MODIFIED TRAINING METHOD FOR FEEDFORWARD NEURAL NETWORKS AND ITS APPLICATION in 4-LINK SCARA ROBOT IDENTIFICATION

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ABSTRACT

In this research the results of applying Artificial Neural Networks with modified activation function to perform the online and offline identification of four Degrees of Freedom (4-DOF) Selective Compliance Assembly Robot Arm (SCARA) manipulator robot will be described. The proposed model of identification strategy consists of a feed-forward neural network with a modified activation function that operates in parallel with the SCARA robot model. Feed-Forward Neural Networks (FFNN) which have been trained online and offline have been used, without requiring any previous knowledge about the system to be identified. The activation function that is used in the hidden layer in FFNN is a modified version of the wavelet function. This approach has been performed very successfully, with better results obtained with the FFNN with modified wavelet activation function (FFMW) when compared with classic FFNN with Sigmoid activation function (FFS) .One can notice from the simulation that the FFMW can be capable of identifying the 4-Links of SCARA robot more efficiently than the classic FFS.

الخلاصة

في هذا البحث نتائج تطبيق الشبكات العصبية الصناعية ذات الدالة المحفزة المطورة لتعرف على أداء الروبوت المكون من أربع درجات من الحرية (٤ - DoF) لذراع الروبوت (SCARA) سيتم وصفها. النموذج المقترح لإستراتجية التعرف يتكون من شبكة التغذية العصبية ذات الدالة المطورة التي تعمل بالتوازي مع نموذج الروبوت SCARA. تم تدريب الشبكات العصبية ذات التغذية الأمامية (FFNN) على الروبوت ، دون الحاجة إلى أي معرفة سابقة عن النظام المراد التعرف علية.الدالة المحفزة المستخدمة في الطبقة المخفية من الشبكات العصبية الأمامية هي نسخة مطورة من دالة الموجات. وقد نفذ هذا التحوير بنجاح كبير ، مع الحصول على نتائج أفضل عند استخدام FFNN ذات الدالة المحفزة المطورة (FFMW) بالمقارنة مع FFNN الكلاسيكية . من خلال النتائج من الممكن ملاحظة أن FFMW قادرة على تحديد ٤ - روابط الى الروبوت نوع SCARA أكثر كفاءة من الشبكات العصبية ذات الدالة المحفزة من نوع Sigmoid.

Key index: **4-link SCARA robot, Identification , FFNN, wavelet activation function, modified wavelet activation function**

1. Introduction

In general, SCARA (Selective Compliance Assembly Robot Arm) robot, is a type of horizontal drive, and is used as the arrangement of parts to a printed wiring board and a product assembly; it is usually controlled by PID compensator to attain an exact movement. In controlling the SCARA robot, the arm head is moved by motors and the system is a Multiple-Input Multiple-Output (MIMO) system, so each link is required its accuracy and incoherency [Akamatsu S and et. al.,2009]. Recently the soft computing methodologies such as fuzzy logic, neural networks, and genetic algorithms have been used to solve the control problems of dynamic systems that are characterized with uncertainties in terms of structure and parameters. These uncertainties cannot adequately be described by deterministic models and therefore conventional control approaches based on such models are unlikely to result in the required performance. In the past two decades, a large number of research results in modeling and parameter identification have been reported. The intensive research in this area has focused on the torque-controlled robots with the dynamics being formulated on the basis of joint torque vs. joint motion [Hui J,2009- Abiyev and et.al.,2008]. System identification is a critical part of system analysis and control. Nonlinear system identification can be roughly divided into two categories, known structure and unknown structure. If the system structure is available a priori, the nonlinear system identification becomes a nonlinear parameter estimation problem [Er-Wei B. and et. al.,2007]. Some of researches use the recurrent neural networks for identification [Jiang Z. 2006- Khireddine M. S. and et. al. 2010- Passold F. 2009].

2. The Proposed Structure

The feed-forward neural network that is used in the non-parametric identification of the SCARA robot as shown in **Fig.1** consists of:

Input layer (12-nodes) each three combination representing position, Velocity, and acceleration.

The Hidden layer (40 nodes)

Output layer (4 nodes). Each node representing the torque of each link in the SCARA manipulator. The proposed model is shown in **Fig. 2**. The activation function that is used in the training algorithm is the modified of the wavelet function which is known as Superposed Logistic Function **(SLOG)** [Kuraz, Y,2005] and is described as equ. (1)

$$f(net) = [\frac{1}{(1+e^{(-net+1)})} - \frac{1}{(1+e^{(-net+3)})} - \frac{1}{(1+e^{(-net-3)})} + \frac{1}{(1+e^{(-net-1)})}] \quad (1)$$

While a modified SLOG function **(MSLOG)** is described in the form as shown in equ. (2)

$$f(net) = K * [\frac{1}{(1+e^{(-net+1)})} - \frac{1}{(1+e^{(-net+3)})} - \frac{1}{(1+e^{(-net-3)})} + \frac{1}{(1+e^{(-net-1)})}] \quad (2)$$

Where $net = \frac{(X*V)-b}{a}$

And $X = input\ vector$ and $V = weights\ of\ hidden\ layer$

The parameters K,a,b are selected by trial and error (K=2.5) in order to scale the data between (-1 and 1), and (a=b=5).

The derivative of equ. (2) is described in equ.(3)

$$f'(net) = K * [(\frac{e^{(-net+1)}}{(1+e^{(-net+1)})^2} - \frac{e^{(-net+3)}}{(1+e^{(-net+3)})^2} - \frac{e^{(-net-3)}}{(1+e^{(-net-3)})^2} + \frac{e^{(-net-1)}}{(1+e^{(-net-1)})^2}] \quad (3)$$

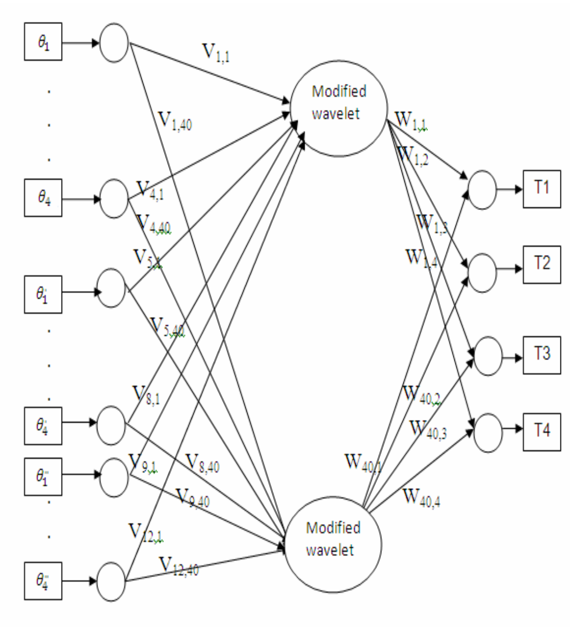


Figure 1 : FeedForward Neural Network With MSLOG

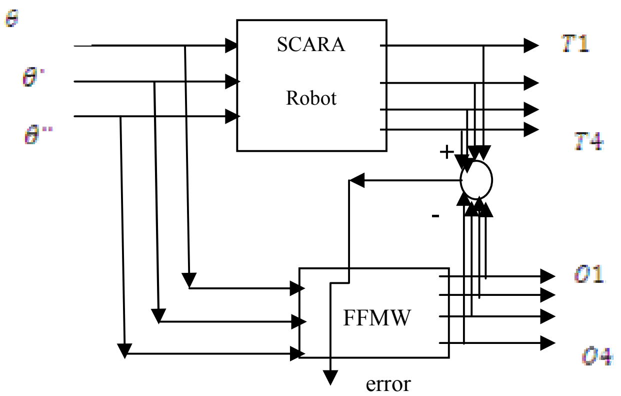


Figure 2 : Identification Model

The behavior of the MSLOG with different values of K is explained in the **Fig. 3**

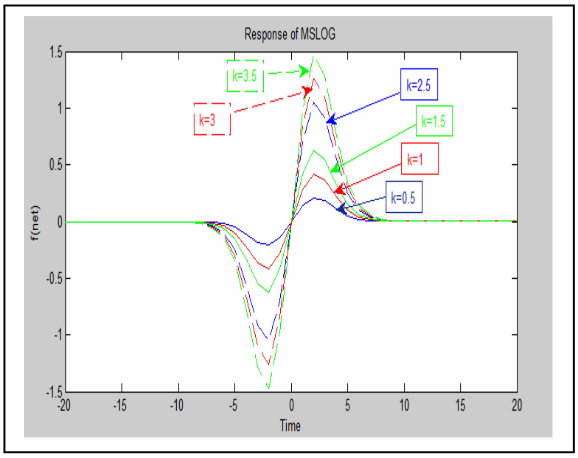
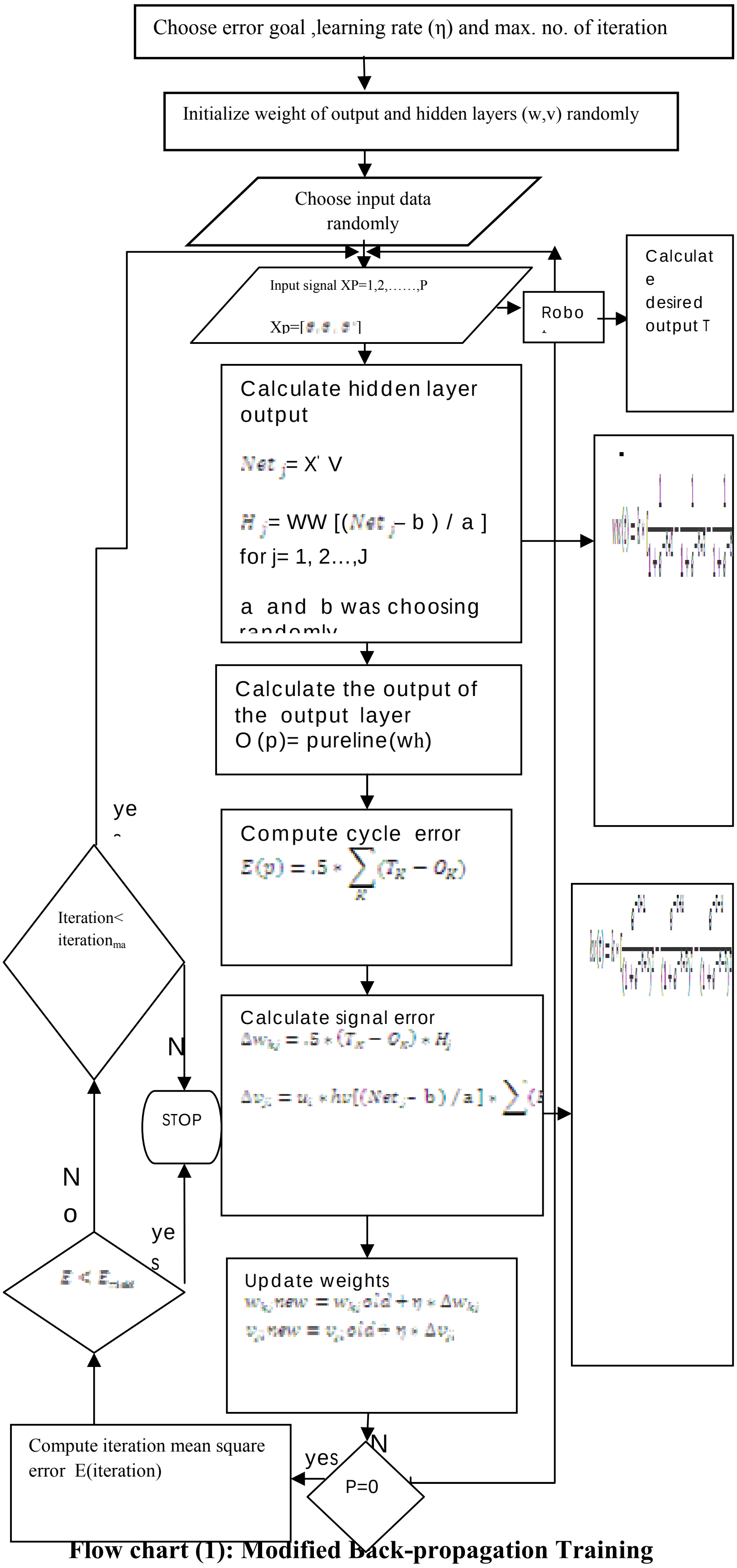


Figure 3 : Behavior of the MSLOG with different values of K

3. The Training Algorithm

The traditional Back-propagation training algorithm [Chaturvedi D., 2008] is used to train the FFS. The FFMW is trained using the modified training algorithm (Modified Back-propagation) which is shown in flow chart (1) the activation function that is used in the hidden layer is MSLOG, while the activation function of output layer is linear. This approach in training method is different from the traditional Back-propagation algorithm that is used sigmoid or tangential activation function in the hidden layer. The training algorithm is shown in flow chart (١). The simulation results are implemented using MATLAB (m-file).



Flow chart (1): Modified Back-propagation Training Algorithm for FFMW

4.The Robot Architecture:

Consider the SCARA manipulator of **Fig. 4**; this manipulator, which is an abstraction of the Calibration of SCARA Manipulator robot of **Fig. 5** [Spong M. W.,2004], consists of an Revolute Revolute Prismatic (RRP) arm and a one degree-of-freedom wrist, whose motion is a roll about the vertical axis. The first step is to locate and label the joint axes as shown. Since all joint axes are parallel, some freedoms are available in the placement of the origins. The origins are placed as shown for convenience using the Denavit -Hartenberg convention (D-H). The x_0 axis is established in the plane of the page as shown in **Fig. 4**. This is completely arbitrary and only affects the zero configuration of the manipulator, that is, the position of the manipulator when the joint parameters are given Table (1).

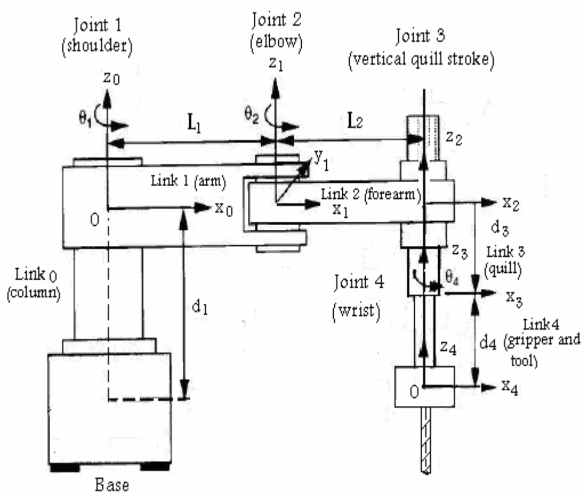


Figure 4: DH coordinate frame assignment for the SCARA manipulator.

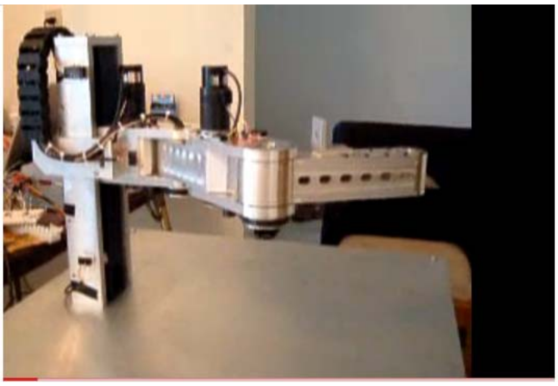


Figure 5: The SCARA Robot.

Table1: D-H parameters of the SCARA robot

i	θi	di	ai	αi
1	θ1	0	L1	0
2	θ2	0	L2	0
3	0	d*	0	0
4	θ4	d4	0	0

The ability to control a robot end effector in three-dimensional space requires the knowledge of a relationship between the robot's joints and the position and orientation of the end effector. The relationship requires the use and an understanding of the rotation matrix (Rot) and the translation vector (Trans). In this convention, each homogeneous transformation A_i is represented as a product of four basic transformations

$$A_i = Rot_{z,\theta_i}\, Trans_{z,d_i}\, Trans_{x,a_i}\, Rot_{x,\alpha_i}$$

$$= \begin{bmatrix} c\theta_i & -s\theta_i & 0 & 0 \\ s\theta_i & c\theta_i & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \times$$

$$\times \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & c\alpha_i & -s\alpha_i & 0 \\ 0 & s\alpha_i & c\alpha_i & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} c\theta_i & -s\theta_i c\alpha_i & s\theta_i s\alpha_i & a_i c\theta_i \\ s\theta_i & c\theta_i c\alpha_i & -c\theta_i s\alpha_i & a_i s\theta_i \\ 0 & s\alpha_i & c\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

where the four quantities θ_i, a_i, d_i, α_i are parameters associated with link i and joint i, and c denoting cosine and s for sine. The four parameters a_i, α_i, d_i, and θ_i in equ. (4) are generally given the names link length, link twist, link offset, and joint angle, respectively. These names derive from specific aspects of the geometric relationship between two coordinate frames [Spong M. W.,2004],.

For SCARA robot, the link parameters are shown in the Table 1, using the (D-H) convention, It is straightforward to compute the matrices A_i as shown below and the forward kinematic is given by equ. (5):

$$A_1 = \begin{bmatrix} c_1 & -s_1 & 0 & a_1 c_1 \\ s_1 & c_1 & 0 & a_1 s_1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_2 = \begin{bmatrix} c_2 & s_2 & 0 & a_2c_2 \\ s_2 & -c_2 & 0 & a_2s_2 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_3 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & d_3 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_4 = \begin{bmatrix} c_4 & -s_4 & 0 & 0 \\ s_4 & c_4 & 0 & 0 \\ 0 & 0 & 1 & d_4 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$T_0^4 = A_1A_2A_3A_4 = \begin{bmatrix} c_{12}c_4 + s_{12}s_4 & -c_{12}c_4 + s_{12}s_4 & 0 & a_1c_1 + c_{12} \\ s_{12}c_4 - c_{12}s_4 & -c_{12}c_4 + s_{12}s_4 & 0 & a_1s_1 + a_2s_{12} \\ 0 & 0 & -1 & -d_3 - d_4 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

It is well known that a robot manipulator can be modeled as a set of (n) rigid bodies connected in a serial chain with torques/forces acting at the joints. By applying the Lagrange equation of motion, the robot dynamic equation is derived as :

$$M(\theta)\ddot{\theta} + C(\theta)\dot{\theta} + F(\dot{\theta}) + G(\theta) + T_d = T \quad (6)$$

where θ is the nx1 vector of joint positions, T is the nx1 vector of applied joint forces/torques, $M(\theta)$ is the $(n\text{x}n)$ symmetric positive-definite manipulator inertia matrix, $C(\theta,\dot{\theta})$ is the (nx1) vector of centripetal and Coriolis torques, $F(\dot{\theta})$ is the (nx1) vector representing torques due to friction acting at the manipulator joints, $G(\theta)$ is the (nx1) vector of gravitational torques and T_d is the (nx1) vector of unknown signals due to un modeled dynamics and external disturbances.

This robot dynamic equation can also be written in a more compact form:

$$M(\theta)\ddot{\theta} + H(\theta,\dot{\theta}) + T_d = T \quad (7)$$

where:

$$H(\theta,\dot{\theta}) = C(\theta,\dot{\theta})\dot{\theta} + F(\theta) + G(\theta) \quad (8)$$

represents torques arising from centrifugal, Coriolis, gravity and friction forces.[Mosquera V., and Vivas A.,]

3. Simulation Results

The proposed model is implemented in 4-DOF SCARA manipulator. The torque of each link is shown in **Fig. 6-9** when the FFMW is used and **Fig. 10-13** when FFS is used. The results show that the proposed model gives excellent results in comparison with the results that the FFS give. The algorithm is implemented offline to identify torque of each link. The mean square error (MSE) of the proposed model is less than the MSE of the FFS, and the MSE when the neural networks with wavelet activation function (FFW) is used. This is shown in **Fig. 14**. The simulation also implemented online in order to show the efficiency of the proposed model. The results also show that the proposed model has good identification in terms with minimum error in comparison with the FFS and FFW. This is shown in **Fig. 15.** Table (2) and table (3) show that the FFMW reaches the error goal much faster than the FFW and FFS.

4. Conclusions

The simulation results show that the FFMW provides good results in comparison with FFS in terms of minimizing mean square error and training time, when offline and online training are used. This is because the nonlinear function that is used in the hidden layer is more efficient than the sigmoid function which the classic FFNN uses. The MSLOG has the capability of solving the nonlinearity of each link in the SCARA robot.

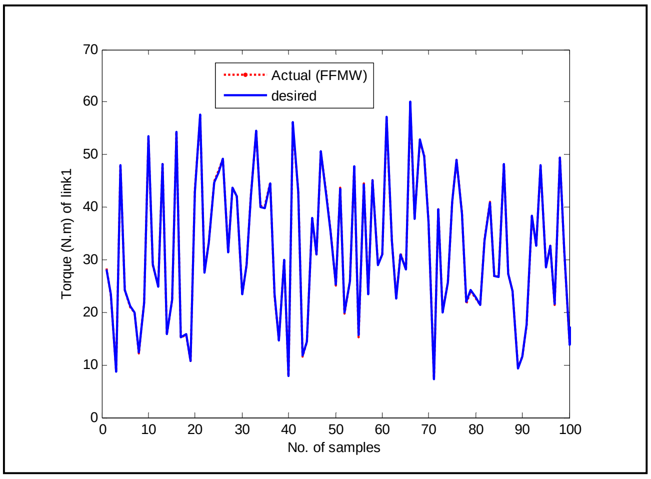


Figure 6 : Torque of link1 when Neural Network with modified Activation function is used

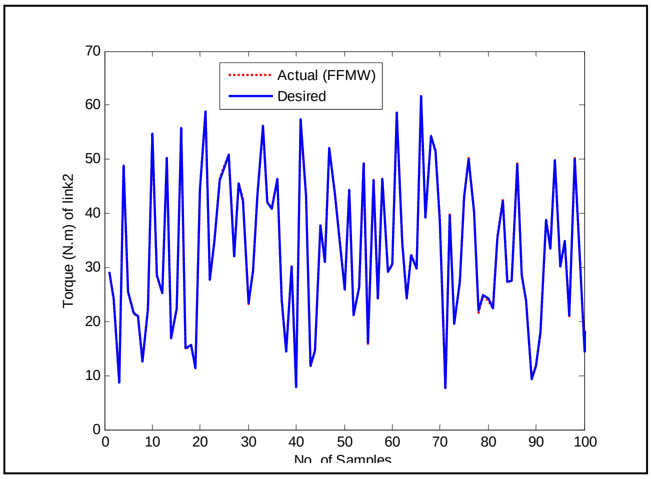


Figure 7 : Torque of link2 when Neural Network with modified Activation function is used

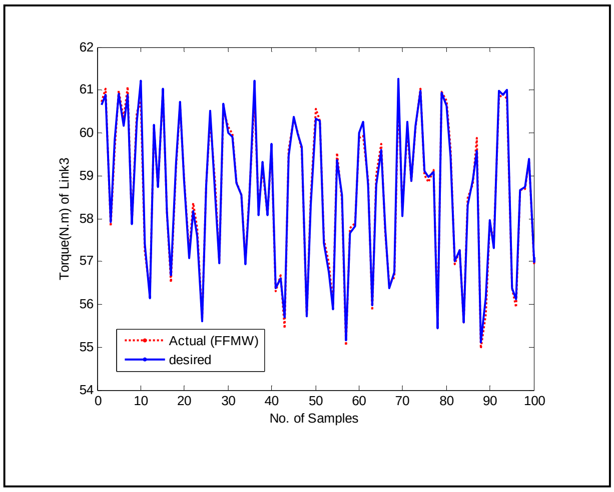


Figure 8 : Torque of link3 when Neural Network with modified Activation function is used

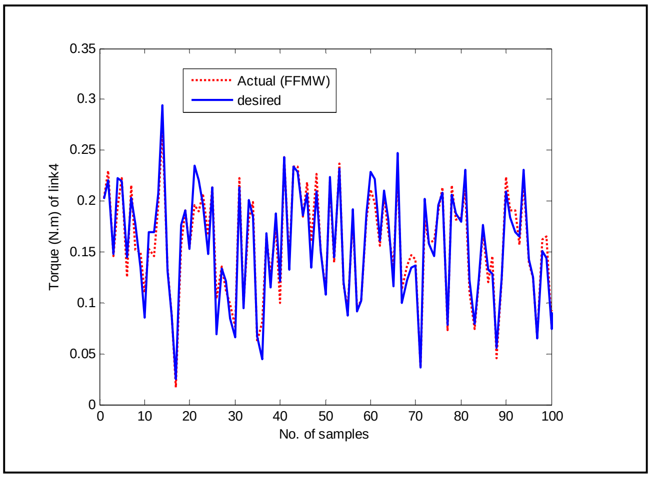


Figure 9: Torque of link4 when Neural Network with modified Activation function is used

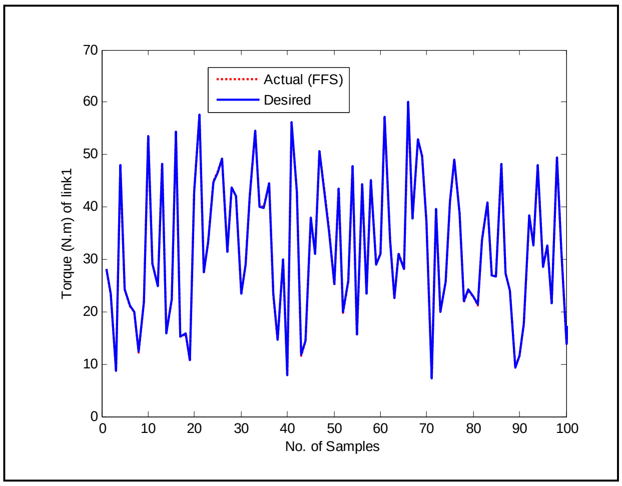


Figure 10: Torque of link1 when Neural Network with sigmoid Activation function is used

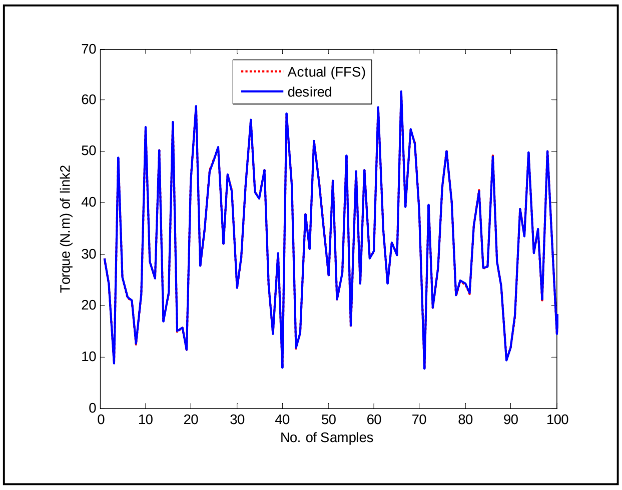


Figure 11: Torque of link2 when Neural Network with sigmoid Activation function is used

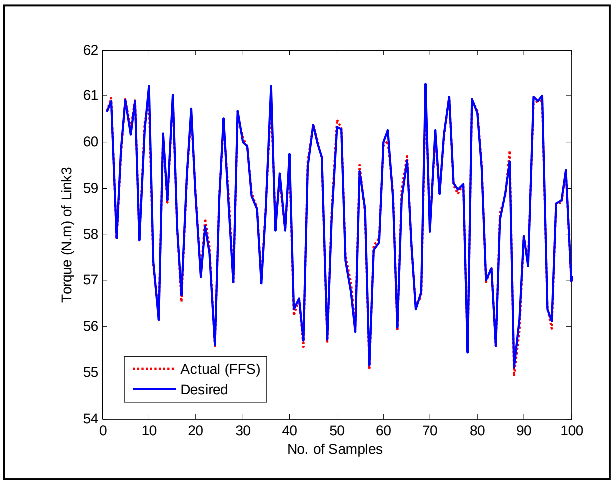


Figure 12: Torque of link3 when Neural Network with sigmoid Activation function is used

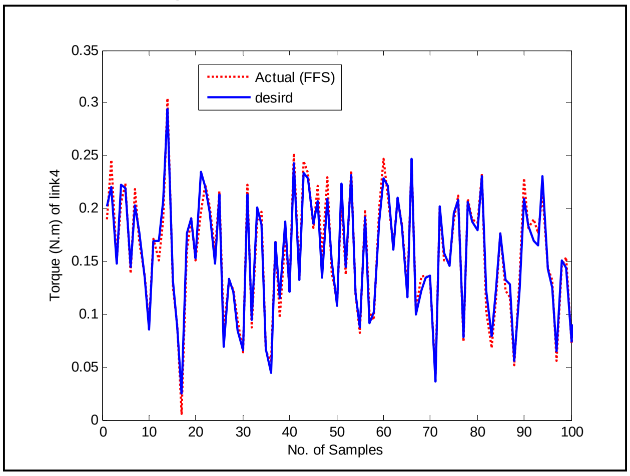


Figure 13: Torque of link4 when Neural Network with sigmoid Activation function is used

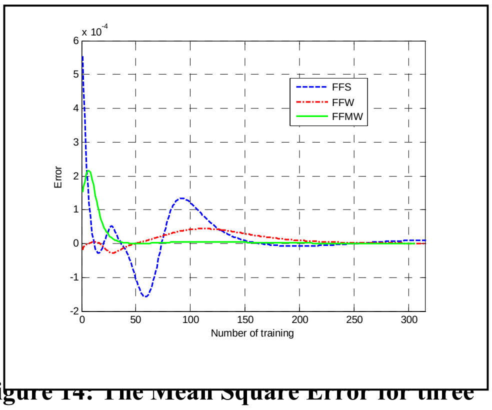


Figure 14: The Mean Square Error for three methods

Table 2: The mean square error when three methods are used

method	MSE	No. of Iteration
FFMW	8.3457e-010	315
FFW	1.0415e-006	315
FFS	9.1036e-006	315

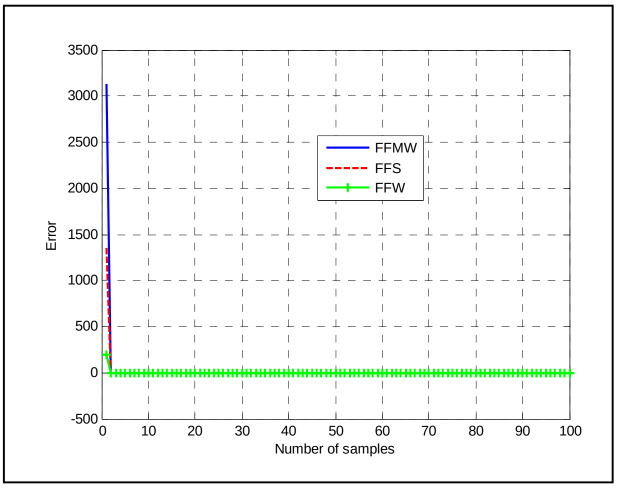


Figure 15: The error for three methods

Table 3: The error when three methods are used

method	Error	No. of samples
FFMW	4.3038e-006	100
FFW	1.3323e-004	100
FFS	3.7152e-005	100

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List of symbols

α_i	Angle of joint i
a	Constant of MSLOG
b	Constant of MSLOG
d_i	Offset of link i
K	Gain of MSLOG
θ	Position
$\dot{\theta}$	velocity
$\ddot{\theta}$	Acceleration
τ	Torque of SCARA robot