High Performance Speed Control of Direct Current Motors Using Adaptive Inverse Control

Aamir Hashim Obeid Ahmed
School of Electrical & Nuclear Engineering
Sudan University of Science and Technology
Khartoum, Sudan
aamirahmed@sustech.edu; Aamir_elec@yahoo.com

Abstract: - At present, the control of a separately excited Direct Current (DC) motor is generally done by means of feedback. This paper proposes the speed control of a separately excited DC motor. The novelty of this paper lies in the application of Adaptive Inverse Control (AIC) for the speed control of a separately excited DC motor. It is actually an open loop control scheme and so in the AIC the instability problem cased by feedback control is avoided and the better dynamic performances can also be achieved. The model of a separately excited DC motor is identified using adaptive filter as well as the inverse model of a separately excited DC motor, which was used as a controller. The significant of using the inverse of a separately excited DC motor dynamic as a controller is to makes a separately excited DC motor output response to converge to the reference input signal. To validate the performances of the proposed new control scheme, we provided a series of simulation results.

Key-Words: - Adaptive Inverse Control, Adaptive Filters, Direct Current Motor, Speed Control.

1 Introduction

Because of their high reliabilities, flexibilities and low costs, DC motors are widely used in industrial applications such as electric vehicles, steel rolling mills, electric cranes, robotic manipulators, and home appliances where speed or/and position control of motor are required. Therefore, the control of the position or/and speed of a DC motor is an important issue and has been studied since the early decades in the last century [1-8]. DC motor are generally controlled by conventional Proportional–Integral–Derivative (PID) controllers, since they designed easily, have low cost, inexpensive maintenance and effectiveness. However, major problems in applying a conventional PID controller in a position or/and speed are the effects of nonlinearity in a DC motor. The nonlinear characteristics of a DC motor such as saturation and friction could degrade the performance of conventional PID controller [9-14]. To overcome the above problems and achieve accurate control performance of speed or/and position control of a DC motor, a novel approach is proposed by using AIC technique. AIC is known to be robust against parameter uncertainties and external disturbances. The basic idea of AIC suggest that open loop control of system dynamics is realized by using a series controller whose transfer function approximate the inverse of the plant transfer function. Compared with traditional methods, AIC can achieve specified dynamic responses more easily and has better ability of disturbance rejection. The key of AIC is how to construct inverse model of controlled system accurately [15-17].

The organization of this paper is as follows. In section II, the mathematical modelling for a separately excited DC motor is given. The basic concept of AIC is briefly reviewed in section III. Section IV the background of adaptive filter is briefly explained. Section V introduces a separately excited DC motor state space model used in the work and the new proposed technique is discussed. Section VI, presents some simulation results on a separately excited DC motor with the new proposed technique. The last section contains the conclusion.

2 Modelling for DC Motor

Direct current machines are characterized by their versatility. By means of various combinations of shunt-, series-, and separately excited field windings they can be designed to display a wide variety of volt-ampere or speed-torque characteristics for both dynamic and steady-state operation. In this paper, a separated excitation DC motor model is chosen according to his good electrical and mechanical performances more than other DC motor models. Figure 1 shows a separately excited DC motor equivalent model [1-2].

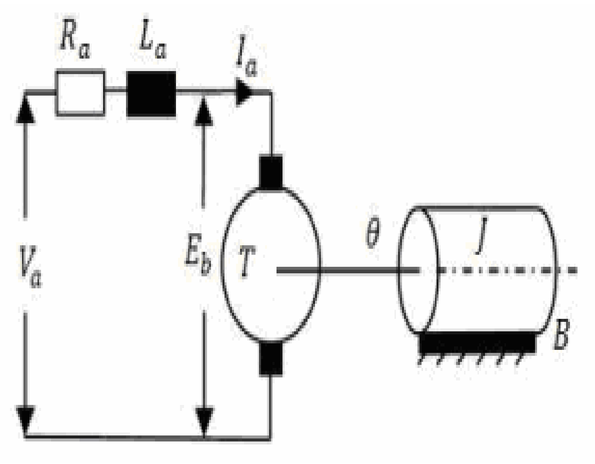

Figure 1: A separately excited DC motor model

The dynamics of a separately excited DC motor may be expressed as:

$$V_a = R_a i_a + L_a \frac{d i_a}{d t} + E_b \tag{1}$$

$$T = J \frac{d\omega}{dt} + B\omega \tag{2}$$

$$E_b = K_b \omega \tag{3}$$

$$T = K_T i_a \tag{4}$$

With the following physical parameters:
V_a: The input terminal voltage, (V).
E_b: The back emf, (V).
R_a: The armature resistance, (Ω).
i_a: The armature current, (A).
L_a: The armature inductance, (H).
J: Motor inertia, (kgm^2).
T: Motor torque, (Nm).
B: Viscous friction coefficient, (Nms).
K_T: The torque factor constant, (Nm/A).
K_b: Back emf constant, (Vs/A).
ω: Angular speed, (rad/s).
θ: Angular position of rotor shaft, (rad).

3 Basic Concept of AIC

AIC is a very novel control technique for the design and analysis in the industry process control system. AIC was named and proposed by professor Widrow in 1986 [17], which do not require a precise initial plant model. AIC technique has been successfully applied to a variety of control problems. The control philosophy is feed forward but feedback is present by means of the adaptation loop of the controller weights. AIC suggests a controller in serial with controlled plant, and the control of the plant dynamics can be achieved by preceding the plant with an adaptive controller whose transfer function approximates the inverse of that of the plant. The objective of this system is to cause the plant output to follow the command input. In AIC the coefficients of the controller are adaptively adjusted by an adaptive algorithm which is controlled by the input signal and the error signal. The structure of AIC consists of three main parts. First, adapt a plant model using adaptive system techniques. Second, need to calculate the inverse model of the plant model and at last the inverse model will serve as a controller to control the plant [17-20].

3.1 Adaptive system modelling

Adaptive system modelling or identification had been widely applied in control system, communication, and signal processing. Figure 2 illustrates how this can be done with an adaptive filter. The unknown system (plant) is connected in parallel with an adaptive filter; where the modelling signal applied simultaneously to the adaptive filter and unknown system. Three major issues are involved in adaptive system identification: The excitation signal, the filter structure, and the adaptation mechanism. The optimal model of the plant was obtained by adapting the weights or coefficients of an adaptive filter so that the mean square error between the output of the plant and adaptive filter output is minimized.

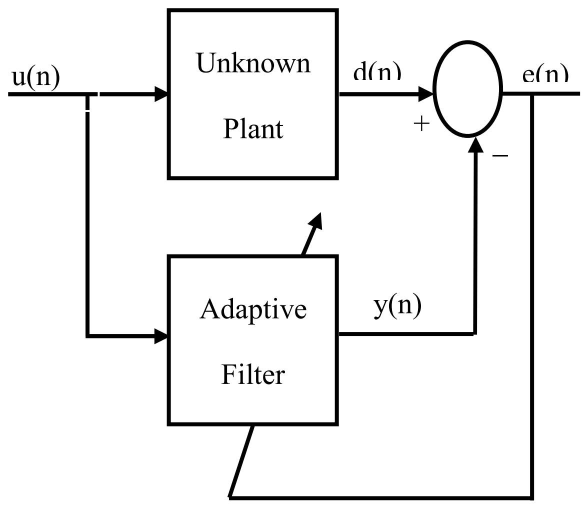

Figure 2: System identification using adaptive filtering

3.2 Adaptive inverse plant modelling

Adaptive filter technique is also used in modelling to calculate the inverse model of the plant. The plant generally has poles and zeros. The inverse of the plant therefore should have zeros and poles. This technique can be used to form the inverse model of minimum-phase plant as well as non-minimum-phase. For example, if the system under investigation is known to be minimum phase, that is, has all of its zeros inside the unit circle in the z-plane, then the inverse will be stable with all its poles inside the unit circle. When the plant is non-minimum-phase, then some of the poles of the inverse will be outside the unit circle and the inverse will be unstable. In the case of unstable plant, conventional feedback technique should be applied to stabilize it. Then the combination of the plant and its feedback stabilizer can be regarded as an equivalent stable plant [19]. The inverse of the plant model can be achieved by placing the adaptive filter at the same path with the plant as shown in Figure 3. The plant input is its command signal. The plant output is the input to adaptive filter. The adaptive algorithm attempts to make the cascade of the plant and adaptive inverse behave like a unit gain. This process is often called deconvolution [17].

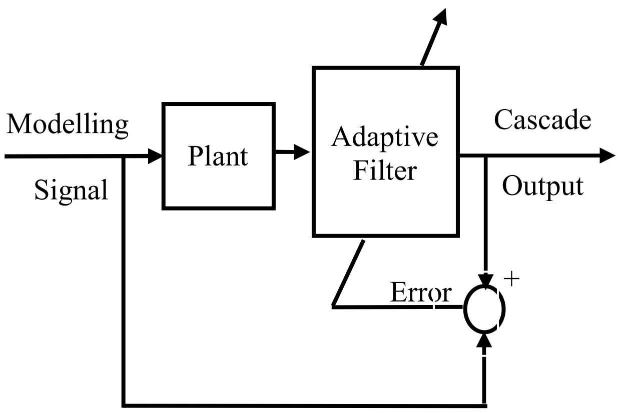

Figure 3: Inverse plant model

4 Adaptive Filters

Adaptive filters have received considerable attention by researchers over the past 25 years. As a result, many adaptive filter structures and adaptation algorithms have been developed during this period. The theory of adaptive filtering is fundamental to AIC. There are two fundamental types of digital filters: finite impulse response (FIR) and infinite impulse response (IIR). An important advantage of the FIR model of IIR model is that the FIR filters always stable. The FIR filter is also called an all zero system, because the weight vector only defines the zeros of the filter whereas the filter's poles all lie at the origin of the unit circle. Furthermore, an adaptive FIR filter is many times preferred over an adaptive IIR filter due to its simplicity and robustness. The adaptive IIR filter generally provides better performance than FIR filter that has the same number of coefficients [21-22]. The adaptive filter consists of two stages, filtering and adaptation. The filtering stage involves computation of output and generation of estimation error by comparing this output with the desired response. In the adaptive stage the tap weight vectors of the FIR filter are adjusted such that estimation error decreases with the each iteration. The key component of an adaptive filter is the adaptation algorithm, which is the method to determine the filter coefficients from the available data. The performance of these adaptive algorithms is highly dependent on their filter order and signal condition. Furthermore, the choice of an adaptive algorithm for any given application is determined by both costs of implementation and performance, with higher cost usually paid for improved performance. There are two different types of adaptation algorithms: a priori and a posteriori, which is based on the difference in coefficient updating methods. When the desired response is estimated using the previous coefficient matrix then it is called a priori. When the estimate is derived using the current coefficient matrix it is called a posteriori. We have used the a priori method for desired response prediction because it is more direct and easier to implement. For FIR adaptive filtering, the most widely adaptive algorithms for updating the filter weights are the Recursive Least Squares (RLS), and Least Mean Squares (LMS) or its normalized version.

4.1 The LMS Algorithm

The LMS algorithm, which was first proposed by Widrow and Hoff in 1960, is the most widely used adaptive filtering algorithm in practice [23]. The LMS algorithm belongs to the family of stochastic gradient linear adaptive filtering algorithm. It is called a stochastic gradient algorithm because it iterates each tap weight in the direction of the gradient of the squared magnitude of the error signal. Although in the subsequent four decades numerous alternative adaptive algorithms have been proposed, it is still one of the most efficient algorithms due to its simplicity of implementation, adaptation robustness, and low computational cost [21]. However, it suffers from a slow rate of convergence and high sensitivity to non stationary environments. Furthermore, its implementation requires the choice of an appropriate value for the step-size that affects the stability, steady-state mean square error (MSE), and convergence speed of the algorithm. For the each iteration the three basic equations governing the operation of the LMS algorithm are listed as follows [24]:

$$y(n) = w(n)^T u(n) = u(n)^T w(n) \quad (5)$$

$$e(n) = d(n) - y(n) \quad (6)$$

$$w(n+1) = w(n) + 2\mu e(n) u(n) \quad (7)$$

Where: u(n) is the input when time is n, w(n) is a weight vector, . w(n+1) is a update of w(n), e(n) is the error between desired signal d(n) and the filter output y(n), and μ stands for step size that effects stability of adaptation and speed of convergence. Usually, the initial values in weight vector w(0) are set to zero. Selection of a suitable value for μ is imperative to the performance of the LMS algorithm, if the value is too small the time the adaptive filter takes to converge on the optimal solution will be too long; if μ is too large the adaptive filter becomes unstable and its output diverges [24-25].

4.2 The Normalized LMS Algorithm

One of the primary disadvantages of the LMS algorithm is having a fixed μ for the every iteration. One approach to overcome this limitation has been to use the NLMS algorithm [21]. The NLMS algorithm, an equally simple, but more robust variant of the LMS algorithm, exhibits a better balance between simplicity and performance than the LMS algorithm, and has been given more attention in real time applications. Furthermore, it possesses many advantages over the LMS algorithm; including having a faster convergence speed and providing for an automatic time-varying choice of the LMS step size parameter that affects the stability, and steady-state MSE. For the each iteration of the NLMS algorithm, the filter tap weights of the adaptive filter are updated according to the following steps:

$$y(n) = w(n)^T u(n) = u(n)^T w(n) \quad (8)$$

$$e(n) = d(n) - y(n) \quad (9)$$

$$w(n+1) = w(n) + 2\frac{\mu}{\gamma + u^T(n)u(n)} u(n)e(n) \quad (10)$$

Where γ is a small positive constant in order to avoid division by zero when the values of the input vector are zero or close to it, the instability due to division by zero is avoided. The parameter μ is a constant step size value used to alter the convergence rate of the NLMS algorithm. Theoretically, it is within the range of 0<μ<2 for stable adaptation, however a more practical step size for NLMS is always less one unity.

4.3 The RLS Algorithm

Compared to the LMS and NLMS algorithms, the RLS algorithm has the advantage of faster convergence and small steady state error but this comes at the cost of increasing the complexity. Hence, the RLS algorithm requires longer computation time as well as a higher sensitivity to numerical instability. These disadvantages make the RLS algorithm unsuitable when a large number of taps is required for modelling. To implement the RLS algorithm, the following steps are executed in the following order [23].

$$y(n) = w(n)^T u(n) = u(n)^T w(n) \quad (11)$$

$$e(n) = d(n) - y(n) \quad (12)$$

$$w(n) = w(n-1) + \frac{P(n-1)u(n)e(n)}{\lambda + u^T(n)P(n-1)u(n)} \quad (13)$$

$$P(n) = \frac{\left[P(n-1) - \dfrac{P(n-1)u(n)u^T(n)P(n-1)}{\lambda + u^T(n)P(n-1)u(n)} \right]}{\lambda} \quad (14)$$

Where: P(n) is the covariance matrix. The algorithm is initialized by setting P (0) = δ*I*, where δ is a small positive constant number, and *I* is the identity matrix. The initial value P(0) can not be zero because it will remain zero. The parameter λ is a positive constant which is less than or equal to unity and generally has a value near 0.99. It is often referred to as the forgetting factor, as it controls the effective length of the memory of the algorithm [26].

5 Speed Control of DC Motor

In this section, we show the designed procedure for the speed control of a separately excited Direct Current motor which is under the control by AIC. Thus, the state space model of a separately excited Direct Current motor is obtained as follows:

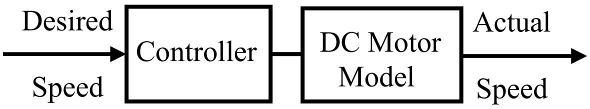

Figure 4: Adaptive inverse control

$$\begin{bmatrix} \dot{i}_a \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} \frac{-R_a}{L_a} & \frac{-K_b}{L_a} \\ \frac{K_T}{J} & \frac{-B}{J} \end{bmatrix} \begin{bmatrix} i_a \\ \omega \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{J} \end{bmatrix} V_a \qquad (15)$$

$$y = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} i_a \\ \omega \end{bmatrix}$$

For a separately excited DC motor modelling and inverse a separately excited DC motor modelling we used the LMS, NLMS, and RLS algorithms. After a separately excited DC motor model is completed, the inverse of a separately excited DC motor modelling can be achieved by placing the adaptive filter at the same path with a separately excited DC motor model. After the controller is established, we can cascade it with a separately excited DC motor model to track the desired reference signal as shown in Figure 4.

6 Simulation Results

To evaluate the effectiveness and performance of the new AIC technique, extensive computer simulation results are presented to compare the performance of the new proposed control strategy under different types of adaptive algorithms. The figure of merit that is used to observe convergence speed of adaptive filters is the MSE.

6.1 The LMS Simulation Results

The FIR filter representing a separately excited Direct Current motor modelled and inverse a separately excited Direct Current motor model has 64 taps with step size parameter value 0.01. The MSE learning curve is shown in Figure 5. The minimum mean square error (MMSE) obtained is -89.5dB, and the LMS algorithm has the slowest convergence time amongst the filtering learning algorithms considered.

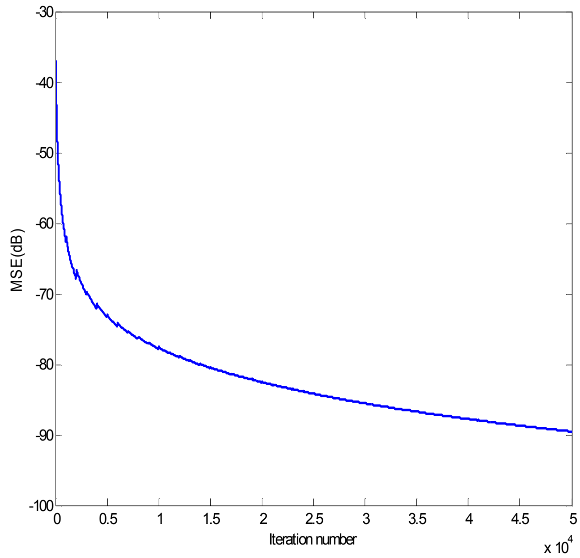

Figure 5: MSE learning curve

In order to verify the robustness of the LMS algorithm against measurement noise, Gaussian zero mean white noise with the variance of 10^{-3} was added to the output of the unknown system (desired signal). The MSE learning curve is shown in Figure 6. The result shows that the convergence time more alters when the measurement noise is added.

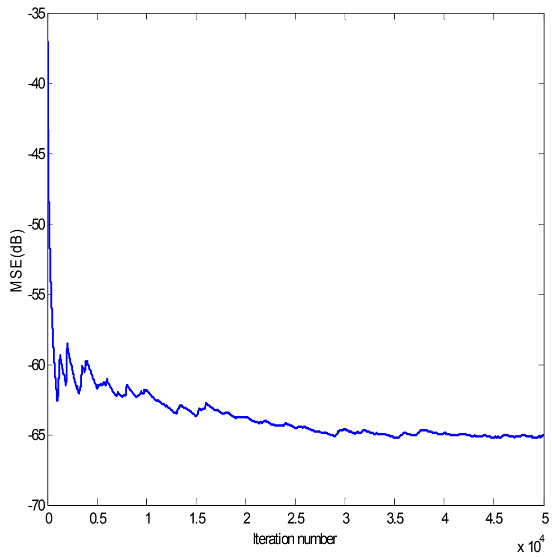

Figure 6: MSE when noise added

Figure 7 shows a separately excited DC motor tracking performance between desired and actual speed signals.

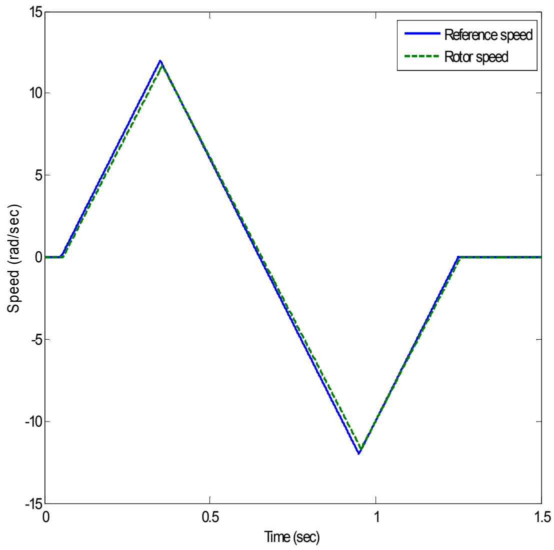

Figure 7: Speed signals

Figure 8 shows a separately excited DC motor speed tracking error. The peak speed error between desired and actual speed signals is within the range $\pm$ 0.55rad/sec.

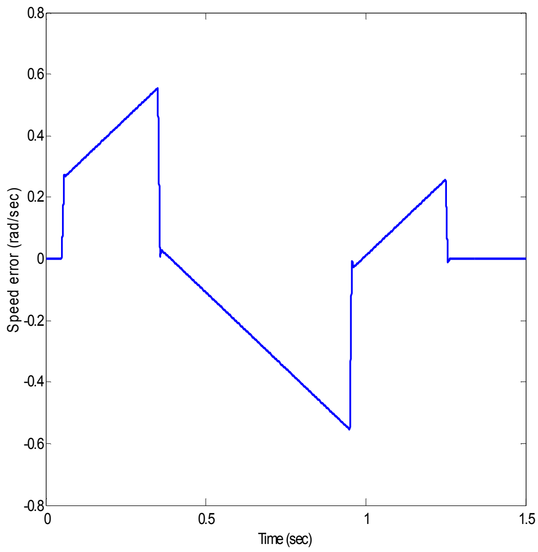

Figure 8: Speed error

6.2 The NLMS Simulation Results

The FIR filter representing a separately excited DC motor modelled and inverse a separately excited DC motor model has 64 taps with step size parameter value 0.05. The mean square error learning curve is shown in Figure 9, which indicates a minimum mean square error of about –81.5dB. This is figure shows that NLMS algorithm converges faster than standard LMS algorithm.

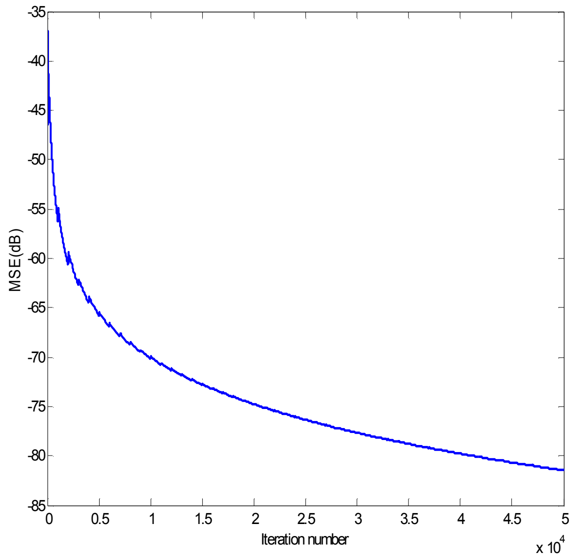

Figure 9: MSE learning curve

In order to verify the robustness of the NLMS algorithm against measurement noise, Gaussian zero mean white noise with the variance of 10^{-3} was added to the output of the unknown system. The mean square error learning curve is shown in Figure 10. Comparing Figure 6, and Figure 10, it is clear that the NLMS algorithm still converge faster than standard LMS algorithm when the measurement noise is added.

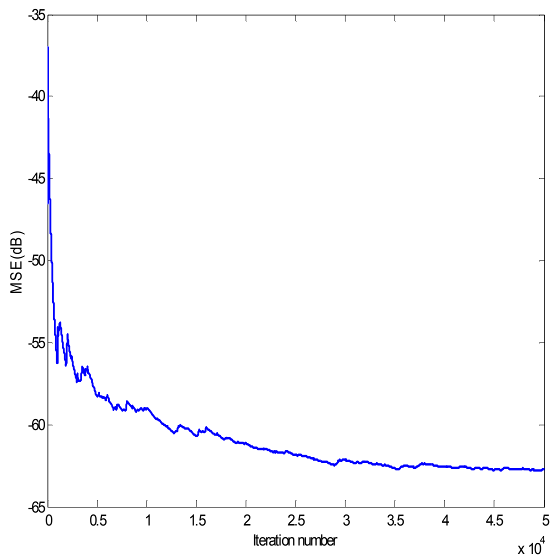

Figure 10: MSE when noise added

A separately excited DC motor tracking performance between desired and actual speed signals is shown in Figure 11.

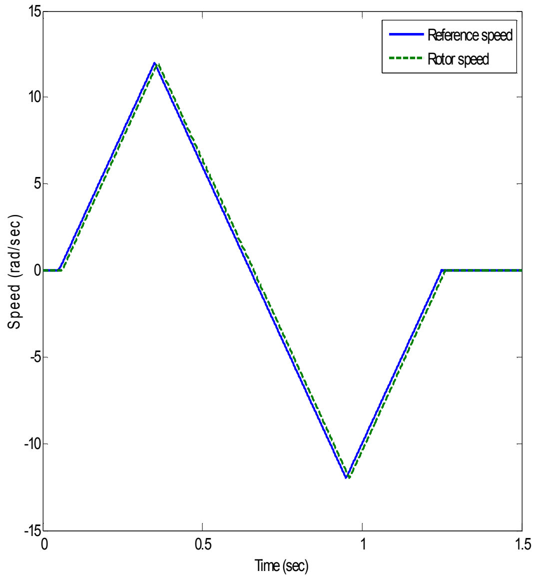

Figure 11: Speed signals

Figure 12 shows a separately excited DC motor speed error. The peak speed error between desired speed signal and actual speed signal is within the range ± 0.42rad/sec. However, the NLMS algorithm shows better peak speed error compared to the conventional LMS algorithm.

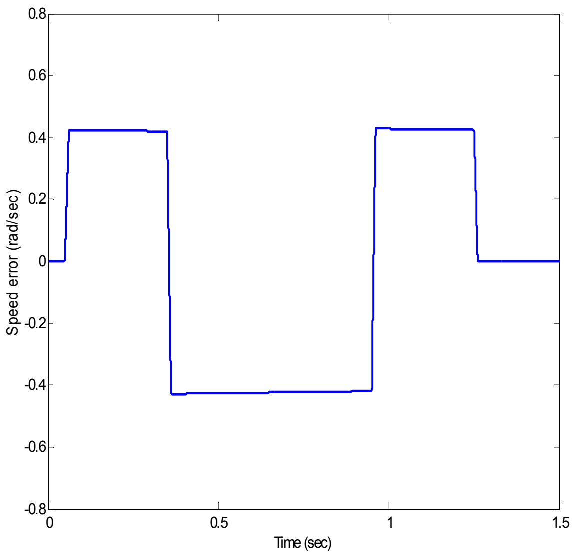

Figure 12: Speed error

6.3 The RLS Simulation Results

The FIR filter representing a separately excited DC motor modelled and inverse a separately excited DC motor model has 16 taps. A greater number of taps is not suitable, because the memory requirement for the algorithm grows approximately with the square of the number of taps. For the RLS algorithm we have initialized the P-matrix with δ=0.04 in order to get fast initial convergence. Figure 13 shows the MSE learning curve when the forgetting factor is set to 0.9999. Simulations show that the algorithm is sensitive to the choice of forgetting factor and it should be close to one. The RLS algorithm requires about 450 iterations to converge with a MMSE of about –65dB. Although, the RLS algorithm has the advantage of having a faster convergence rate than the conventional LMS and NLMS algorithms, which means that the RLS algorithm model more accurately than the another two adaptive algorithms with fewer taps.

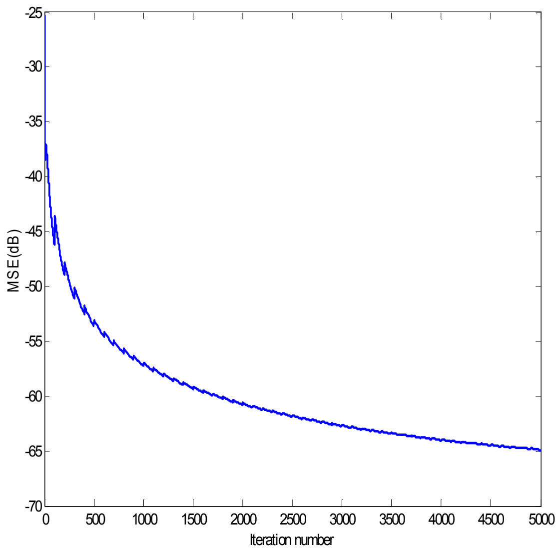

Figure 13: MSE learning curve

In order to verify the robustness of the RLS algorithm against measurement noise, Gaussian zero mean white noise with the variance of 10^{-3} was added to the output of the unknown system. The MSE curve is shown in Figure 14. The result shows that the RLS algorithm is more robust than the other introduced adaptive algorithms and convergence time still better when the measurement noise is added.

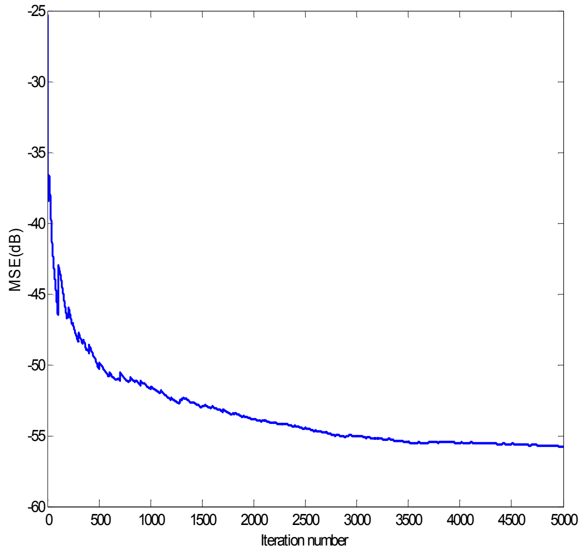

Figure 14: MSE when noise added

Figure 15 shows a separately excited DC motor tracking performance between desired and actual speed signals.

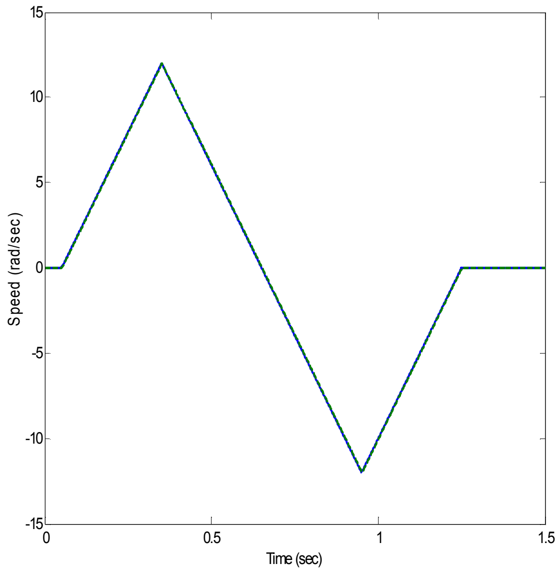

Figure 15: Speed signals

A separately excited DC motor speed error is shown in Figure 16. The peak speed error between desired and actual speed signals is within the range ± 0.076rad/sec. Comparing Figure 8, Figure 12, and Figure 16, it is clear that the RLS produces smaller peak speed error than the standard LMS, and NLMS algorithms.

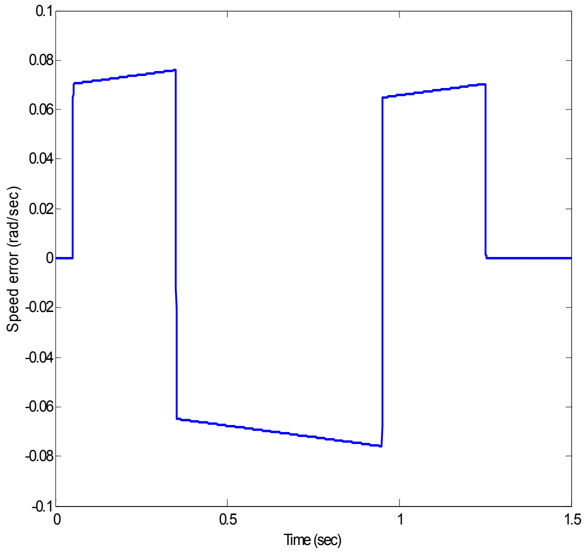

Figure 16: Speed error

6.4 Results Comparison

The results show that the RLS algorithm, by considering the convergence time and the accuracy of the converged model is superior to the other introduced adaptive algorithms. Comparing Figure 7, Figure 11, and Figure 15, it can be concluded that high precision speed tracking performance can be achieved using the three adaptive algorithms. However, the RLS algorithm gives smaller peak speed error compared to the standard LMS and NLMS algorithms. This means that the RLS algorithm can track the rotor speed command more accurately than the conventional LMS and NLMS algorithms. Robustness of the three adaptive algorithms against measurement noise is also verified. All three types of adaptive algorithms exhibit small sensitive to the measurement noise. However, the RLS algorithm still gives better convergence time compared to the other introduced algorithms.

7 Conclusion

In this paper, a new methodology adaptive inverse control is submitted to design the speed control of a separately excited DC motor. To validate the performances of the new proposed control technique, we provided a series of simulations and a comparative study between the LMS, NLMS and the RLS adaptive algorithms. Simulation results show that the RLS algorithm shows better performance than the other two adaptive algorithms.

References:

[1] Y. J. Huang, T. C. Kuo, 'Robust position control of DC servomechanism with output measurement noise', Electr. Eng., Vol. 88, pp. 223-238, 2006.

[2] Rubaai, Kotaru, 'Online identification and control of a DC motor using learning adaptation of neural networks', IEEE Trans. Industry Application, Vol. 36, pp. 935–942, 2000.

[3] S.J.Chapman, 'Electric Machinery Fundamentals', 4th Edition, New York, McGraw-Hill Companies, 2005.

[4] Moleykutty George, "Speed Control of Separately Excited DC Motor", American Journal of Applied Sciences 5 (3), 227-233, 2008.

[5] Boumediene Alloua, Abdellah Laoufi, Brahim Gasbaoui, and Abdessalam Abderrahmani, "Neuro-Fuzzy DC Motor Speed Control Using Particle Swarm Optimization", Leonardo Electronic Journal of Practices and Technologies, Issue 15, pp. 1-18, July-December 2009.

[6] Meena Tushir and Smriti Srivastava, Type-2 fuzzy logic controller Implementation for tracking control of DC motor, International Journal of Computer Network and Security, Vol. 3 No. 1, 2005.

[7] B Sharmila and N Devarajan, Performance of Networked DC Motor with Fuzzy Logic Controller, IJCSI International Journal of Computer Science Issues, Vol. 7, Issue 4, No 9, July 2010.

[8] G. Madhusudhana Rao, B. V. Sanker Ram, A Neural Network Based Speed Control for DC Motor, International Journal of Recent Trends in Engineering, Volume 2, No. 6, 121-124, November 2009.

[9] K. Ang, G. Chong, Y. Li, 'PID control system analysis, design, and technology', IEEE Trans. Control System Technology, Volume 13, pp. 559 – 576, 2005.

[10] O. Yaniv, M. Nagurka, 'Robust, PI controller design satisfying sensitivity and uncertainty specifications', IEEE Trans. Automation Control, Vol. 48, pp.2069-2072, 2003.

[11] H. Kim, I. Maruta, T. Sugie, 'Robust PID controller tuning based on the constrained particle swarm optimization', Automatica, Vol. 44, Iss. 4, pp.1104 -1110, 2008.

[12] Boumediene Alloua, Abdellah Laoufi, Brahim Gasbaoui, and Abdessalam Abderrahmani, Setting Up PID DC Motor Speed Control Alteration Parameters Using Particle Swarm Optimization Strategy, Leonardo Electronic Journal of Practices and Technologies, Issue 14, pp. 19-32, January-June 2009.

[13] Brijesh Singh, Surya Prakash, Ajay Shekhar Pandey and S.K. Sinha, Intelligent PI Controller for Speed Control of D.C. Motor , International Journal of Electronic Engineering Research, Volume 2, Number 1, pp. 87–100, 2010.

[14] Manafeddin Namazov, DC motor position control using fuzzy proportional-derivative controllers with different defuzzification methods, Turkish Journal of Fuzzy Systems, Vol.1, No.1, pp. 36-54, 2010.

[15] T. Y. Chou, T. H. Liu, T. T. Cheng, 'Design and implementation of an adaptive inverse controller for a micro-permanent synchronous motor control system', IET Electr. Power Appl., Vol. 3, Iss. 5, pp.471- 481, 2009.

[16] X. Shuying, Z. Chengjin, X. Xiangli, 'Adaptive inverse induction machine control based on variable learning rate BP algorithm', IEEE Pro. Automation and Logistics, Jinan, China, Vol. 7, No. 4, pp. 2367-2372, 2007.

[17] B.Widrow, E.Walach, 'Adaptive Inverse Control', Prentice Hall Inc., NJ. 1996.

[18] B.Widrow, S.D.Stearns, 'Adaptive signal processing', Prentice-Hall, Englewood Cliffs, New Jersey, 1985.

[19] G.L.Plett, 'Adaptive inverse control of linear and nonlinear system using dynamic neural networks', IEEE Transactions on neural network, Vol.14, No.2, March 2003.

[20] Hui Wang, Dao-Ying PI, You-Xian Sun, "Online SVM regression algorithm based adaptive inverse control", International Conference on Intelligent Computing, August 2005, China.

[21] S.Haykin, 'Adaptive filter theory', 4th ed. Englewood Cliffs, New Jersey Prentice Hall, 2001. .

[22] J.Kim, E.T.Perry, 'Performance analysis of the self correcting adaptive filters', IEEE, pp.316-319, 2005.

[23] M.H.Hayes, 'Statistical digital signal processing and modelling', Jon Wiley and Sons, 1996.

[24] J.Kim, E.T.Perry, 'Performance analysis of the self correcting adaptive filters', IEEE, pp.316-319, 2005.

[25] R.R.Bitmead, B.D.O.Anderson, 'Performance of adaptive estimation algorithms in dependent random environments', IEEE Trans. On Automation Control, Vol. AC-25, pp.788-794, 1980.

[26] Y.Ahmed, F.Jawed, S.Zia, M.S.Aga, 'Real time implementation of adaptive channel equalization algorithms on TMS320C6x DSP processors', IEEE, 2004.

Aamir Hashim Obeid Ahmed received the B.Tech. (first class honours) and the M.Sc degrees in Electrical Engineering from Faculty of Engineering, Sudan University of Science and Technology (SUST), Khartoum, Sudan in 1996 and 2002 respectively. Dr. Aamir obtained PhD (2010) in Electrical Engineering from SUST. Dr. Aamir is working as Assistant Professor in Electrical Engineering Department, Sudan University of Science and Technology. He is head of control sector. His research interest includes nonlinear position/speed control techniques in vector control of induction machines, application of fuzzy logic for controlling linear and nonlinear control systems. Dr. Aamir had supervised many undergraduates and postgraduates projects.