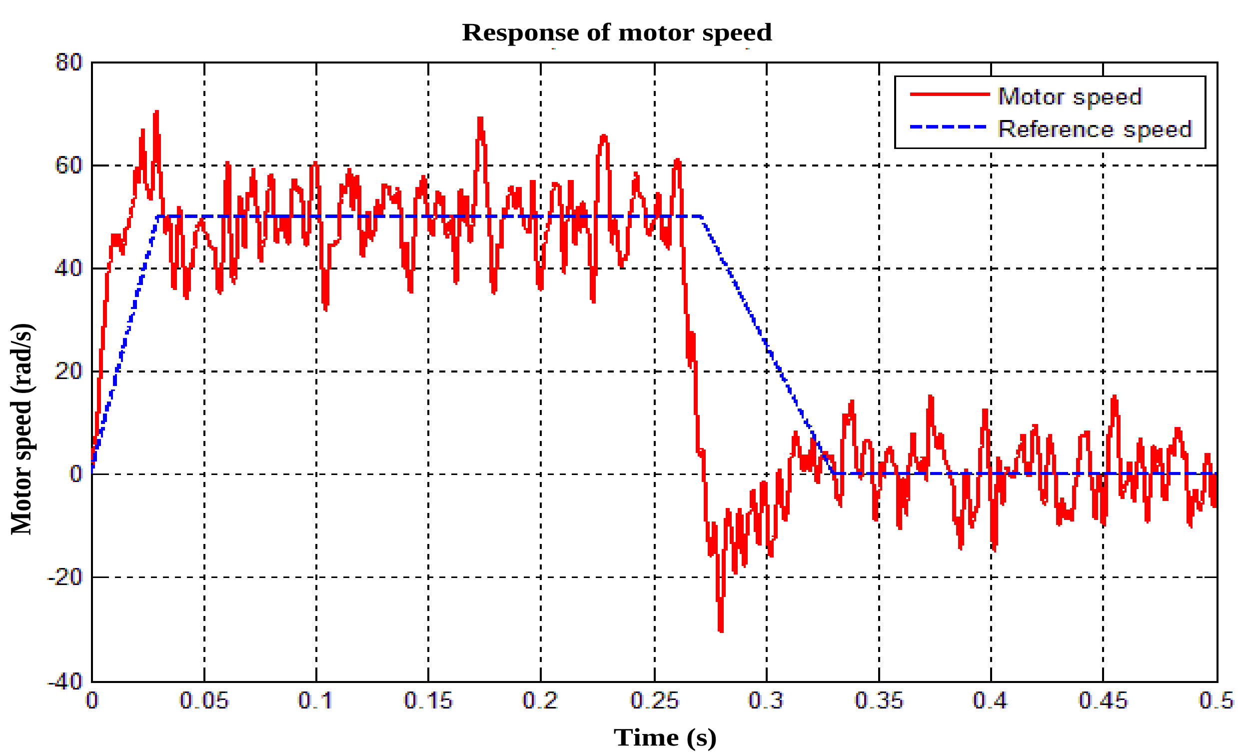

Figure 27. Performance of trajectory tracking with static PID under the uncertain condition of test 2.

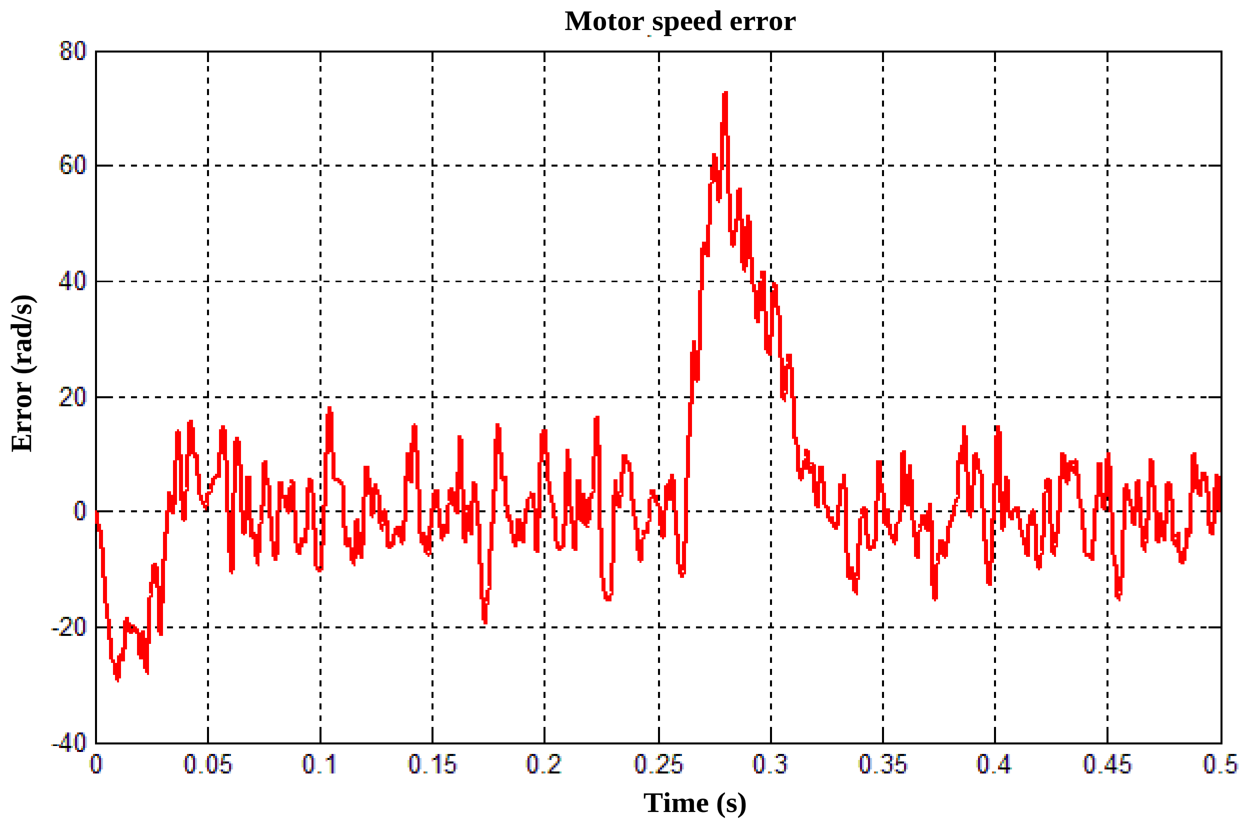

Figure 28. Error of speed tracking with static PID in test 2.

In another perspective, under the aggressive uncertain condition, BELBIC furnishes the objective of speed tracking perfectly. In Figure 24, small variations on the speed response at the starting time can be seen but the oscillations in the transient part of the response are rapidly eliminated and the response reaches its steady state. The high accuracy in tracking of the reference signal announces this fact that BELBIC is superior in terms of fast response, zero steady-state error, and burdening insensitivity property against functional changes of system and the load disturbance. An interesting point here is better performance of BELBIC in comparison with previous uncertain situation although the severity of the uncertainties becomes larger. A clear interpretation is that the proposed control structure is able to learn these sudden changes as part of its objective of capturing the nonlinear dynamics of PMSM. Therefore, previous experience under the uncertainty, kept forever in Amygdala as an emotional evaluation, enhances the performance of BELBIC in other subsequent situations. This auto learning along with the model free structure of BELBIC, resulted in the adaptation of the controller coefficients, facilitate the control of the PMSM independent of parameter variations and abrupt disturbances. The generated command voltage (V_d) by both proposed controllers, depicted in Figures 25 and 29, become more oscillatory and considerable instantaneous peaks are introduced. Albeit the maximum generated peak of V_d based on static PID is smaller than the similar item in BELBIC to some extent, however, the oscillations remain in the generated V_d by the classic controller, while intelligent counterpart burdens the capability of removing them and reaching its steady state level in an acceptable time. This issue is claimed on the case of the phase currents, shown in Figures 29 and 30, as well. In Table 3, numerical comparisons based on the performance indices are found.

In the following, the performance of BELBIC is investigated under the benchmark of set point variations. In the first experiment, an incremental step command is applied to the system. The reference signal presents the property of low to high speed trajectory in a short period. Step command signals from 40 up to 140 (rad/s) of the motor are applied and testing results for the command and actual speed are presented in Figure 31. It is noteworthy that these step changes can also express a sudden load being applied to the motor. It can be

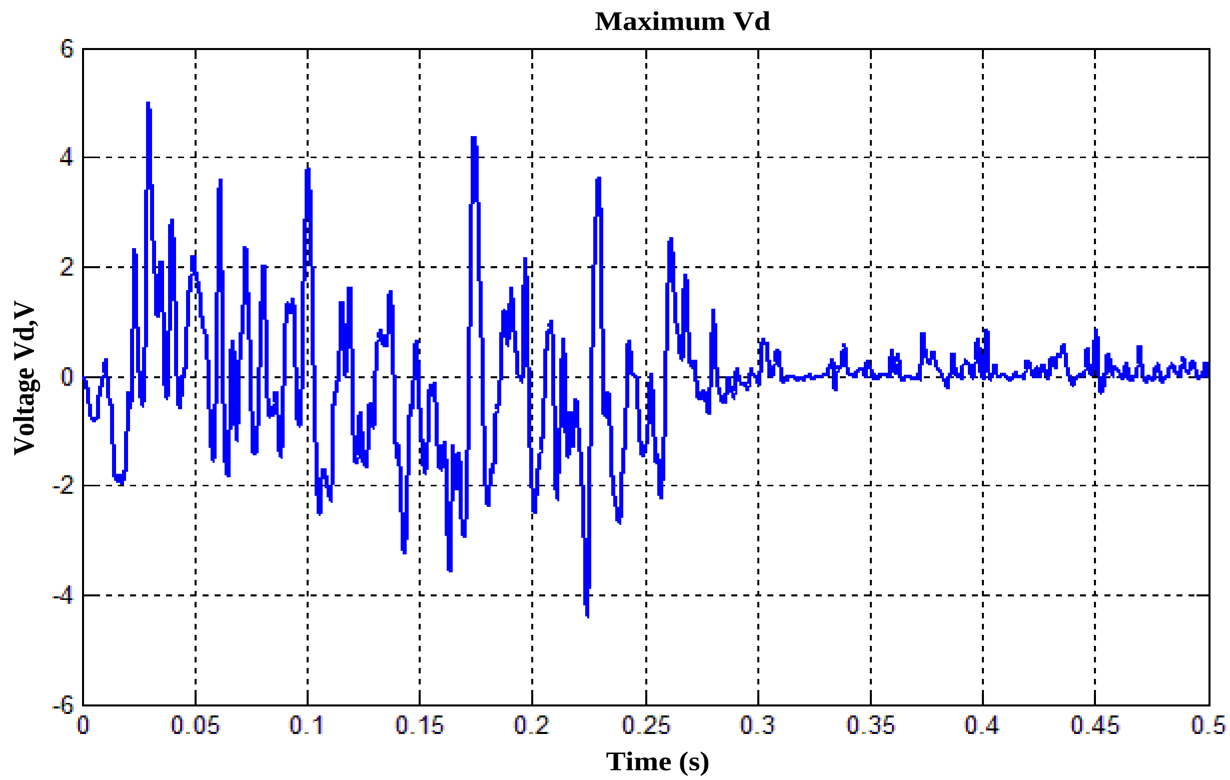

Figure 29. Direct voltage (Vd) based on static PID In test 2.

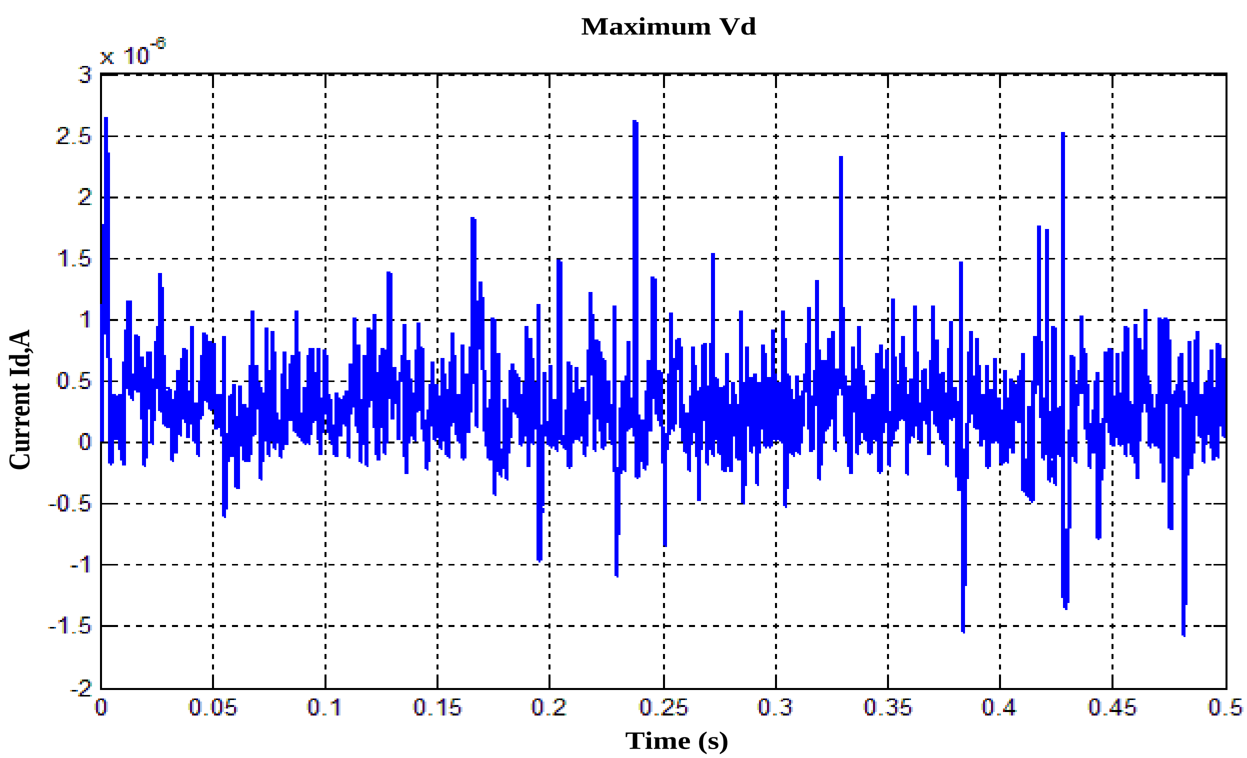

Figure 30. Motor phase current based on static PID in test 2.

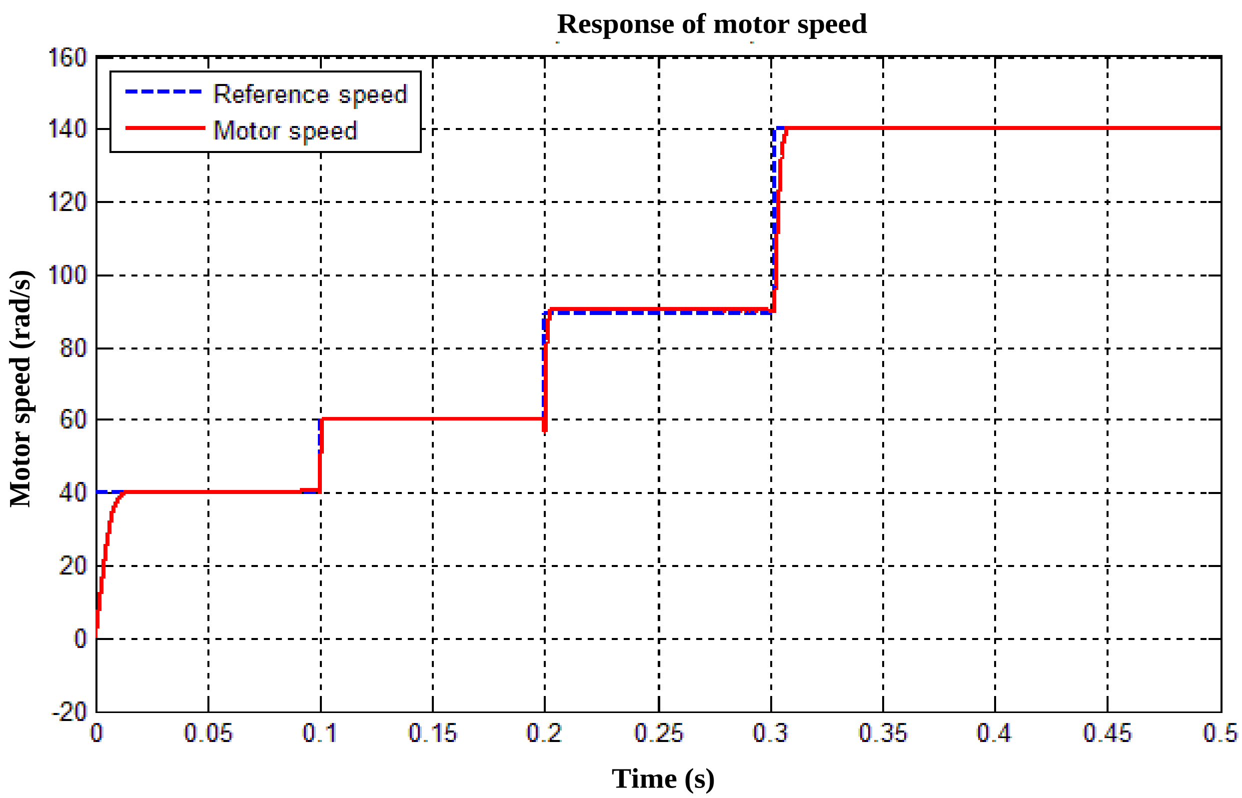

Figure 31. Speed tracking with BELBIC for ascending set point.

observed that BELBIC has the ability to track the speed under the changing speed command. In the second test, performance of BELBIC is considered by applying a sinusoidal reference track with random disturbances. Figure 32 illustrates variation of the actual speed and the desired reference speed versus time. The motor speed is tracked precisely in the presence of various operating points and unpredictable disturbances. It is observed that the proposed control structure is able to learn this sudden change as part of its objective of capturing the nonlinear dynamics of the system.

Fruition of adaptive characteristic in BELBIC structure, which is offered by fast auto learning, submits the fact that this controller can fulfill the objective of speed tracking independent of mechanical configuration changes of system. Furthermore, robustness in presence of set point which varies by elapsing the time and external disturbances, could be considered as a consequential property.

Conclusion

In this paper, the problem of speed tracking of stepper motor was discussed based on a novel intelligent strategy which mimics the emotional learning in limbic system of mammalians.

To examine the efficiency of the proposed strategy, performance of emotional controller was investigated under certain and different uncertain situations. For performance evaluation, a classic type of controller called static PID was also applied on the system. In both certain and uncertain condition, BELBIC offered superior performance in comparison with static PID. In dealing with mechanical perturbations, sensitivity and lack of adaption in static PID controller caused significant deviations of speed response from the reference signal. Considerable oscillations, overshoot, undershoot and steady sate error were the main drawbacks of classic controller in profile tracking. In contrast, BELBIC had an outstanding ability to encounter applied uncertainties. The simulation results indicated that BELBIC is reliable and useful control method. The structure of BELBIC supports good freedom in terms of control objectives to reach the desired response. These make BELBIC effective and flexible in high performance drive applications. Moreover, fast auto learning ability and model free control structure of BELBIC are meritorious properties useful for the broad range of the industrial applications.

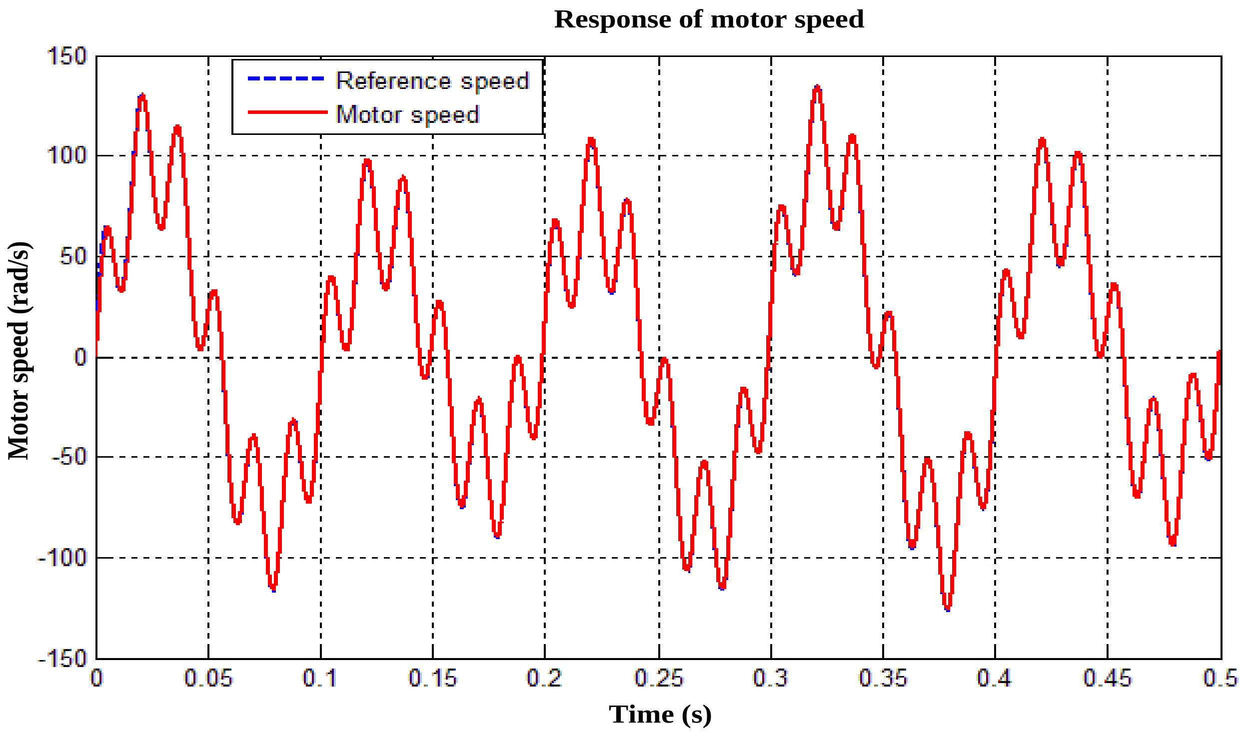

Figure 32. Sinusoidal reference tracking in presence of random disturbance.

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