

Design of a Speed Adaptive Controller for DC Shunt Connected Motors using Neural Networks

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Abstract

Improving the applicability of electrical machines depends on knowing their performance on different operation conditions. In this paper a technique based on B-spline neural networks for obtaining a high performance of direct current shunt motors is proposed. This algorithm sets the control signal on line without the need to know a system model and, therefore, their performance is not dependent on the equilibrium point of design and prior knowledge of the parameters. Motor operation is subjected to highly demanding conditions for variant speed reference, also takes advantage of the feature of including a load torque from zero to full with minimal impact on the rotor speed. Time domain simulations and laboratory measurements in a test direct current shunt motor demonstrate the applicability of the proposal.

Keywords: Automatic Learning, DC shunt motors, Model-Free Control, Neural Networks.

Introduction

Currently, electrical machines are presented in a wide variety of applications from use in homes to remote research applications on land, in air, in water and finally in space, each with its own characteristics and specific protections [1]. However, the demanding operation conditions are increasingly, consequently it is necessary to develop new proposals for operation, control and protection [2][3].

Although direct current, DC, machines have been studied, there are still many possibilities for its use as motors and generators [4]. It is an open research topic mainly for implementation purpose with robust performance and low digital control demand. Therefore, it must be demonstrated satisfactory performance in a wide range of operating conditions and adaptability characteristics in face to the changing demands of the load torque and environmental conditions. DC motors are used in many areas such as mobile robotics, industrial robotic arms, elevators, cranes, drills, in addition, its simple model (some configurations) facilitates their use as test systems for evaluating new drivers [4].

The control area is widely in electric motors [4]-[9]. There are several controllers based on conventional PID linear techniques or a combination, robust based on sliding mode, adaptive algorithms, asymptotic differentiation, neural networks, and fuzzy logic. Most of them require full or partial information of the mathematical model and motor parameters, limiting its application because control laws are dependent on having available these values [4]-[6]. Consequently, if are not known, the performance of the control law is degraded. Additionally, some of them have a high computational cost which restricts its operation in real time applications [5].

In particular the analysis and design of DC motors controllers is emphasized for so called direct current permanent magnet, or separate excitation, reaching simple linear models, and justifying its performance against certain operating conditions [4]-[6][9]. Its operation is guaranteed around equilibrium point and also is highly dependent on prior knowledge of the motor parameters. In this configuration the inrush current is limited only by the armature resistance, this resistance is relatively high for small motors and there are no problems. But for motors of several kilowatts, the armature resistance is small, then an excessively high armature current is presented in starter condition at rated voltage [10]. Therefore, a starter resistor is connected in

series with the armature winding, causing losses and the need to include and disconnect starting resistors.

The DC motor configuration discussed in this paper has the distinction of having a nonlinear model, which makes its control a non-simple task [10]. Also, conventional controllers in some cases may not be sufficient due that the wide range of operating conditions. With this configuration is intended that the change in the mechanical load torque from zero to full, have a minimal impact on the rotor speed, also it changes over time. This analysis allows visualizing that the electrical DC motors have wide applicability, but is required to expand the existing studies with the inclusion of adaptive control techniques to cover highly demanding conditions, which the motor could be subjected.

The use of artificial neural networks, ANN, offers an attractive alternative for tracking speed of DC motors. The ANN are able to model and control on line nonlinear and non-stationary systems. Technique nature makes it robust, adaptive and optimal controller that can be used in independent or hybrid configurations with existing techniques. These features allow being an important option for practice engineers who are in face with the physical systems changing and high demands of connected loads. ANN are particularly attractive for controlling electric motors. At the same time, they consider the complexity of the physical system and provide a realistic control with less computational time for an effective and robust control in a wide operating range. B-spline neural networks, BSNN, are a particular class of neural networks that have exhibited important results in various physical systems [11]-[13]. This paper presents the design and performance with the qualities required for a real time application. The results exhibit its ability to adapt and how to face the change in load torque and motor conditions.

The proposed controller shows that only a previous off line training for some operating conditions is required and based on weights updating together with the base functions shape, it adapts to changes in the original design without losing its high performance. The result is an adaptive controller that enhances the motor operation even in different operation condition where the design was done.

DC Shunt Motor Model

There are various configurations of DC motors, where one in particular provides important operating characteristics where the rotor speed does not change appreciably as the load torque varies from zero to its nominal value [10]. Fig. 1 shows a connection diagram of the motor under study.

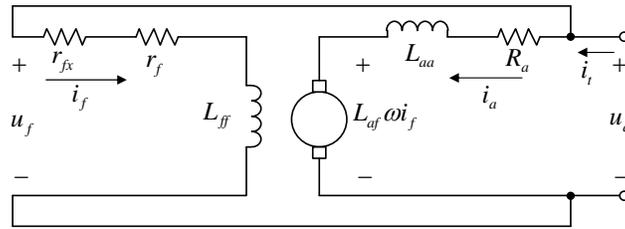


Figure 1. Equivalent circuit of a direct current shunt motor

We can see that the voltage source supplies both the field winding and the armature winding, therefore the total current is the sum of the two circulating currents. Considering a linear voltage-current relation for resistive and inductive elements, the DC motor model is obtained by,

$$L_f \frac{d}{dt} i_f = -R_f i_f + u_f \quad (1)$$

$$L_a \frac{d}{dt} i_a = -R_a i_a - L_{af} i_f \omega + u_a \quad (2)$$

The relation among electrical system and the mechanical system is determined by,

$$J \frac{d}{dt} \omega = -b\omega + L_{af} i_f i_a - \tau_L \quad (3)$$

where the electric torque is $\tau_e = L_{af} i_f i_a$. The mathematical model exhibits that it is a coupled nonlinear system. Therefore, conventional linear controllers guarantee the operation around an equilibrium point. The equilibrium points of the system can be determined by,

$$i_f = \frac{u_{in}}{R_f} \quad (4)$$

$$i_a = \frac{(bR_f^2 + R_f L_{af} \tau_L) u_{in}}{L_{af}^2 u_{in}^2 + bR_a R_f^2} \quad (5)$$

$$\omega = \frac{-R_a R_f^2 \tau_L + L_{af} R_f u_{in}^2}{L_{af}^2 u_{in}^2 + bR_a R_f^2} \quad (6)$$

where $u_{in} = u_a = u_f$. It can be seen that the equilibrium points depend on the voltage applied on terminals, the load torque and motor parameters. Therefore, the motor has multiple equilibrium points; it depends precisely on the operating condition.

The conventional PI controller used in this study is designed to have stable poles by $k_p = 10$ and $k_i = 100$.

Adaptive B-Spline Controller

Considering the nonlinear nature of DC motors described in section two and a linear controller, a problem arises with the regulation of the interest variables. If it is possible the control law must get a driver that is robust even tracking speed trajectories over time. In that sense, in this work an adaptive controller based on B-spline neural networks is proposed. Its design consists of two stages: first in defining the structure and characteristics of the inputs and the training rule; the second part is an on line learning where the ANN can determine changes in the reference signal, load torque and motor parameters.

In the off line training corresponding to the first part of the design, data of the interest variables, armature voltage and instantaneous rotor speed are used. With these data the neural network structure is validated, if the closed loop control meets expected performance proceeds to its on line operation, where continuous learning of new operational and/or parametric variations of the motor is done.

Among the objectives of the proposed controller we are looking to have a robust but simple design features and implementation on an experimental level. Time domain simulations and laboratory results demonstrate these aspects. In this work the diagram, Fig. 2, defines the proposed neural controller and the output is defined by [14],

$$y = \sum_{i=1}^p a_i w_i = \mathbf{a}^T \mathbf{w} \quad (7)$$

where w_i and a_i are the i -th weighting factor and the i -th basis function output, respectively; p is the number of weights of the neural network structure. The base function output changes with a nonlinear relationship of the input values, defined by the base function shape. For the proposed controller two monovariate functions of third order are used. The weight vector is updated by an instantaneous learning rule, defined by [14]

$$\Delta w(t) = \frac{\eta e_\omega(t)}{\|\mathbf{a}(t)\|_2^2} \mathbf{a}(t) \quad (8)$$

where η is the learning rate and e_ω is the error between the desired and actual rotor speed. The update of the weights depends on the base functions output and the learning rule; therefore, the neural network performance is not conditional on the reference type (constant or variable) or to the actual operating condition. The operational test conditions for defining the neural network structure are shown in Table 1.

Table 1. Operation Conditions for off line Training

Load Torque τ_L (Nm)	Rotor Speed ω (rad/sec)
0.5	30
0.3	100
1.25	50
1.1	70
0.4	120
0.75	45

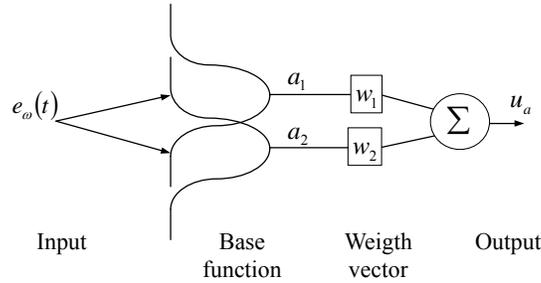


Figure 2. Proposed adaptive controller structure with the main elements

There are some applications of adaptive controllers based on B-spline neural networks where how to define the base functions, neural network structure and a training rule is explained [11]-[13]. Clearly simple structure facilitates the form of implementation and adaptation to different systems, in addition, the number of neurons, structure and shape of base functions have similarity in all these cases, therefore, and same structure is able to extend systems of different characteristics.

It is important to note that the implementation of these controllers prior knowledge of the operation and control system analysis is required. Finally, this particular BSNN structure makes them a very attractive structure that can be exploited in hybrid with other control strategies that can be linear, robust or adaptive configurations.

Test DC Shunt Motor

In order to evaluate the speed regulation, digital simulations and laboratory tests are accomplished using the DC motor arrangement described in Fig. 1, under different disturbances. The parameters used in the simulation studies are presented in Table 2; these values are approximate of the physical system. It is shown that the proposed with an initial off line training controller for tracking reference is sufficient to face the change on motor kind and the operation change.

To verify the proposed controller robustness the analysis is divided in two parts: a) simulation with BSNN controller; b) laboratory tests with BSNN controller. For simplicity the load in simulation study is represented proportional to velocity as,

$$\tau_L = B\omega \quad (9)$$

where the constant B is calculated by trial and error procedure, considering the current and voltage measured in laboratory tests in steady state with different load values.

Table 2. Motor Parameters of a DC Shunt Motor

Parameter	Value	Unit
R_a	7.5	Ω
R_f	469.75	Ω
L_a	55.3	mH
L_f	2.4123	H
L_{af}	2.2881	H
J	0.0013	Kg-m ²
b	1e-4	N.m.s

Simulation Results

Two scenarios are presented for adaptive controller analysis based on DC shunt motor, section 2. These results exemplify the adaptive controller evolution in possible real world scenarios, but strictly they are not necessary for laboratory experiments. DC motor is subjected to two tests scenarios: case 1 with tracking reference speed from 0 to 52 rad/sec considering a constant load torque 0.5 Nm is applied, after that a load torque change in $t = 5$ to 1.2 Nm, and finally is reduced to 0.1 Nm; case 2 a similar speed reference but with different magnitude is considered, also in $t = 5$ sec a variable load between 0.2 and 1 Nm is added.

Fig. 3 displays the DC motor speed controlled by the B-spline neural network. The transient and steady state condition exhibits a good performance for tracking a reference shape. Similar performance is maintained in the presence of load torque change, the modification considers a load constant for each adjustment. The reference signal is in blue color.

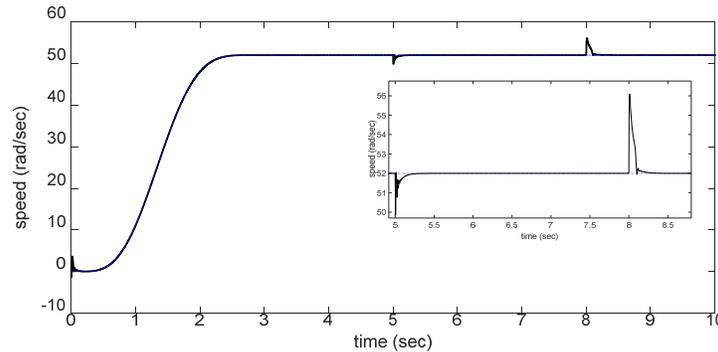


Figure 3. Rotor speed performance for reference tracking, case 1.

Fig. 4 presents the electrical torque required for operating conditions demanded in case 1. The armature current evolution is in accordance with DC motor performance, it is clear that the main overshoot is presented when the rotor speed change from 0 to 52 rad/sec with a constant load torque, Fig. 5. The oscillations are eliminated faster with the proposed adaptive controller. The settling time is near to 0.1 sec for BSNN.

The adaptive neural controller performance is guarantee by two main features: the off line training and the second the continuous learning in each sample time, and is reflected in the weight factor. This evolution is exhibited in Fig. 6 by one on the two weights of the B-spline neural network structure, the main change is presented when some of the motor system

configuration change, and obviously in steady state condition its value is maintained constant due that the error magnitude is near to zero. The learning rate is related to the velocity response of the weight factors, in this case it has a initial value equal to 5100 obtained in the previous training. This performance is expected while the continuous learning rule (8) is operating.

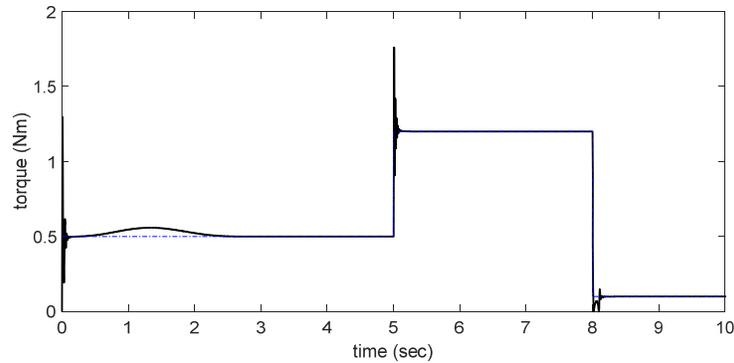


Figure 4. Electrical torque evolution, case 1.

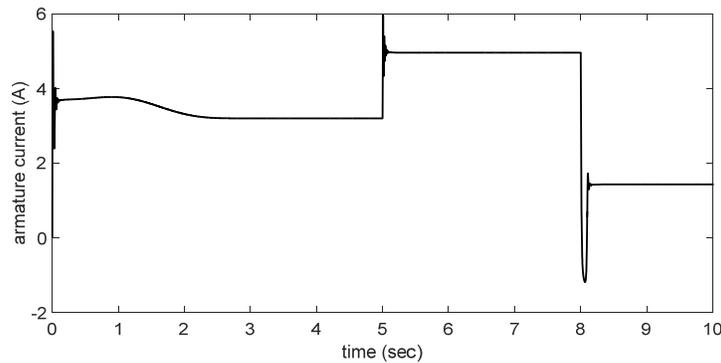


Figure 5. Armature current behavior, case 1.

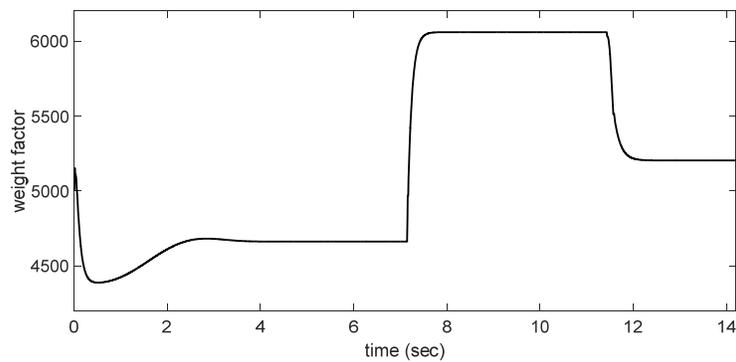


Figure 6. Weight factor evolution, case 1.

In Fig. 7 the rotor speed is presented, when the motor is exposed to operation conditions described in case 2. The BSNN has the ability of being updated to a new operating condition, improving its performance. The propose technique has a good performance because a speed tracking operation is demanded, additionally when the load torque is modified as a time function, the adaptive controller also achieves the reference speed requirements. This kind of performance is one of the main advantages of the adaptive controller when a design structure was well conditioned. The error between reference and actual speed is less than 1.5 rad/sec in transient period.

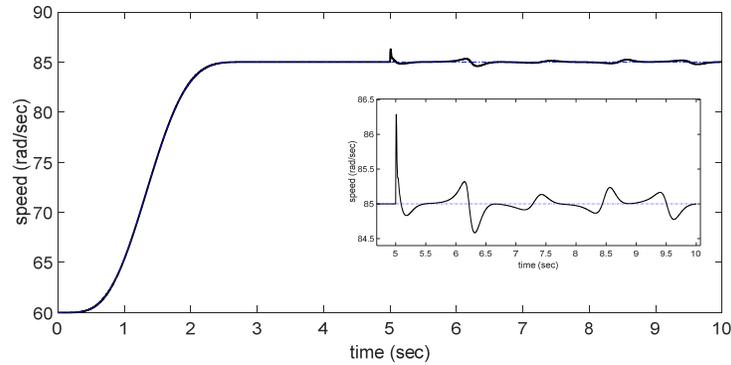


Figure 7. Rotor speed performance for reference tracking, case 2.

The input current for armature winding applied to the motor has an evolution as shows in Fig. 8. It is evident that the proposed controller confirms its faster response, therefore it could maintain similar behavior for both cases and different system requirements. In this study the input voltage is the only control variable, initially the motor is operating at 60 rad/sec with constant load torque.

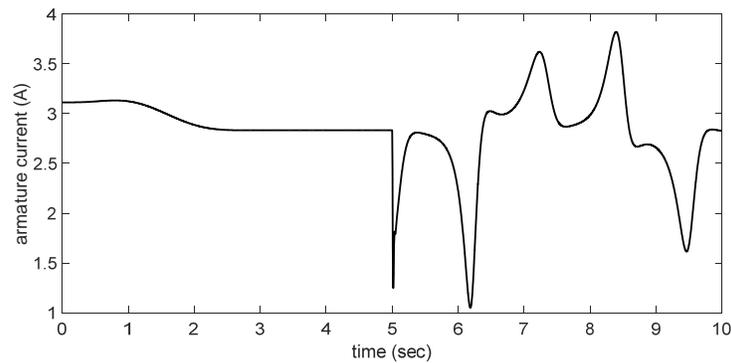


Figure 8. Armature current performance, case 2.

As a DC shunt motor, the field current is variable but the magnitude presented is fewer that armature current, Fig. 9. This feature allows complex load torque specifications for variable rotor speed. The behavior is a consequence of external load demands.

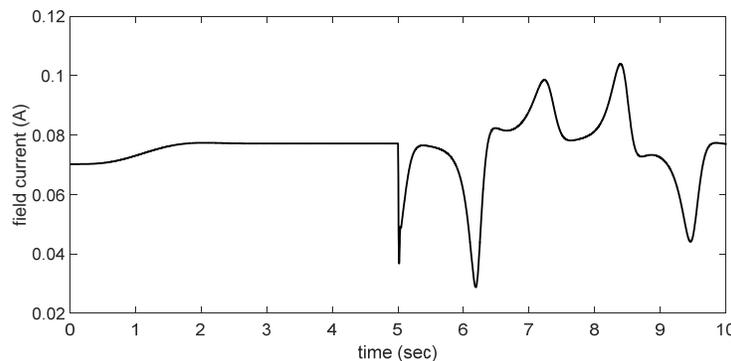


Figure 9. Field current evolution, case 2.

Measurement variables in laboratory test motor

The performance and applicability of the proposition are proved by hardware implementation on a laboratory DC motor. This strategy allows controlling appropriately the motor speed where

the load and set point is modified. The neural control is able to adapt by itself to different operating conditions, in other strategies turn out to be diminished in some situations, especially under different operating conditions for which its parameters have been tuned. Thus, the feedback signals to the BSNN are pertinent for a suitable control of the DC motor (shunt connected) velocity exhibiting a well performance for different operating points without modifications in control law. The applicability is demonstrated by laboratory results, some interest variables are presented in Fig. 10-13.

The DC motor to three scenarios was exposed. First case a, all variables are zero, after the speed reference is changed to 52 rad/sec, considering a constant load torque. An AC synchronous generator connected to the motor rotor is used as load. In this case the generator has an excited constant system, no electrical elements are wire to AC terminals.

The rotor speed and total current are showed in Fig. 10 and 11. The DC motor performance is in accordance with the simulations results. The proposed BSNN controller is able to regulate the speed with a desired behavior without knowledge of the system model and parameters. It is enough a collected data from the physical system in this case input voltage a rotor speed or and approximate mathematical model to know some possible characteristics about interest variables in transient and steady state condition.

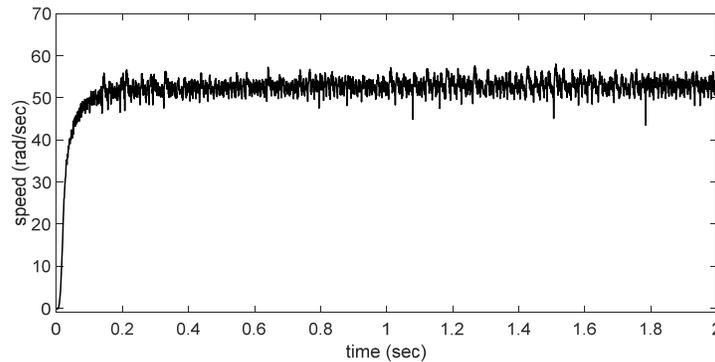


Figure 10. Rotor speed performance for reference tracking, case a.

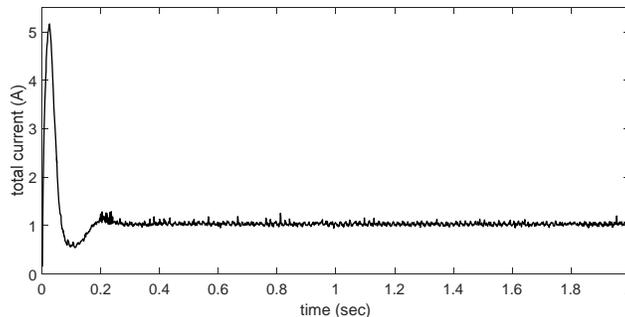


Figure 11. Total current performance, case a.

The second case b exhibits the reference tracking performance when the value is changed from 80 to 60 rad/sec. The controller has a good evolution when the speed reference is diminished, Fig. 12. The laboratory test where develop with operation conditions similar to simulation test. Discrepancies with simulations are due to a rough estimation of parameters. The comparison is only for demonstrating the behavior of the proposed adaptive controller.

The final case c includes a load torque with different values, first the rotor speed achieves 80 rad/sec; after that at $t = 3$ sec an AC synchronous generator is included. At $t = 4.5, 6$ and 8 seconds a three phase resistive load is inserted in the generator terminals, the resistive load is increased in each time. In the last part at $t = 11.7$ sec the resistive load is disconnected from the

generator terminals. The total current exemplify the system performance, all variables attain a behavior with similar features with all presented study cases.

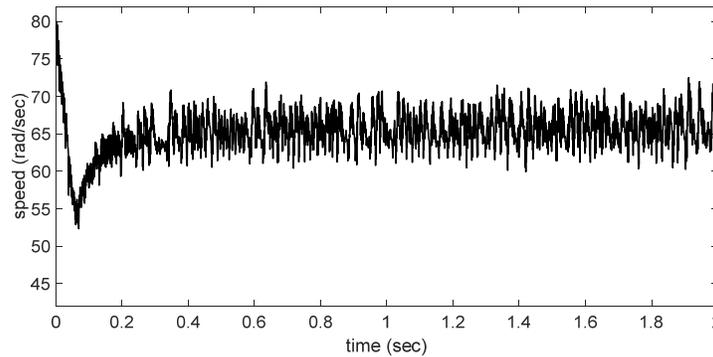


Figure 12. Rotor speed performance for reference tracking, case b.

The adaptability of the proposed controller has been presented by prior off line design. A mathematical model with approximate motor parameters was used, and the design was performed by data collected by the model and laboratory test system. The performance of the proposed adaptive controller is evaluated by simulation model analysis and results obtained experimentally. The observed performance validates the initial design methodology.

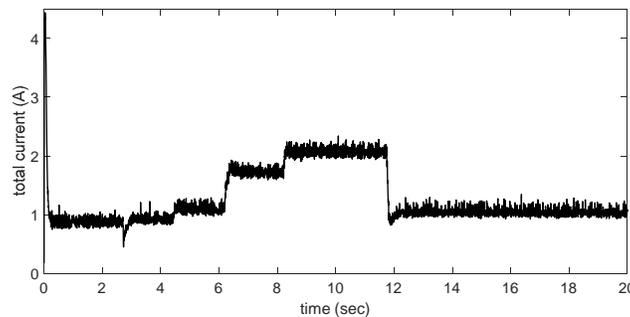


Figure 13. Total current behavior, case c.

Conclusions

It has been shown that with a prior off line neural network design we achieve a robust and adaptive controller, the instantaneous learning rule permits that the controller adapts by itself in each demanded operation condition. The same behavior is exhibited with real world operation conditions for the motor. For this proposition is not need the use of mathematical model furthermore the dependency of motor parameters is omitted. The main feature is an adaptive nature and an easy way to implement in physical motor. The hardware implementation validates the proposed design; several operation conditions are taking into account.

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