**Bulletin of Electrical Engineering and Informatics**
Vol. 12, No. 5, October 2023, pp. 2733~2744
ISSN: 2302-9285, DOI: 10.11591/eei.v12i5.5018


# A PSO optimized RBFNN and STSMC scheme for path tracking of robot manipulator

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**Article Info**

***Article history:***

Received Oct 16, 2022
Revised Nov 2, 2022
Accepted Dec 6, 2022

***Keywords:***

2–link robot manipulator
Minimum parameter learning
Particle swarm optimization
RBFNN
STSMC

**ABSTRACT**

This article presents the design of super twisting sliding mode control (STSMC) based on radial basis function neural network (RBFNN) for path tracking of two link robot manipulator. The proposed controller is utilized to guarantee and achieve that the surface of sliding can be in equilibrium point within a short time and avoid the problem of chattering at the output. The Lyapunov theory is used in presenting a new convergence proof. Also, the particle swarm optimization (PSO) algorithm is employed to give the optimal parameter values of the proposed controller. Simulation results explain the goodness of the proposed control method for trajectory tracking of 2-link robot manipulator when compared with SMC strategy. Results demonstrate that the the percentage improvement in mean square error (MSE) of using STSMC when compared with the standard SMC are 15.36%, 16.94% and 12.92%, for three different cases respectively.



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## 1. INTRODUCTION

For the time being, many studies have been focused in order to develop the capabilities of high–quality machines which can be compared with humans, with respect to many matters like safety, energy efficiency as well as the motions. The motions control has widely discussed for robot manipulators, but it is yet a challenging throttle since that such systems represent nonlinear systems, the parameters of model may be a time varying and can be uncertain, as well as the disturbances effect on operational conditions of system. Such difficulties demand the necessity to utilize advanced control methods to find solutions of the motions problem, such as fuzzy and neural controllers, sliding mode control (SMC), and adaptive control. Many researches and studies dealt with the subject of robotic systems and the various ways to control them in order to ensure better performance for such systems. According to Kim *et al*. [1], a terminal SMC had been combined with a time delay control in order to control the motions of the robotic excavator. The article results explained that the proposed controller gave good results to eliminate the effects of vibrations and disturbances and other difficulties in the robotic excavator. A combination of recursive terminal SMC and extended state observer was suggested, where, the tracking control of position for electro hydraulic system was confirmed to be bounded within a finite time using the theory of Lyapunov. The paper results shown that the suggested control scheme was unsensitive to the uncertainties of model as well as the external disturbances [2].

The control complexity of robot systems under the effects of disturbances and with taking the uncertainties in consideration was addressed. The fuzzy neural network-fuzzy system-backstepping control method was proposed, where the simulation results guaranteed an efficient, stable and accurate control [3]. Research by Choi *et al*. [4], adaptive SMC was designed, where the experiment and simulation results explained its goodness in providing a high precision of motion tracking. Proportional derivative control method with adjustable gains was suggested to control 2 degree-of-freedom (DOF) robot manipulator and solve the problem of regulation for the robot manipulators in the joint space. Results shown that the proposed controller and the proposed Lyapunov function achieved the asymptotically stability for the closed–loop system equilibrium point [5]. A fractional proportional-integral-derivative (PID) control strategy was designed to improve the better trajectory of minimum–jerk robotic manipulators. The gains of the proposed control scheme were optimized using particle swarm optimization (PSO) algorithm. The simulation outcomes demonstrated that the optimal proposed method improve the system performance [6].

Barrie *et al*. [7] focused on the state estimation and sensing for soft robots, a learning depending on framework to contact stress distribution and force prediction in the real time by employing finite element analysis models and deep learning was presented. The simulation results proved that such techniques were robust tools to decrease the computational complexity under alteration in the contact point, viewing angle, object material, occlusion level and object shape. A deep learning algorithm was suggested taking benefits of the environment finding the optimal behavior method to control the robotic manipulation and overcome the problem of the applications in such domain, like the efficiency of sample [8]. Nasir *et al*. [9] proposed a new hybrid scheme combining two algorithms (spiral dynamic algorithm and bacterial foraging algorithm). The proposed algorithm was used to obtain the optimal parameters of the fuzzy controller which had been employed to control the tracking of robot manipulator. Results explained that the suggested algorithm gives the accurate controller parameters for tracking with faster convergence speed. There are many challenges appeared in designing the controller such as the uncertainties and the robotic manipulator nonlinearities, so in [10], the model predictive control and a modified neural network algorithm had been suggested in order to achieve the performance stability requirements. The trajectory control of industrial robot manipulators using SMC, terminal SMC and backstepping control was discussed in [11]. The proposed controller guaranteed the stability requirements and the fast convergence via Lyapunov theory. Generally, the first order (SMC) is a simple control structure, but it is not suitable to achieve the stability requirements especially for more difficult systems because of the chattering problem at the output during its switching at high frequency [12]. The super-twisting SMC is an effective scheme used to solve many problems such as the instability of bus voltage for the bidirectional (DC–DC) converter in the photovoltaic [13]. The proposed controller replaces the (sign) function with the (saturation) function in order to overcome the chattering problem at the output. The experimental results explained that the super-twisting SMC controller method can minimize the fluctuation domain for the bus voltage, maintain the robustness and reduce the stability time.

The super twisting sliding mode control (STSMC) is a strong controller and can be used to achieve the stability requirements, so the super-twisting SMC scheme was suggested in steering the vehicle to obtain a good maneuvering especially in the cornering road [14]. Simulation results proved that the proposed controller offered a good performance in many terms such as the speed increasing and the stability of vehicle. The experimental studies for the active power filter shown that the adaptive STSMC has the best suppression of the harmonic and the steady-state properties of the dynamic systems than other control methods [15]. To avoid different restrictions of using the simple structure of (SMC), a control structure of higher order has been utilized in many applications, like the second order STSMC which is an efficient control scheme and characterized with many advantages including the following [16]: i) a little effect of chattering by using (STSMC) in comparison with using the traditional SMC; ii) the system states can be reached to the equilibrium points within a finite time by using STSMC, where the sliding variable and the sliding variable derivative equal to zero value in finite time; and iii) the STSMC scheme achieves the exact convergence.

In this study, an adaptive STSMC can alter the control torque depending on the tracking errors, which reduces the chattering problem that appear in the SMC. The combination between the intelligent control scheme and the STSMC method reduced the error at the output of system and improve the quality and the transient response of the (2-DOF) robot manipulator. When the robotic system has uncertain parameters and there is a disturbance effects on it, the mathematical model of robotic system may be difficult to realize. Also, better results with very high precision must be achieved, so, a robust optimal STSMC with neural network based radial basis function (RBF) are designed to solve such difficulties. The gain of the parameters of proposed scheme are tuned using (PSO) algorithm. The unknown parameters in the system can be approximated by using radial basis function neural network (RBFNN) with minimum parameter learning (MPL), where the values of weights are altered online depending on adaptive laws in order to control and improve the system output. Lyapunov function is utilized in the new developed convergence proof. Simulation results explain that the optimal STSMC and RBFNN achieve the performance more efficient. The rest of this paper is organized as follows: section 2 presents the dynamic model of 2-DOF robot manipulator. Section 3 presents the design of STSMC scheme–based RBFNN with MPL. The optimization of parameters of the proposed control scheme using PSO algorithm is explained in section 4. In section 5, the simulation results are presented. Section 6 gives the conclusion of this paper.

## 2. DYNAMIC MODEL OF 2-DOF ROBOT MANIPULATOR

The (2–DOF) robot manipulator represents a mechanical system which utilizes many computer controllers for supporting end effector or single platform. It becomes gradually less solid with additional components. The (2–DOF) robot manipulator is generally limited in a workspace; where, for instance, it usually can't exceed obstacles. The calculations are usually difficult and may lead to many solutions, such that the desired performance of robot manipulation may be achieved [17]. The robot manipulator is a (2–DOF) planar arm consist of two links and a rotate joint as explained in Figure 1. Electrical motor is used to actuate every link, where one is located in the base and the another one is located in the radius. The two links and the axes of motor are directly connected.

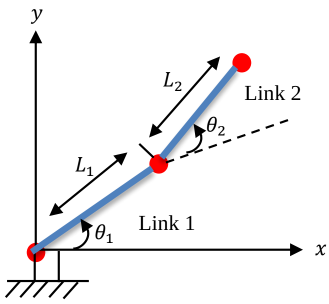



Figure 1. Schematic block diagram of 2–DOF robot manipulator

In this study, $m_1$ and $m_2$ are the link masses which concentrated at end of links, $L_1$ and $L_2$ are the length of links. The positions of the two links have been represented with the vector $[\theta_1\ \theta_2]^T$. The dynamic of 2 links manipulator is defined by [18] as:

$$M(\theta)\ddot{\theta} + C(\theta,\dot{\theta})\dot{\theta} + G(\theta) + F(\dot{\theta}) + u_d = u \tag{1}$$

Where the matrix of the inertia $M(\theta)$ is:

$$M(\theta) = \begin{bmatrix} d_1 + d_2 + 2d_3\cos(\theta_2) & d_2 + d_3\cos(\theta_2) \\ d_2 + d_3\cos(\theta_2) & d_2 \end{bmatrix} \tag{2}$$

The Coriolis and centrifugal forces $C(\theta,\dot{\theta})$ vector given as:

$$C(\theta,\dot{\theta}) = \begin{bmatrix} -d_3\dot{\theta}_2 sin(\theta_2) & -d_3(\dot{\theta}_1 + \dot{\theta}_2) sin(\theta_2) \\ d_3\dot{\theta}_1 sin(\theta_2) & 0 \end{bmatrix} \tag{3}$$

The gravitational forces $G(\theta)$ vector is defined as:

$$G(\theta) = \begin{bmatrix} d_4 g cos(\theta_1) + d_5 g cos(\theta_1 + \theta_2) \\ d_5 g cos(\theta_1 + \theta_2) \end{bmatrix} \tag{4}$$

Where $d_1 = (m_1 + m_2)L_1^2$, $d_2 = m_2 L_2^2$, $d_3 = m_2 L_1 L_2$, $d_4 = (m_1 + m_2)L_1$ and $d_5 = m_2 L_2$, and $d = [d_1, d_2, d_3, d_4, d_5] = [2.9, 0.76, 0.87, 3.04, 0.87]$. The friction force $F(\dot{\theta}) = 0.2\, sgn(\dot{\theta}_2)$. The control input is the torque $(u)$ which is produced by the electro-hydraulic rotary actuators on the joint of robot. The unknown disturbance $(u_d)$ is defined as $u_d = [0.2\sin(t) \quad 0.2\sin(t)]^T$. Where (1) can be rearranged as:

$$\ddot{\theta} = M(\theta)^{-1}[u - C(\theta,\dot{\theta})\dot{\theta} - G(\theta) - F(\dot{\theta}) - u_d] \tag{5}$$

It is clear to notice that, the angular positions are ($\theta_1$ and $\theta_2$), their derivative is the angular velocity ($\dot{\theta}_1$ and $\dot{\theta}_2$). Thus, a dynamic model can be given as:

$$\frac{d}{dt}\begin{bmatrix} \theta_1 \\ \theta_2 \\ \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix} = \begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \\ M(\theta)^{-1}[u - C(\theta,\dot{\theta})\dot{\theta} - G(\theta) - F(\dot{\theta}) - u_d] \end{bmatrix} \tag{6}$$

## 3. THE DESIGN OF SUPER TWISTING SLIDING MODE CONTROL SCHEME–BASED RBFNN WITH MINIMUM PARAMETER LEARNING

The STSMC represents a strong scheme that can limit the effect of chattering with keeping the different properties of SMC. The STSMC involves two terms, the first one is a discontinuous function for sliding variable, and the other term is a continuous function for the sliding variable derivative. When the system oscillates with high frequency and a small amplitude depending on a desired trajectory, this procedure is referred as the motion of sliding mode [19]. The parameters of STSMC are not related to disturbance and the parameters of system. Thus, the STSMC characteristics improves the robustness of systems with a good response speed. Also, the STSMC avoids the chattering problem at the output. The sliding motion may be very difficult to retain balanced when the system final trajectory reaches the sliding mode surface [20]. For (2–DOF) manipulator the tracking error $e = [e_1\ e_2]^T$ at each joint can be given as:

$$e(t) = \theta_d(t) - \theta(t) \tag{7}$$

Where $\theta_d = [\theta_{d1}\ \theta_{d2}]^T$ and $\theta = [\theta_1\ \theta_2]^T$ are the desired and actual angles of the links. The goals of control are satisfied when ($e(t)\ \rightarrow 0$, $\dot{e}(t) \rightarrow 0$ as $t \rightarrow \infty$). The function of the sliding mode surface is defined as:

$$s = \delta e + \dot{e} \tag{8}$$

Where $s = [s_1\ s_2]^T$, the positive parameter of design is $\delta$ and $\delta = [\delta_1\ \delta_2]^T$, then the derivative of (8) gives:

$$\dot{s} = \delta\dot{e} + \ddot{e} = \delta\dot{e} + \ddot{\theta}_d - \ddot{\theta} \tag{9}$$

By substituting (2) into (9), we can have:

$$\dot{s} = \delta\dot{e} + \ddot{\theta}_d - M(\theta)^{-1}[u - C(\theta,\dot{\theta})\dot{\theta} - G(\theta) - F(\dot{\theta}) - u_d] \tag{10}$$

In order to eliminate the chattering problem at the system output while keeping the different properties of SMC, a second order robust strategy, STSMC has been suggested. The control signal of STSMC composed of two parts, the equivalent control ($u_{eq}$) which works to maintain the variables on sliding surface without taken in consideration the effect of disturbances and the uncertainty. The other part is the switching control ($u_{sw}$). Thus, via STSMC, the control signal has been adopted as [21]:

$$u = M(\theta)(u_{eq} + u_{sw}) \tag{11}$$

The control law is denoted as:

$$u_{eq} = \delta\dot{e} + \ddot{\theta}_d + M(\theta)^{-1}C(\theta,\dot{\theta})\dot{\theta} + M(\theta)^{-1}G(\theta) \tag{12}$$

The switching control can be denoted as:

$$u_{sw} = -K\sqrt{|s|}sign(s) + m \tag{13}$$

$$\dot{m} = -Bsign(s) \tag{14}$$

Where the parameters ($K$ and $B$) are positive constant, $K = [K_1\ K_2]^T$and $B = [B_1\ B_2]^T$. The switching control can be designed basing on the (STSMC) and written as:

$$u_{sw} = -K\sqrt{|s|}sign(s) - B\int sign(s)dt \tag{15}$$

The final control output can be written as:

$$u = M(\theta)[\delta\dot{e} + \ddot{\theta}_d + M(\theta)^{-1}C(\theta,\dot{\theta})\dot{\theta} + M(\theta)^{-1}G(\theta) - K\sqrt{|s|}sign(s) - B\int sign(s)dt] \tag{16}$$

$$\dot{\theta} = \dot{\theta}_d - \dot{e} = \dot{\theta}_d - (s - \delta e) = \dot{\theta}_d - s + \delta e \tag{17}$$

By substituting, in (1),

$$\begin{aligned} &M(\ddot{\theta}_d - \dot{s} + \delta\dot{e}) + C\dot{\theta} + G + F + u_d = u \\ &M\dot{s} = M(\ddot{\theta}_d + \delta\dot{e}) + C(\dot{\theta}_d - s + \delta e) + G + F + u_d - u \\ &\qquad = M(\ddot{\theta}_d + \delta\dot{e}) - Cs + C(\dot{\theta}_d + \delta e) + G + F + u_d - u \end{aligned} \tag{18}$$

Let $f = M(\ddot{\theta}_d + \delta\dot{e}) + C(\dot{\theta}_d + \delta e) + G + F$, so:

$$M\dot{s} = -Cs + f + u_d - u \tag{19}$$

In order to improve the performance, eliminate the error and chattering problem of the classical SMC and to achieve the tracking accuracy, a combination of RBFNN and STSMC is designed. The feedforward RBFNN is utilized to approximate and estimate the system unknown function [22]. The MPL scheme is employed to reduce the online adaptive elements number to only one element [23], where the MPL can be utilized in RBF neural control to decrease the burden of computational and increase the performance of the system in real time.

The structure of RBFNN consists of the input layer, hidden layer, and output layer as given in Figure 2, where the input layer collects the nodes of input signals nodes and transmits them to the hidden layer which adopts the Gaussian function RBFs. The output layer selects the linear transformation function in order to implement the weighted evaluation on hidden layer signal. The proposed controller is shown in Figure 3.

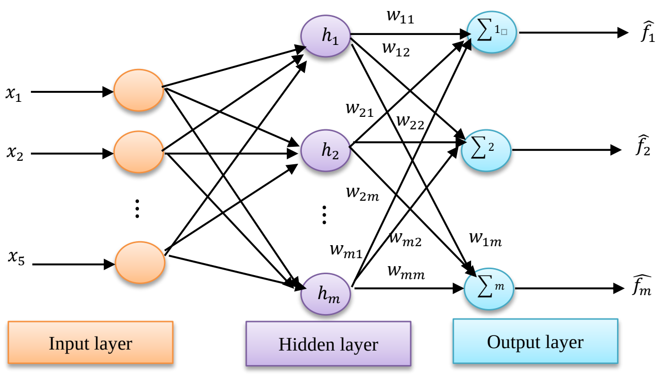



Figure 2. Structure of RBFNN

Particularly, the modeling information that given in (1) is often unknown, so the unknown function $(f)$ will be approximated using RBF network based on MPL, thus the controller will be designed without need to know these parameters. At $(i^{th})$ joint, the RBF neural algorithm is denoted as:

$$h_{ij} = e^{\frac{\|x_i - c_{ij}\|^2}{\sigma_{ij}^2}}, j = 1, 2, \ldots, g \tag{20}$$

$$f_i = w_i^T h_i + \varepsilon_i \tag{21}$$

Where the RBF input is $x_i = [e_i\ \dot{e}_i\ \theta_{di}\ \dot{\theta}_{di}\ \ddot{\theta}_{di}]$ and $g = 5$, the approximation error is $(\varepsilon_i)$, the value of ideal weight is $(w_i)$, and $h_i = [h_{i1}\ h_{i2}\ h_{i3} \ldots h_{im}]$. The RBF inputs are selected as: $X = [x_1\ x_2\ x_3\ x_4\ x_5]$, where $x_1 = e$, $x_2 = \dot{e}$, $x_3 = \theta_d$, $x_4 = \dot{\theta}_d$ and $x_5 = \ddot{\theta}_d$. The estimation of $(w_i)$ is defined as $(\widehat{w}_i)$, then,

$$\widetilde{w}_i = w_i - \widehat{w}_i \tag{22}$$

According to Shamloo *et al*. [24], the minimum parameter is defined as $(\phi = max_{1\le i\le n}\{\|w_i\|^2\})$, where, $(\phi > 0)$, the estimation of $(\phi)$ is $(\hat{\phi})$, and $\tilde{\phi} = \hat{\phi} - \phi$. Demonstrate the following:

$$W = \begin{bmatrix} w_1 \\ w_2 \\ . \\ . \\ w_n \end{bmatrix}, H = \begin{bmatrix} h_1 \\ h_2 \\ . \\ . \\ h_n \end{bmatrix}, \text{and } \widetilde{W} = \widehat{W} - W$$

According to general linear operator Ge *et al*. [25],

$$W^{\circ}H = \begin{bmatrix} w_1^T h_1 \\ w_2^T h_2 \\ . \\ . \\ w_n^T h_n \end{bmatrix}, s^{\circ}s = \begin{bmatrix} s_1^T s_1 \\ s_2^T s_2 \\ . \\ . \\ s_n^T s_n \end{bmatrix}, H^{\circ}H = \begin{bmatrix} h_1^T h_1 \\ h_2^T h_2 \\ . \\ . \\ h_n^T h_n \end{bmatrix},$$

so $(f)$ can be defined as:

$$f = W^{\circ}H + \varepsilon \tag{23}$$

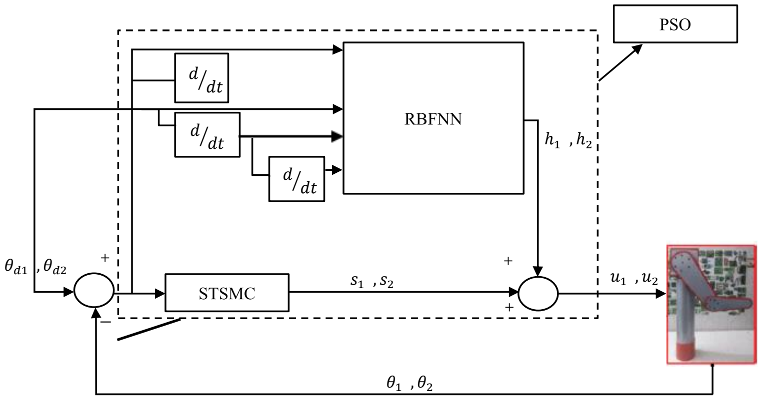



Figure 3. Structure adaptive STSMC based RBFNN of 2–DOF robot manipulator

The control law is designed as:

$$u = \frac{1}{2}\hat{\phi}s^{\circ}(H^{\circ}H) + K_v s - u_{sw} \tag{24}$$

By substituting (24) in (19), we will have:

$$M\dot{s} = -(C + K_v)s + f + u_d - \frac{1}{2}\hat{\phi}s^{\circ}(H^{\circ}H) + u_{sw} \tag{25}$$

To achieve the stability requirement, the Lyapunov function is defined as [26]:

$$V = 2B\sqrt{s} + \frac{1}{2}(K\sqrt{|s|}sign(s-m))^2 + \frac{1}{2}m^2) + \frac{1}{2\gamma}\tilde{\phi}^2 \tag{26}$$

Where $(\gamma)$ is a constant and $(\gamma > 0)$, the quadratic form for $(V)$ is defined as: $V = \Omega^T P\Omega + \frac{1}{2\gamma}\tilde{\phi}^2$, where $\Omega = \begin{bmatrix}\sqrt{|s|}sign(s) & m\end{bmatrix}^T$. $V = \frac{1}{2}s^2 + \frac{1}{2\gamma}\tilde{\phi}^2$, and $P = \begin{bmatrix}K^2 + 4B & -K \\ -K & 2\end{bmatrix}$. $\dot{V} = \dot{\Omega}^T P\Omega + \Omega^T P\dot{\Omega} + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}}$, $\dot{V} = \dot{s}sign(s)\left(2B + \frac{1}{2}K^2\right) - K\sqrt{|s|}sign(s) - \frac{Km\dot{s}}{2\sqrt{|s|}} + 2m\dot{m} + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}}$. The adaptive law is designed as:

$$\dot{\hat{\phi}} = \frac{\gamma}{2}\sum_{i=1}^{n} s_i^2 \,\|h_i\|^2 \tag{27}$$

Where $(n)$ denotes to links number and in this paper $(n = 2)$. In order to satisfy the requirements of stability, the condition that $\dot{V} \leq 0$ must be satisfied and the gains of STSMC method $(K)$ and $(B)$ must achieve the following conditions:

$$K > 2\Delta \text{ and } B > \frac{K\Delta^2}{8(K-2\Delta)} \tag{28}$$

Where the bounded constant is $\Delta$ and $\Delta > 0$.

## 4. THE OPTIMIZATION OF PARAMETERS OF THE PROPOSED CONTROL SCHEME USING PARTICLE SWARM OPTIMIZATION ALGORITHM

During the evolution design of STSMC based RBFNN control scheme for the robot manipulator, non-linear optimal control for multi-DOF electro-hydraulic robotic manipulators four parameters have been appeared in the design, denoted as $(\delta$, $K$, $B$, and $K_v)$. In order to achieve the performance and the stability of closed loop system, it is essential to optimize the design parameters since the procedure of trial and error for alteration the design parameters are not actually practical and it is impossible to detect the optimal values of the design parameters. In this work, the PSO technique is applied to find the best optimal parameters of the proposed controller to improve the dynamic performance for the (2-DOF) robot manipulator. The (PSO) swarm intelligence method can easily be used to solve the optimization problems and find the optimum solution. This algorithm has been was firstly proposed via (Kennedy and Eberhart) in 1995 [27]. The PSO algorithm is based on three basic steps, these are: i) generating the velocities and positions of the particles, ii) adaptation of positions, and iii) adaptation of velocities.

At each iteration, particle velocity is computed as [28]:

$$V_i^{m+1} = w.V_i^m + A_1.rand(p_{best} - Y_i^m) + A_2.rand(g_{best} - Y_i^m) \tag{29}$$

Where the weights ($w$, $A_1$, and $A_2$) represent the inertia, self-confidence, and the confidence of swarm respectively. The proper range of ($A_1$, and $A_2$) values is between (1–2), but in many problems, it is suitable to choose the value (2) [21]. A random value with zero number for the inertia weight and mean weight are generated randomly by ($rand$) function as:

$$w = w_{max} - (w_{max} - w_{min})\, {}^{p}/_{p_{max}} \tag{30}$$

Where ($p$ and $p_{max}$) are the present and maximum iterations number, the maximum weight and minimum weight are denoted as ($w_{max}, w_{min}$) respectively. The suitable values of $w_{max}$ is 0.9 and $w_{min}$ is 0.4 [21]. The position is updated by [31]:

$$Y_i^{m+1} = Y_i^m + V_i^{m+1} \tag{31}$$

Where ($Y_i^m$ and $Y_i^{m+1}$) are the present position and updated position values, containing the proposed controller parameters which are needed to be tuned. The proposed control method using PSO for (2–DOF) robot manipulator is depicted in Figure 4. The PSO algorithm is running many times to find the optimum parameters and the cost function of the proposed controller and finally, terminate the algorithm. In order to obtain the best optimum values of the controller parameters, the cost function is based on minimization the following (8):

$$Cost = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_1^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_2^2} \tag{32}$$

Where the error at each link ($j = 1{,}2$) is ($e_1$ and $e_2$) respectively.

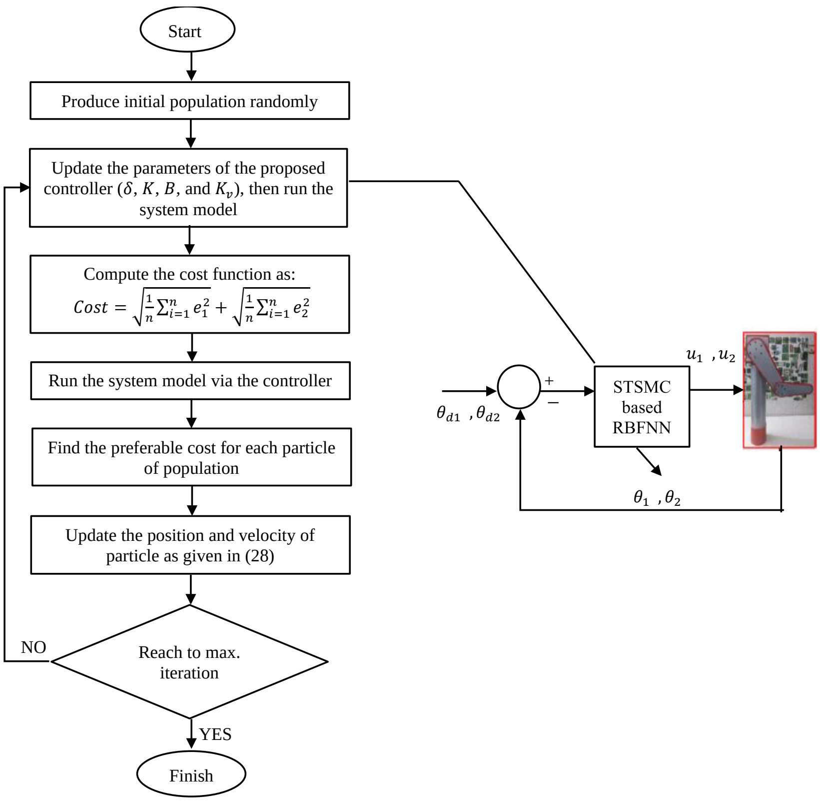



Figure 4. Flowchart of the PSO technique for tuning parameters of STSMC based RBFNN

## 5. SIMULATION RESULTS

In this study, the effectiveness and the quality of the proposed STSMC based on RBFNN is designed to control the tracking of 2–DOF robot manipulator. The parameters of the proposed control scheme of STSMC and RBFNN controller is optimized via PSO algorithm and compared with the SMC controller. Figures 5(a) and (b) explains the fitness function tracing versus (100) iterations using PSO method at each joint of robot manipulator, where it is a clear that best parameters of the proposed controller can be obtained with a good performance and minimum optimization time using PSO technique. The optimal design parameters of the proposed controller are listed in Table 1. In this study, results have been discussed for three types of trajectories under the consideration of the system uncertainties for STSMC based RBFNN scheme and SMC scheme. The selected trajectories are expressed as in the following:

- $\theta_{1,d} = 1.25 - \frac{5}{7}e^{-t} + \frac{7}{20}e^{-4t}$ , $\theta_{2,d} = 1.25 - e^{-t} + \frac{1}{4}e^{-4t}$
- $\theta_{1,d} = 1 - \cos(t)$, $\theta_{2,d} = 1 - \cos(2t)$
- $\theta_{1,d} = 0.1sin\ (3t)$, $\theta_{2,d} = 0.1\cos\ (3t)$

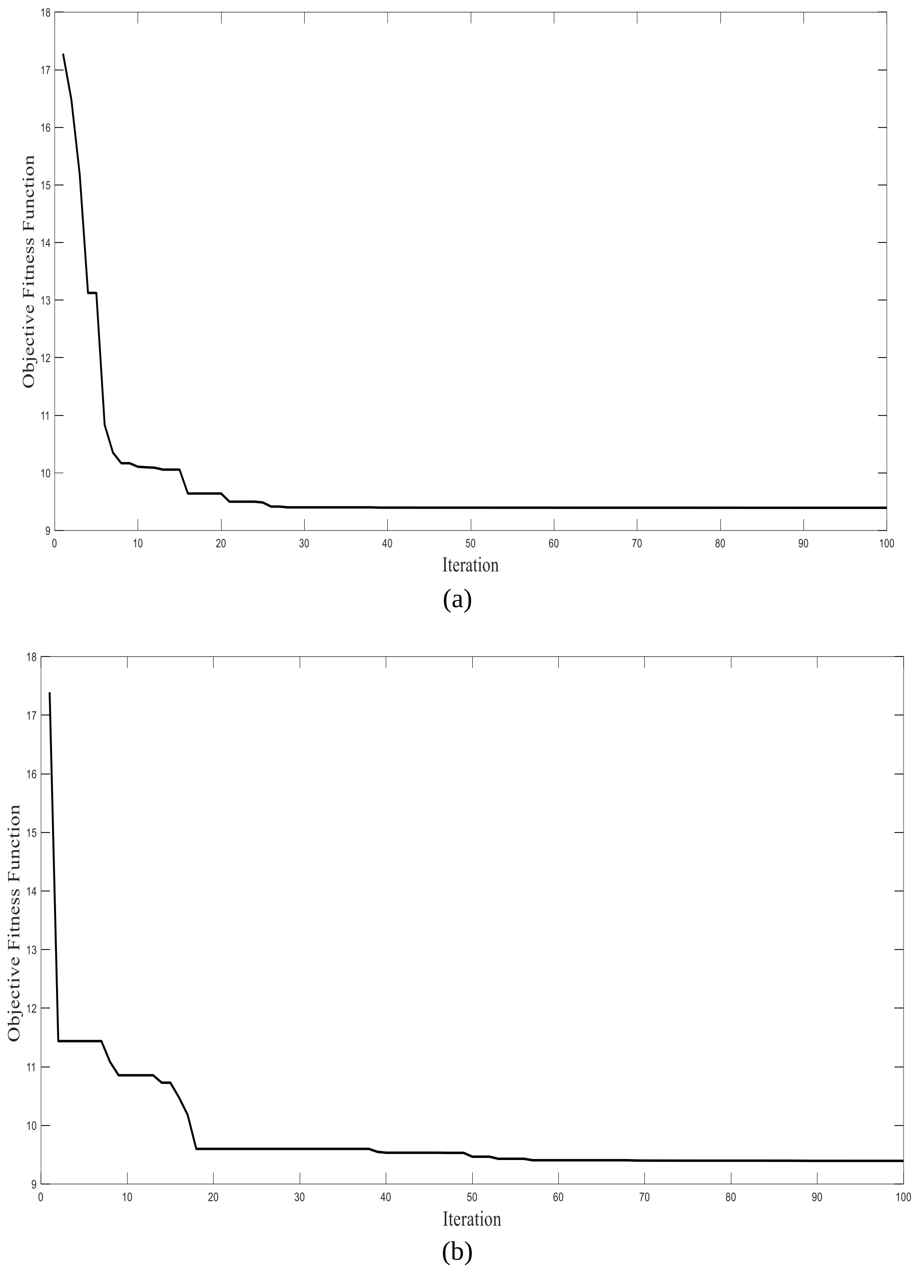



Figure 5. Behaviors of the fitness function depending on PSO for (a) STSMC and RBFNN and (b) SMC

Figures 6(a) and (b) demonstrates the tracking of the angular position at each joint of robot manipulator for the first trajectory, where the transient amplitude of the output responses with the suggested control method STSMC and RBFNN optimized with PSO is improved and effectively minimize the chattering at the output response and it is better than using SMC strategy. As shown in Figures 7(a) and 7(b), Figures 8(a) and (b), the maximum overshoot is decreased for the angular position at each link for the second and third trajectories using the proposed controller. The STSMC based on RBFNN strategy has a superior performance and achieves the robustness characteristics. The mean square error (MSE) of the two links by utilizing the proposed control schemes can be given in Table 2. Where the STSMC based RBFNN controller has a superior value of MSE than SMC method for the three trajectories.

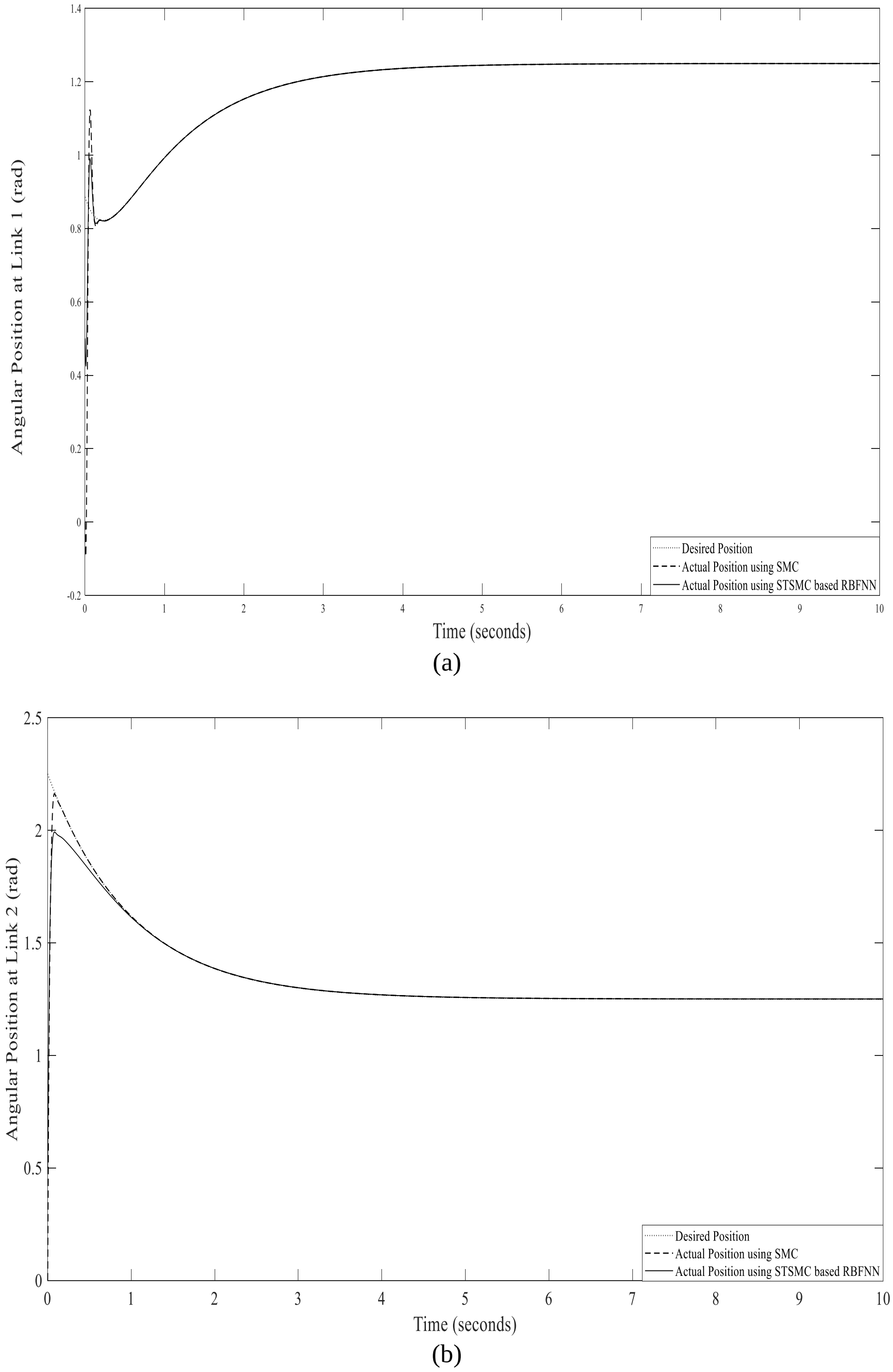
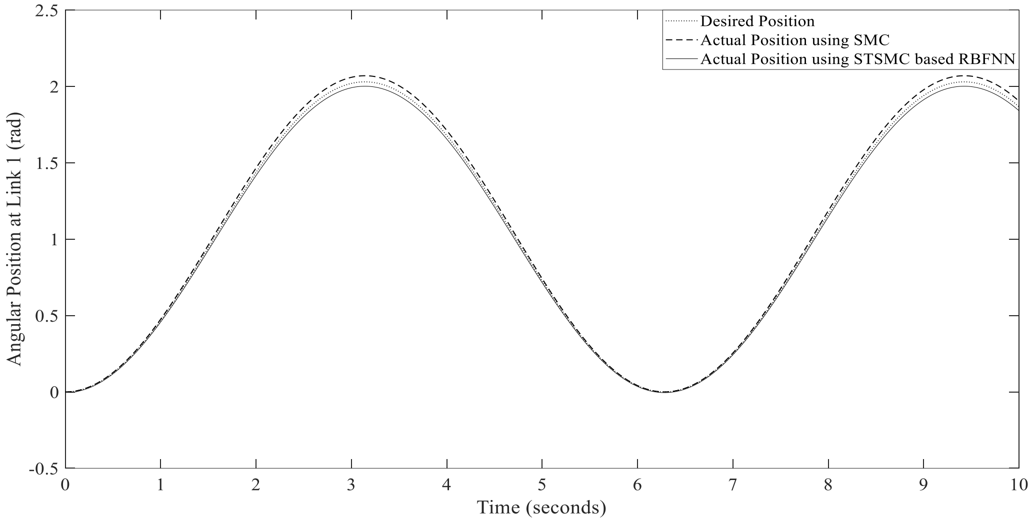


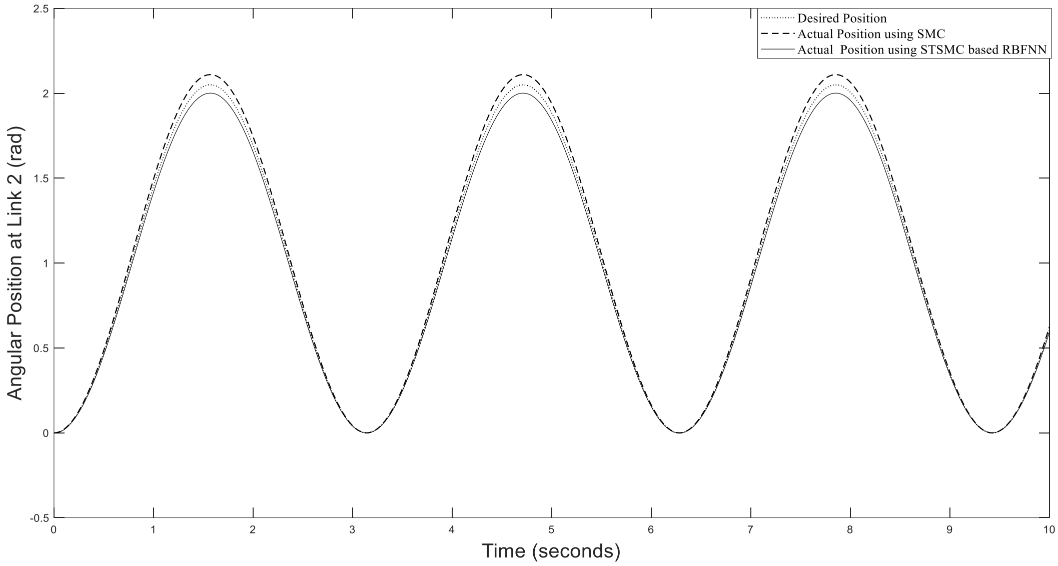

Figure 6. Angular position tracking for the first trajectory at (a) link 1 and (b) link 2

Table 1. The optimal parameters of proposed controller

| Parameters at each joint ($j = 1{,}2$) | Optimal values of the designed parameters |
|---|---|
| $\delta_1$ | 150.1415 |
| $K_1$ | 149.6059 |
| $B_1$ | 75.1257 |
| $K_{v1}$ | 187.3421 |
| $\delta_2$ | 121.4902 |
| $K_2$ | 137.3878 |
| $B_2$ | 69.2216 |
| $K_{v2}$ | 196.6432 |




(a)

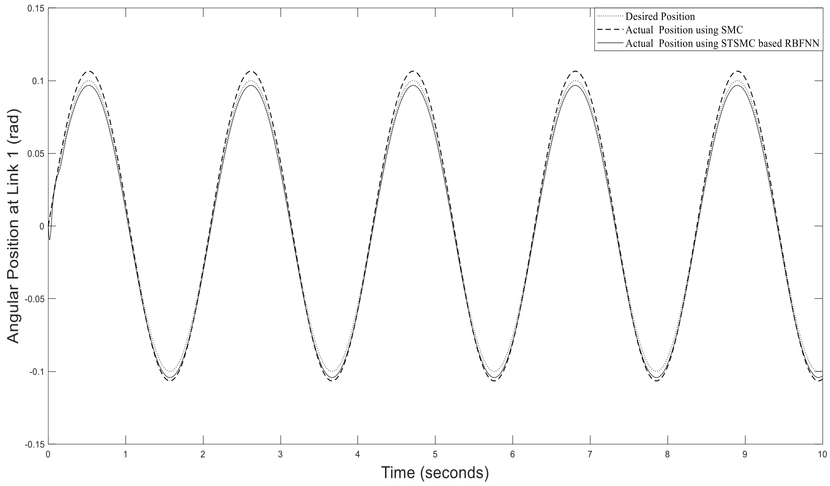



(b)

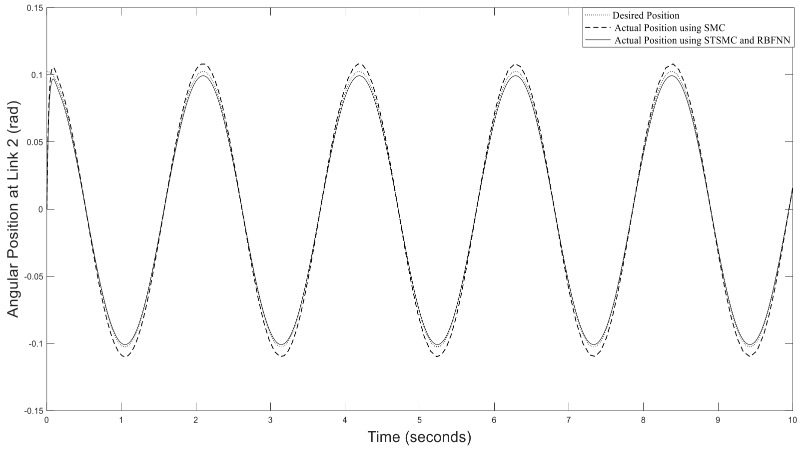
Figure 7. Angular position tracking for the second trajectory at (a) link 1 and (b) link 2

Table 2. The MSEs for both links of the proposed controllers

| The trajectory | STSMC based RBFNN | SMC |
|---|---|---|
| The 1st trajectory | $6.39 \times 10^{-5}$ | $4.16 \times 10^{-4}$ |
| The 2nd trajectory | $9.03 \times 10^{-6}$ | $5.33 \times 10^{-5}$ |
| The 3rd trajectory | $9.89 \times 10^{-6}$ | $7.65 \times 10^{-5}$ |




(a)




(b)

Figure 8. Angular position tracking for the third trajectory at: (a) link 1 and (b) link 2

## 6. CONCLUSION

The STSMC method based on RBFNN is designed to control the movements of joints of robot manipulator. A control scheme has been established so that an accurate tracking is achieved. The proposed control scheme integrates the advantages of STSMC control method which can deal with the uncertainty of the system and satisfy the stability requirements of the system. The optimized parameters of the suggested controller have been obtained using PSO technique. The proposed control scheme performs better than SMC scheme. Results demonstrate that the RBFNN STSMC method can better solve the tracking problem of robot manipulators when compared with the conventional SMC method, the STSMC based on RBFNN controller guarantee the stability requirement of the system and minimize the effect of uncertainties. The proposed control strategy may be used for more complex (6–DOF) robot arm in a future work.

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