Iraq J. Electrical and Electronic Engineering
Vol.2 No.1 , 2006

المجلة العراقية للهندسة الكهربائية والالكترونية
مجلد 2 ، العدد 1 ، 2006

Speed Control of Steel Rolling Mill using Neural Network

Abduladhem A. Ali [1]   **Alaa M. Abdulrahman** [2]

[1] *Department of Computer Engineering, College of Engineering, University of Basrah Basrah, Iraq, E-mail: abduladem@hotmail.com*

[2] *Department of Electrical Engineering, College of Engineering, University of Basrah Basrah, Iraq.*

السيطرة على قوائم درفلة الحديد باستخدام الشبكات العصبية

د.عبد العظيم عبد الكريم علي   علاء محي الدين عبد الرحمن
قسم هندسة الحاسبات   قسم الهندسة الكهربائية
كلية الهندسة-جامعة البصرة

Abstract

In this paper a fully neural network-based structure have been proposed to control speeds of rolling stands of a steel rolling mill. The structure has property of controlling the motors speed such that the loop height between each successive stands tracks the required height reference. Synchronization between these stands is also maintained so that the metal flow rate from first stand to the last stand is kept constant. This structure is robust against the disturbance effects such as, torque loading, plant parameter change... etc. The results reveal performance of the structure as a comparison with the conventional control method for a practical worksheet data.

Keywords:

Steel Rolling Mill, Neural Networks, DC-Motor speed control, and Multimachine control.

الخلاصة:

يتناول البحث استخدام منظومة سيطرة تعتمد بالتكامل على الشبكات العصبية للتحكم بسرعة خطوط درفلة الحديد. يمكن للتركيبة المقترحة السيطرة على سرعة مجموعة الخاصة بالدرفلة بحيث يمكنها من التحكم بارتفاع الحلقة التي يتم تركيبها بين مختلف قوائم الدرفلة، بحيث تتطابق مع الارتفاع النموذجي. كما يتم التحكم بالتزامن بين هذه القوائم بحيث يتم الحفاظ على نسبة ثابتة لسريان المعدن بين القائم الأول والأخير في خط الدرفلة. ان المنظومة المقترحة قوية التحكم ضد التغيرات و التأثيرات الخارجية مثل تغير عزم التحميل وتغير المتغيرات الداخلية للمنظومة. تمت دراسة هذه المنظومة ومقارنتها مع منظومات التحكم التقليدية لبيانات عملية.

1. Introduction

Steel production is still one of the major basic industries with a huge amount of material and energy consumption. Faults on the rolling line system cause to reduce the benefits and to waste time. Most of these causes are due to weak in speed control of the rolling machines and loosing in synchronization of the rolling system [1].

Neural Networks (NNs) have been implemented practically in several industries. New schemes based on NNs are developed for a number of different rolling process problems such as estimating the exact rolling force to achieve the right thickness [2], and an estimator employed for condition monitoring and fault diagnosis [3].

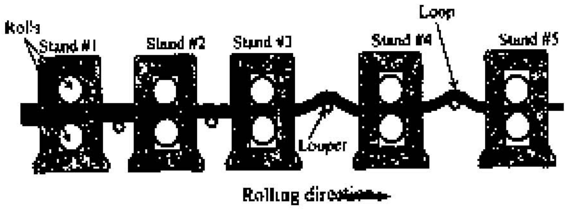

Figure 1- Steel Rolling system

Speed regulation of the motors and synchronization maintain between the successive stands are important problems to be handled in hot line rolling mills [1]. Conventional controllers (such as PI-algorithm) are lack of robustness, therefore disturbances affect the system synchronization and quality of the production. Loopers have been utilized to construct loops between the successive stands to increase quality of the production.

In this paper NN technique is employed to control driver of the rolling stand motor that is of a DC-Motor type. NN based loop height controller is also presented. This form of control has property of synchronization maintain between different stands. Hence, a fully-NN technique for steel rolling system is developed.

2. Steel Rolling Mill

Rolling is a process of shaping the steel into a linear element with a constant cross-section. The line production consists of a specific number of rolling stands depending on type of the product or size of its cross-section. Each rolling stand contains two rolls, which are driven by a DC-Motor, as shown in Figure 1.

The production starts rolling from first stand, which is source of the steel metal, with a specific size of cross-section. The metal is passed through all the stands with different cross-sections. Last stand represents speed governor of the train and here the output product will have the desired cross-section [4].

3. Combined controlled DC-Motor (CCDCM)

Due to the permission for wide range of speed operation and the precise control of a separately excited DC-Motors, so that these motors are widely used in industrial processes. CCDCM has separate sources on the armature and the field windings, which could drive these motors over their rated speed values.

In a CCDCM armature voltage controller alone is employed for the motor speeds under its rated value at constant field voltage. When the speed exceeds its rated value the field-weakening controller will enter in operation in combination with the armature controller [4]. Complete non-linear equations of the DC-Motor are described below [5],

$$\dot{N}(t) = -\frac{1}{\tau_m} N(t) + \frac{k \cdot \varphi(t) \cdot I_a(t)}{J} - \frac{1}{J} T_L(t) \tag{1}$$

$$\dot{I}_a(t) = -\frac{1}{\tau_a} I_a(t) - \frac{k \cdot \varphi(t) \cdot N(t)}{L_a} + \frac{1}{L_a} V_t(t) \tag{2}$$

$$\dot{I}_f(t) = -\frac{1}{\tau_f} I_f(t) + \frac{1}{L_f} V_f(t) \tag{3}$$

Where, $N(t)$ -motor speed, $\varphi(t)$ = field flux, $I_a(t)$ =armature current, $T_L(t)$ = load torque, $I_f(t)$ = field current, $V_t(t)$ = armature voltage applied, and $V_f(t)$ = field voltage applied. Other parameters are detailed in Appendix A.

Block diagram representation of a CCDCM including its controllers is shown in Figure 2. Controller parameters are obtained such that the following constraints are investigated:

- Motor speed $N(t)$ tracks its reference,
- Back emf $e_a(t)$ not exceeds its rated value,
- Armature current $I_a(t)$ below its maximum, and

Field voltage $V_f(t)$, and consequently $I_f(t)$, are above their minima.

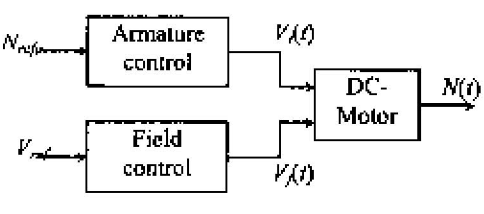

Figure 2 – CCDCM block diagram

4. Loop Control and Synchronization Maintain

Quality of the production can be improved by including loops between subsequent rolling stands, which will reduce effect of the tighten when tensions are not required. Loops are formed by loopers, which are either rolls risen by a piston or a dual arms risen by motors. Loopers are put to work when head of the production enters the next (downstream) stand, where sensors are used to detect existing of the production [1].

Speed synchronization between the successive stands can be achieved by ensuring the flow rate of metal from the first stand to the last one be constant. The flow rate relation is shown in (4) from [1],

$$v_1 \cdot S_1 = v_2 \cdot S_2 = \dots = v_i \cdot S_i = \dots = v_M \cdot S_M \tag{4}$$

Where, v_i = linear velocity of stand i, and S_i = output cross-section of stand i. Change of velocity of any stand will cause to change the loop length between this stand and the downstream stand, and consequently the loop height. Length of the loop and its height can be obtained from the following relations [4],

$$l_i(t) = T_i \cdot (v_i(t) - \frac{v_{i+1}(t)}{\mu_i}) + l_{ri} \tag{5}$$

$$h_i(t) = 0.5 \cdot \sqrt{l_i^2(t) - L^2} \tag{6}$$

Where, $l_i(t)$ = loop length of stand i, T_i = time span of the line to reach the downstream stand, $\mu_i = S_i/S_{i+1}$ = cross-section correction factor, l_{ri} = reference loop length, L = the distance between successive stands, and $h_i(t)$ = loop height.

Block diagram representation of the rolling system is shown in Figure 3 for M stands, where the block Con_i represents the loop length and its height measurements. The loop control is based on a PI-algorithm.

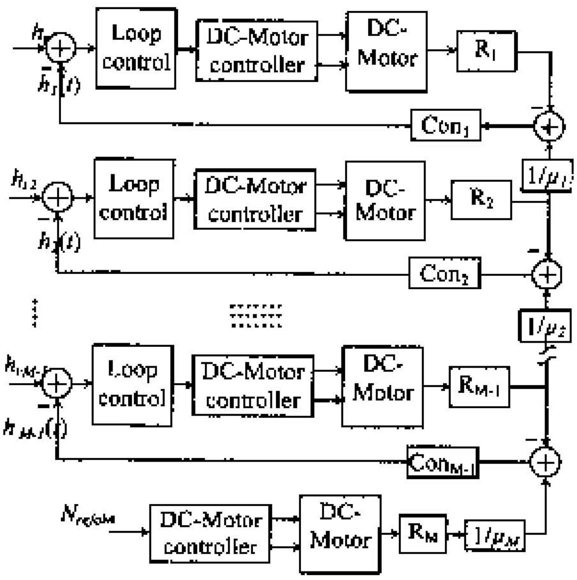

Figure 3 - Rolling system

5. Fully-based Neural Network Structure

Implementation of artificial NN as intelligent techniques in rolling mill processes promises for obtaining better results and reduces cost of operation [2], [3]. A fully-based NN structure employs two different networks in the control. One of them utilized as a DC-Motor controller and the other as a loop controller.

In the last decade various works have been emerged showing that Dynamic Neural Network (DNN) is quite effective in modeling non-linear dynamical systems [6]. DNN is a novel configuration composed of interconnection of feedforward multilayer and recurrent NNs. Narendra discussed two types of control, which are direct and indirect adaptive control where he employed an indirect control method depending on separation of the control input, hence prior knowledge of the plant is required [6].

Direct control method is poor of the plant Jacobean, due to its position, which is in front of the plant. Psaltis employed as a replacement a simple difference equation [7]. Widrow used an extra NN as a path for the output error propagation to the NN controller employing feedforward NN [8]. Such a similar method was utilized by Lightbody using DNN and Jacobean of the plant was replaced by a sensitivity model based on linearization of the plant identifier [9].

Above methods are poor of generality or the path identifier is relied on approximate methods, therefore Ali employed a DNN to the controller as the path based on the Backpropagation learning algorithm to pass the output error to the controller [10]. Both control methods (the direct and the indirect) will be used in the rolling structure for the purpose of generality.

6. DC-Motor Control

The problem is to design a controller, which generate the desired control inputs ($V_r(t)$ and $V_f(t)$) such that the DC-Motor output $N(t)$ tracks a desired reference model and achieves the required constraints of the plant mentioned previously.

The DC-Motor controller used is based on indirect control method using inverse control. Inverse Dynamic Neural Network (IDNN) with the structure shown in Figure 4, where it uses input and output dynamics of the plant as its inputs. TDL represents a time delay line of z^{-1} elements. The patterns (input-output pair) used to train the IDNN are two randomly selected to the speed set-point, N_{refo}. One belongs to the armature controller operation region and the other belongs to the field controller operation region. The values are (N_{refo}=875 RPM, N_{refo}=2100 RPM).

This network has the following characteristics, a = 9, b = 20, c = 2, where a, b, and c are number of neurons in the input, the hidden, and the output layers, respectively. A tangent activation function is employed in neurons of the hidden layer.

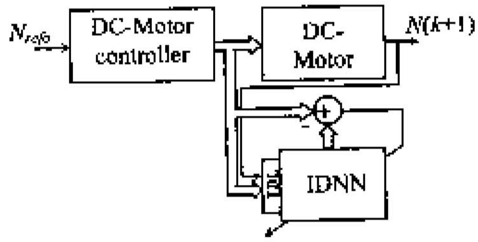

Figure 4 - Inverse Identification

Dynamic back-propagation algorithm is utilized to find the optimum weights of the DNN employed, which uses the following equations to update the weights, [6], [10],

$$v_{jl}(k+1) = v_{jl}(k) + \eta_v \cdot \Delta v_{jl}(k), \quad w_{li}(k+1) = w_{li}(k) + \eta_w \cdot \Delta w_{li}(k) \tag{7}$$

$$\Delta v_{jl}(k) = -\partial E(k) / \partial v_{jl}(k), \quad \Delta w_{li}(k) = -\partial E(k) / \partial w_{li}(k) \tag{8}$$

$$E(k) = \sum_{c=1}^{m} \varepsilon_c^2(k) \tag{9}$$

$$\varepsilon_c(k) = y_d^c(k) - y_N^c(k) \tag{10}$$

Where, v_{jl} is the weight connection between #j output neuron and #l hidden neuron, w_{li} is the weight connection between #l hidden neuron and #i input neuron, η_v and η_w are learning rates of the weights v_{jl} and w_{li}, respectively. Δv_{jl} and Δw_{li} are gradient of the sum squared error $E(k)$ with respect to their corresponding weights $v_{jl}(k)$ and $w_{li}(k)$ respectively. $\varepsilon_c(k)$ is the difference between the NN output $y_N^c(k)$ and the plant output (or input) $y_d^c(k)$ to be identified

On-line training is the most suitable method for dynamical systems and especially in practical applications [11], [12]. This method of updating is used throughout the paper because it is much quicker than off-line (batch update) and it helps the network to escape from local minima [13].

Adaptation of the weights is continued till the performance measure, which is the error squared $E(k)$, is converged towards zero as shown in Figure 5. The learned network can now be employed to control the DC-Motor as represented by the structure shown in Figure 6. A non-linear Model Reference Adaptive System (MRAS) is used [10].

Figure 7 represents the motor speed and its reference responses for 1400 RPM set-point. Where it is tested to a load change of 20 N.m. at time 40 sec., and a set-point change to a value of 2100 RPM (i.e. above rated speed of the DC-Motor by about 350 RPM) at time 80 sec.

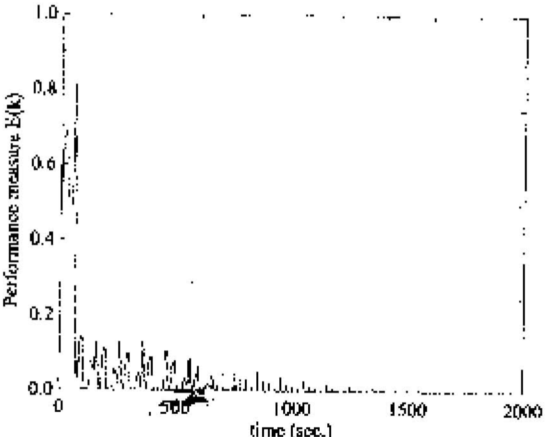

Figure 5 – Inverse identifier error

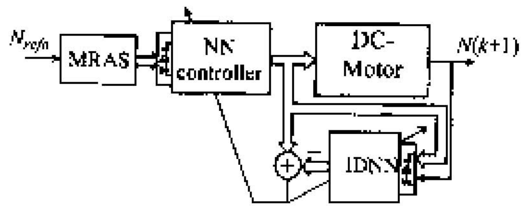

Figure 6 - Inverse control structure

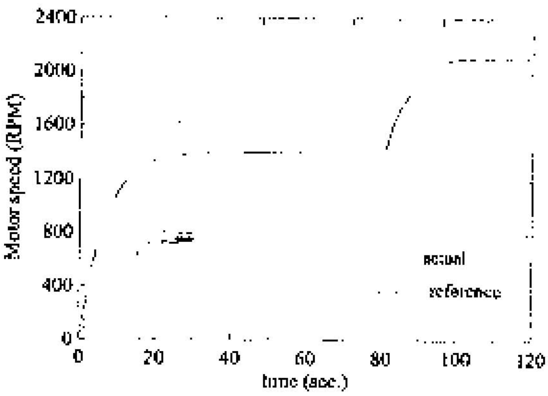

Figure 7 – Motor speed responses under tests

7. Loop Control

A DNN was employed in the loop control, which uses the direct control method. A path is required to propagate the error between the height reference and the actual loop height to update weights of the loop control network. Therefore, an extra DNN is proposed to be used as the path, where identification structure of the path is shown in Figure 8.

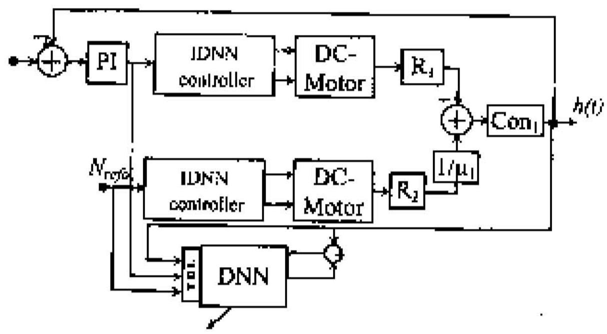

Figure 8 – Identification of the loop control path

This network has the following characteristics, a = 15, b = 40, c = 1, and a tangent activation function employed in neurons of the hidden layer. Learning was complete by (50 000 epochs) as illustrated by the performance measure shown in Figure 9.

Structure of the loop control is shown in Figure 10, where it employs a DNN. The loop controller is trained by applying a set-point of (N_{refo} = 1925 RPM) and a height reference of (h_r = 0.3 m), where Figure 11 represents training of the loop height controller.

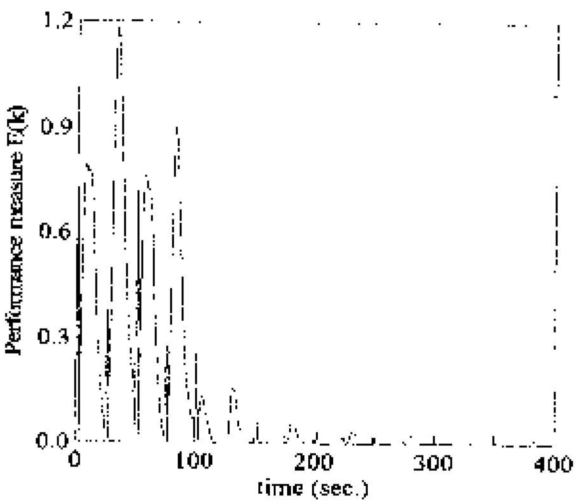

Figure 9 - Error response of identifier of the loop controller path

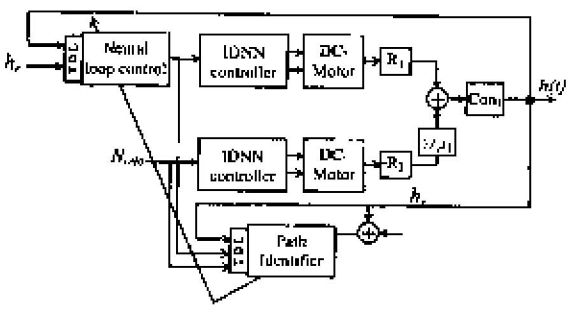

Figure 10 – Direct Control of the Loop controller

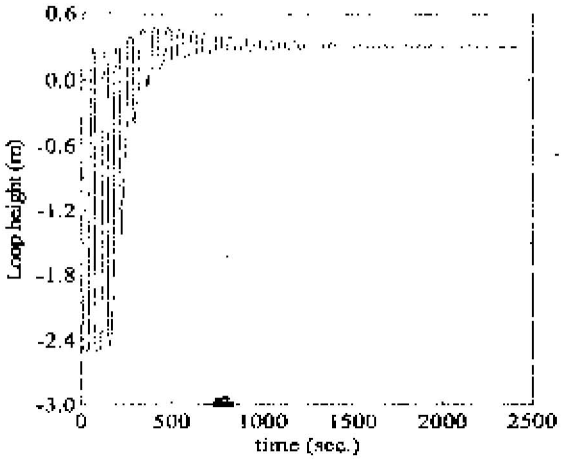

Figure 11 – Loop height response between two stands

To test the rolling system against disturbance effects, data from a typical worksheet has been chosen that is named as L50 (scheme 24) [1], which is of 10 stands. Figure 12 and Figure 13 illustrate motors speeds and the loop height responses for the conventional control method. The system has been disturbed twice, firstly a load change on stand number 8 at time 80 sec., and secondly the viscous parameter change of stand number 9 at time 120 sec., and the effects are obvious. These tests have been applied on the fully-neural network rolling system as shown in Figures 14-15, where Figure 14 represents DC-Motors speeds and Figure 15 represents the loop height responses. As obvious the load torque effect and the parameter change has been minimized clearly.

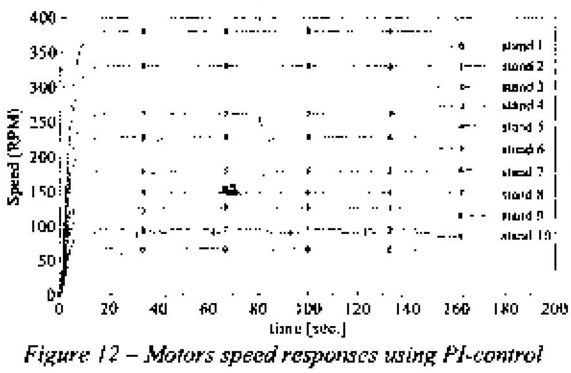

Figure 12 – Motors speed responses using PI-control

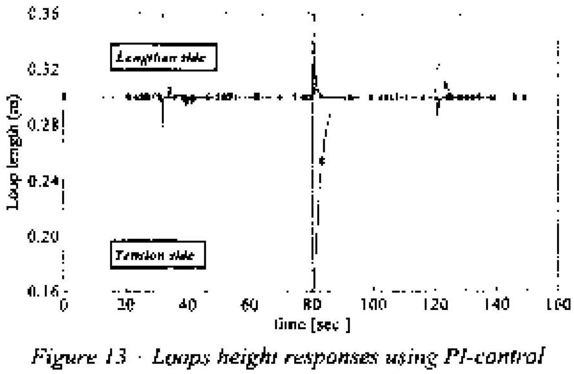

Figure 13 - Loops height responses using PI-control

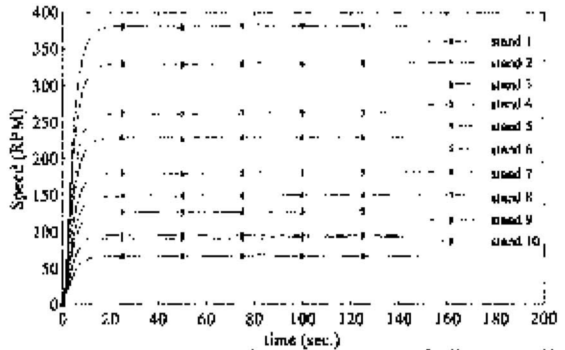

Figure 14 – Motors speed responses using DNN controller

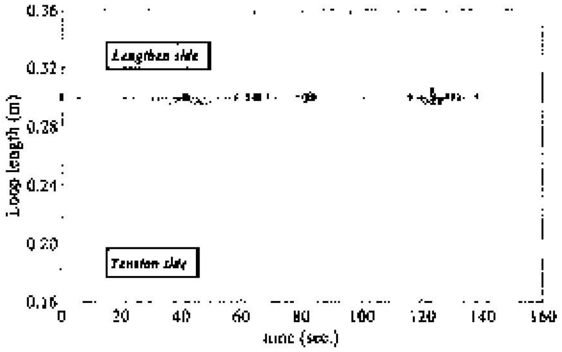

Figure 15 – Loop height responses using DNN controller

8. Conclusions

Both types of control, the direct and the indirect adaptive control, have been employed successfully on controllers of the Steel Rolling Process. Inverse dynamics of the DC-Motor have been identified correctly using a DNN. The inverse network obtained is used to control speed of the DC-Motor below and over its rated value to obtain a CCDCM. A robust DC-Motor against disturbance effects has been obtained, and the simulation results reveal that.

A fully-based NN control structure have been proposed to control the loop height and to maintain the synchronization between different rolling stands. The loop controller is based on the direct control method using DNN. The system is robust against the common rolling process perturbations, like plant parameter change, loading and set-point changes.

References

[1] Iraq Steel Industry, "Khor Al Zubir Wire Rolling Line Stand Synchronization", Manual frame LTN1, CEM C[ie] Electro Mecanique 1976.

[2] Martinetz, T.; Protzel, P.; and Gramckow, O. "Neural Network Control for Rolling Mills". Proceeding of the Second European Congress on Intelligent Techniques and Soft Computing. Aachen, Germany 1994.

[3] Tervo, J.; Mustonen, M.; and Korhonen, R. "Intelligent Techniques for Condition Monitoring of Rolling Mills". Proceeding of the European Symposium on Intelligent Techniques, pp 1009-1012 ,2000.

[4] Abdulrahman, A. M. "Neural Control of Multimachine systems" M.Sc. thesis, Department of Electrical Engineering, University of Basrah, Iraq 2002.

[5] Egami, T.; and Morita, H. "Efficiency Optimized Model Reference Adaptive Control System for a DC-Motor". *IEEE Transactions on Industrial Electronics* Vol.37, pp. 28-33, 1990.

[6] Narendra, S. B.; and Parthasarthy, K." Identification and Control of Dynamical Systems Using Neural Networks". *IEEE Transactions on Neural Networks* Vol.1, pp. 4-27 1990.

[7] Psaltis, D.; and Sideris, A." A Multilayered Neural Network Controller". *IEEE Control Systems Magazine* Vol.8, pp. 17-21 1988.

[8] Nguyen, D.; and Widrow, B. "Neural Networks for Self Learning Control Systems". *IEEE Control Systems Magazine* Vol.10, pp. 18-23, 1990.

[9] Lightbody, G.; and Irwin, G. "Nonlinear Control Structures based on Embedded neural System Models". *IEEE Transactions on Neural Networks* Vol.8, pp. 553-567 1997.

[10] Rugas, R." *Neural Networks a Systematic Introduction*". Springer 1996.

[11] McLoone, S.; and Irwin, G." Fast Parallel Off-line Training of Multilayer Perceptrons". *IEEE Transactions on Neural Networks* Vol.8, pp. 646-652 1997.

[12] Liu, T.; Elbuluk, M.; and Hussein, I. "Speed and Position Estimation and DSP Implementation in Permanent Magnet Synchronous Motors Drives Using Neural Networks". Proceeding of the fifth Brazilian Power Electronics Conference 1999.

[13] Lawrence, S.; Giles, L.; and Fong, S." Natural Language Grammatical Inference with Recurrent Neural Networks". *IEEE Transactions on Knowledge and Data Engineering* Vol.12, pp.126-140 2000

Appendix A

DC-Motor plant parameters:

The following parameters are chosen from a typical nameplate sheet and the frame selects is Frame 505 [1],

J: rotational inertia	$J = 2.2$ kg/m^2
B: viscous friction constant	$B = 0.314$ N.m.s/rad.
τ_m :mechanical time constant	$\tau_m = J/B = 7$ s
L_a : armature inductance	$L_a = 0.008$ H
R_a : armature resistance	$R_a = 0.1\ \Omega$
τ_a : armature time constant	$\tau_a = 0.08$ s
L_f : field inductance	$L_f = 60$ H
R_f : field resistance	$R_f = 75\Omega$
τ_f : field time constant	$\tau_f = L_f / R_f = 0.8$ s

and K: is the magnetization field current saturation curve with slope 6.25 mWb/A and saturated at 10 mWb.