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Controlling a Two-Link Robot using Sliding Mode Control Combined with Neural Network

Ayoub Belkheir and El Mehdi Mellouli
Laboratory of Engineering, Systems, and Applications (LISA)
Sidi Mohamed Ben Abdellah University Fez, Morocco
E-mail: belkheir.ayoub@usmba.ac.ma, mellouli_elmehdi@hotmail.com

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Abstract: This research focuses on designing and controlling a MIMO (Multiple Input and Multiple Output) two-link robot using a mix of Sliding Mode Control (SMC) and artificial intelligence (specifically, Radial Basis Function Neural Network (RBFNN)). In the first section, we present the model dynamics of this system in the state space. Then, in the second section, we provide a new approach in which we attempt to identify the optimum performance and attain stability in finite time by predicting the nonlinear dynamics of the system and also reducing the disturbance and uncertainty impacts on the system using artificial intelligence. And, by examining the Lyapunov function we can prove the stability of the system. Based on the simulations of the new technique presented in the latter portion of this work, we illustrate and enhance the superiority of our methodology over existing ways, their positive outcomes, and their effectiveness in time tracking, stability, and robustness.

Keywords: Two-link robot, Normal sliding mode control, Artificial intelligence, Lyapunov function, Non-linear function.

1. Introduction

In all industrial sectors, automatic systems are becoming increasingly crucial. This makes quality control in terms of speed, security, and resilience extremely important, and as a result, this sector has become increasingly vital over the past 20 years. Because of this, commercial enterprises research this area in an effort to create new techniques that will lessen disturbance, perturbations, and uncertainties and therefore improve system stability.

One of the most common robots in the industrial sector is the two-link robot [3, 4, 5, 8, 12, 14, 26, 27], which is specifically employed in the manufacture of cars and airplanes. Due to the fact that speed and stability are crucial for this sort of robot, various societies attempt to research this type of robot in order to provide alternative methods for its optimum control and application.

Since sliding mode control has been researched for so long, it is currently one of the most popular technics used in nonlinear control theory. The literature has numerous studies on sliding mode control and its extensions, including [1, 2, 4, 7, 8, 10, 11, 15, 24]. The goal of sliding mode control in recent years has been to produce finite-time convergence to the equilibrium of the relevant closed-loop system.

Artificial neural networks [3, 12, 14, 22] have been used to model nonlinearities rather frequently. A neural network is among the strongest approximators because it can estimate any nonlinearities with arbitrary precision as its size and complexity increase. Due to their effectiveness, neural networks are also widely used to identify and control nonlinear systems. For the underlying nonlinearity, neural networks are used in the majority of these works as nonlinear models.

The combination of SMC and neural networks is applied in many research, but in this work, we will try to use SMC as a sliding manifold and RBFNN [21, 22, 23] to estimate the unknown dynamics of the hidden state in order to make the system more robust and stable.

To guarantee the stability of the two-link robot system using normal Sliding Mode Control, and RBF neural network, we study the Lyapunov function [3, 4], to know the strength of this strategy.

At the begging of this paper, we will present the two link-robot models, in the second part we will describe the proposed strategy, after that, the third part will show the results of our proposed two-link robot control strategy, and, the conclusion and perspective will be the last part.

2. Two-link Robot Model

The two-link robot represented in Fig. 1. model is expressed as follows [4, 26, 28]:

$$\begin{gathered} M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = T \\ \dot{T} = J.i - B.T - E.\dot{q}, \end{gathered} \tag{1}$$

where q, i, and T are the angle, current, and torque respectively of the two-link robot.

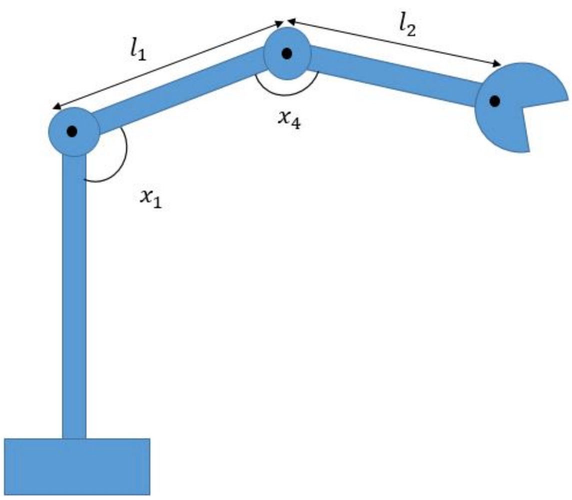

Fig. 1. Two-link robot model.

And B, J, and E represent the diagonal matrices that depend on the temperature, the thermo- dynamics parameters, and the initial conditions.

$M(q)$, $C(q,\dot{q})$, and G(q) are the positive-definite symmetric inertia matrix, the centrifugal forces, and the gravitational matrices respectively. Here

$$M(q) = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix},$$

where

$$\begin{aligned} M_{11} &= I_1 + I_2 + 4m_2 l_1^2 + 4m_1 m_2 l_1 l_2 \cos(q_2) \\ M_{12} &= I_2 + 2m_2 l_1 l_2 \cos(q_2) \\ M_{21} &= I_2 + 2m_2 l_1 l_2 \cos(q_2) \\ M_{22} &= I_2 \end{aligned}$$

and $C(q,\dot{q}) = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}$,

where

$$\begin{aligned} C_{11} &= -2m_2 l_1 l_2 \dot{q}_2 \sin(q_2) \\ M_{12} &= -2m_2 l_1 l_2 (\dot{q}_1 + \dot{q}_2) \sin(q_2) \\ M_{21} &= -2m_2 l_1 l_2 \dot{q}_1 \sin(q_2) \\ M_{22} &= 0 \end{aligned}$$

and

$$G(q) = \begin{bmatrix} m_2 g l_2 \sin(q_1 + q_2) + m_1 g l_1 \sin(q_1) \\ m_2 g l_2 \sin(q_1 + q_2) \end{bmatrix}$$

This system is represented in state space as follows:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= x_3 \\ \dot{x}_3 &= f_1(x) + g_{11}(x_1, x_4)u_1 + g_{12}(x_1, x_4)u_2 \\ \dot{x}_4 &= x_5 \\ \dot{x}_5 &= x_6 \\ \dot{x}_6 &= f_2(x) + g_{21}(x_1, x_4)u_1 + g_{22}(x_1, x_4)u_2, \end{aligned} \tag{2}$$

where

$$\begin{aligned} &\mathrm{x} = [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5 \quad x_6]^T \\ &\mathrm{U} = [u_1 \quad u_2]^T \\ &f(x) = [f_1(x) \quad f_2(x)]^T \end{aligned}$$

$$g(x_1, x_4) = \begin{bmatrix} g_{11}(x_1, x_4) & g_{12}(x_1, x_4) \\ g_{21}(x_1, x_4) & g_{22}(x_1, x_4) \end{bmatrix}$$

3. The Control Strategy

3.1. Control Law

Let's take the two following sliding surfaces:

$$\begin{gathered} S_1 = \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 \\ S_2 = \ddot{e}_2 + \lambda_3 \dot{e}_2 + \lambda_4 e_2, \end{gathered} \tag{3}$$

where λ_1, λ_2, λ_3 and λ_4 are the positives constants and $e_1$and e_2 are the angle errors of q_1 and q_2 respectively which are expressed as following:

$$e_1 = x_1 - x_{1d} \text{ and } e_2 = x_4 - x_{4d} \tag{4}$$

and x_{1d} , x_{4d} are the desired trajectories, which are represented in Fig. 2.

Now, we derive the sliding surface:

$$\begin{gathered} \dot{S}_1 = \dddot{e}_1 + \lambda_1 \ddot{e}_1 + \lambda_2 \dot{e}_1 \\ \dot{S}_2 = \dddot{e}_2 + \lambda_3 \ddot{e}_2 + \lambda_4 \dot{e}_2 \end{gathered} \tag{5}$$

From equations (4),

$$\dot{S}_1 = \ddot{x}_1 - \ddot{x}_{1d} + \lambda_1 \ddot{e}_1 + \lambda_2 \dot{e}_1$$
$$\dot{S}_2 = \ddot{x}_4 - \ddot{x}_{4d} + \lambda_3 \ddot{e}_2 + \lambda_4 \dot{e}_2 \quad (6)$$

And from equation (6) and using equation (2), we find:

$$\dot{S}_1 = f_1(x) + g_{11}(x_1, x_4)u_1 + g_{12}(x_1, x_4)u_2 - \ddot{x}_{1d} + \lambda_1 \ddot{e}_1 + \lambda_2 \dot{e}_1$$
$$\dot{S}_2 = f_2(x) + g_{21}(x_1, x_4)u_1 + g_{22}(x_1, x_4)u_2 - \ddot{x}_{4d} + \lambda_3 \ddot{e}_2 + \lambda_4 \dot{e}_2 \quad (7)$$

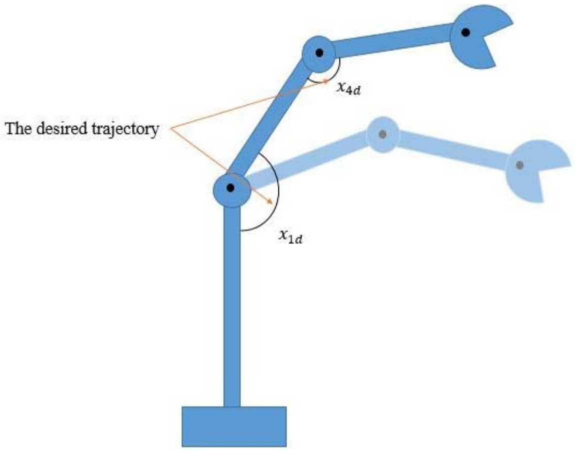

Fig. 2. Desired trajectory x_{1d} and x_{4d}.

To guarantee the stability of the system we define the Lyapunov function:

$$V_1 = \frac{1}{2} S_1^2 \quad \text{and } V_2 = \frac{1}{2} S_2^2 \quad (8)$$

The system is stable if the derivative of the Lyapunov function $\dot{V}$ is negative, which means that:

$$\dot{V}_1 = \dot{S}_1 S_1 < 0 \text{ and } \dot{V}_2 = \dot{S}_2 S_2 < 0 \quad (9)$$

That's why we define the sliding surface derivative:

$$\dot{S}_1 = -K_1 \text{sgn}(S_1) \text{ and } \dot{S}_2 = -K_2 \text{sgn}(S_2) \quad (10)$$

where K_1 and K_2 are the positive constants.

Using the equations of (7), and to be satisfying to the condition (9), we can write the control laws as follows,

$$U_1 = \frac{1}{g_{11}(x_1, x_4)} [\ddot{x}_{1d} - f_1(x) - g_{12}(x_1, x_4)u_2 - \lambda_1 \ddot{e}_1 - \lambda_2 \dot{e}_1 - K_1 sgn(S_1)]$$
$$U_2 = \frac{1}{g_{22}(x_1, x_4)} [\ddot{x}_{4d} - f_2(x) - g_{21}(x_1, x_4)u_1 - \lambda_3 \ddot{e}_2 - \lambda_4 \dot{e}_2 - K_2 sgn(S_2)] \quad (11)$$

In order to force the system to track the desired trajectory, minimize errors, guarantee stability, and use artificial intelligence as a way to estimate the unknown dynamics and the nonlinear dynamics of the system to define new control laws more performances and efficiencies.

3.2. Approximating the Unknown Dynamics and Nonlinear Functions using Artificial Intelligence

In this section, we will see how we develop the algorithm using a neural network, which their role is to approximate the nonlinear f_1 and f_2 of the system, in order to force the system to track the desired trajectory x_{1d} and x_{4d}.

To approximate f_1 and f_2 we build an RBFNN network, which is based on radial basic function, their role is to give an approach to a non-linear function (Fig. 3).

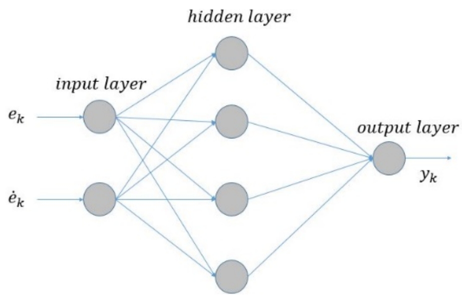

Fig. 3. Radial Basis Function Neural Network or RBFNN.

The RBFNN is a neural network that contains three layers: the input layer, is to take the data from the feedback errors e_1 and e_2, the hidden layer where each node contains a radial basic function as an activation function, and the output of each node is defined as a Gaussian function.

$$h_i(y) = \exp\left(-\frac{\|y_k - c_i\|^2}{b_i^2}\right) \quad (12)$$

where $y_k = [e_k \quad \dot{e}_k]^t$ (k=1,2) is the input of the neural network, c_i is a center vector of each hidden layer node with the same dimension as y, $\|y_k - c_i\|$ represent the Euclidean distance the input and each hidden node, and b_i is a positive scalar of each hidden node.

And the output layer calculates the estimated function based on the output of each node on the hidden layer using the following expression:

$$Y_i(y) = \sum_{j=1}^{N} w_{ij} h_j(x) \quad (13)$$

From equations (12) and (13), the nonlinear estimates are as follows:

$$\hat{f}_1(\mathrm{x}) = \hat{w}_1{}^t.[\,h_i(y)] \text{ and } f_1(\mathrm{x}) = w_1{}^t.[\,h_i(y)]$$
$$\hat{f}_2(\mathrm{x}) = \hat{w}_2{}^t.[\,h_i(y)] \text{ and } f_2(\mathrm{x}) = w_2{}^t.[\,h_i(y)], \quad (14)$$

where $\hat{w}_1{}^t$, $\hat{w}_2{}^t$, and $w_1{}^t$ and $w_2{}^t$ are the approximated weights and the ideal weights of the network respectively.

The control lows will be as follow:

$$U_1 = \frac{1}{g_{11}(\hat{x}_1,\hat{x}_4)}[\ddot{x}_{1d} - \hat{f}_1(x) - g_{12}(\hat{x}_1,\hat{x}_4)u_2 - \lambda_1\ddot{e}_1 - \lambda_2\dot{e}_1 - K_1 sgn(S_1)]$$
$$U_2 = \frac{1}{g_{22}(\hat{x}_1,\hat{x}_4)}[\ddot{x}_{4d} - \hat{f}_2(x) - g_{21}(\hat{x}_1,\hat{x}_4)u_1 - \lambda_3\ddot{e}_2 - \lambda_4\dot{e}_2 - K_2 sgn(S_2)] \quad (15)$$

So,

$$\dot{S}_1 = -\tilde{f}_1(\mathrm{x}) - K_1.sgn(S_1)$$
$$\dot{S}_2 = -\tilde{f}_2(\mathrm{x}) - K_2.sgn(S_2), \quad (16)$$

where

$$\tilde{f}_1(\mathrm{x}) = (w_1{}^t - \hat{w}_1{}^t).[\,h_i(x)]$$
$$\tilde{f}_2(\mathrm{x}) = (w_2{}^t - \hat{w}_2{}^t).[\,h_i(x)] \quad (17)$$

Then,

$$\tilde{f}_1(\mathrm{x}) = \tilde{w}_1{}^t.[\,h_i(y)] \text{ and } \tilde{f}_2(\mathrm{x}) = \tilde{w}_2{}^t.[\,h_i(y)] \quad (18)$$

where $\tilde{f}_1(\mathrm{x})$ and $\tilde{f}_2(\mathrm{x})$ are the difference between the ideal and estimated unknown dynamic function, $\tilde{w}_1{}^t = w_1{}^t - \hat{w}_1{}^t$ and $\tilde{w}_2{}^t = w_2{}^t - \hat{w}_2{}^t$ are the difference between the ideal and the approximated weight.

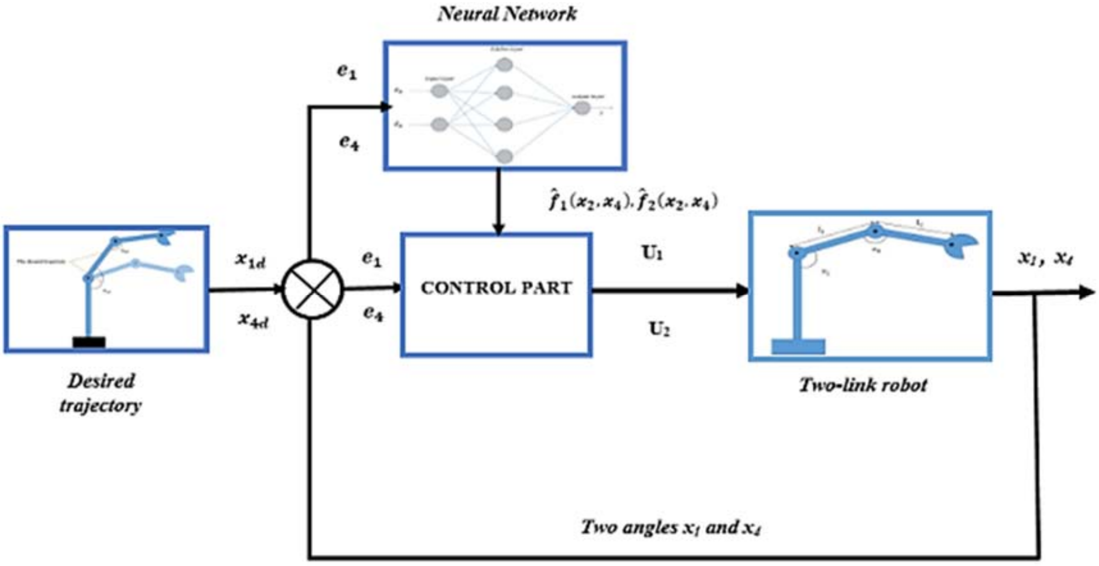

Fig. 4. Proposed approach.

3.3. Stability Analysis

To make the system stable we define the Lyapunov function as in [10]:

$$V_{1\_rbnn} = \frac{1}{2}S_1{}^2 + \frac{1}{2}\beta_1\tilde{w}_1{}^t\tilde{w}_1$$
$$V_{2\_rbnn} = \frac{1}{2}S_2{}^2 + \frac{1}{2}\beta_2\tilde{w}_2{}^t\tilde{w}_2, \quad (19)$$

where β_1 and β_2 are the positive constants.

The derivative of the equation of the Lyapunov functions is written as follows:

$$\dot{V}_{1\_rbnn} = \dot{S}_1 S_1 - \beta_1\tilde{w}_1{}^t\dot{\tilde{w}}_1$$
$$\dot{V}_{2\_rbnn} = \dot{S}_2 S_2 - \beta_2\tilde{w}_2{}^t\dot{\hat{w}}_2 \quad (20)$$

From (16) and (18), we find:

$$\dot{V}_{1\_rbnn} = -\tilde{w}_1{}^t(S_1.[\,h_i(x)] + \beta_1\dot{\hat{w}}_1) - K_1.sgn(S_1)$$
$$\dot{V}_{2\_rbnn} = -\tilde{w}_2{}^t(S_2.[\,h_i(x)] + \beta_2\dot{\hat{w}}_2) - K_2.sgn(S_2) \quad (21)$$

We assume that the terms $\dot{\hat{w}}_1$ and $\dot{\hat{w}}_2$ are:

$$\dot{\hat{w}}_1 = -\frac{1}{\beta_1}S_1[\,h_i(x)]$$
$$\dot{\hat{w}}_2 = -\frac{1}{\beta_2}S_2[\,h_i(x)] \quad (22)$$

So, using the results of (22) and the equations in (21), the system will be stable and the derivative of V_{1_rbnn} and $\dot{V}_{2\_rbnn}$ are satisfied to the Lyapunov theory

$$\begin{aligned}\dot{V}_{1\_rbnn} &= -K_1.\,sgn(S_1) \leq 0 \\ \dot{V}_{2\_rbnn} &= -K_2.\,sgn(S_2) \leq 0\end{aligned} \qquad (23)$$

From equations (20) and (24), we can assume that the system is stable and it will obtain the sliding manifold in finite time.

4. Simulation

In this section, we share the findings as well as the criteria that guided the creation of our plan. We test the strength of the neural network structure we suggest and evaluate its effectiveness using the sliding mode control.

4.1. Simulation 1

In this simulation we will take the parameter gain values of the sliding manifold λ_1 =25, λ_2 = 2000, λ_3 = 20, and λ_4 = 1500, then we find the following results with $x_{1d} = \cos(t)$ and $x_{1d} = \cos(t)$ are desired trajectory (Figs. 5-10).

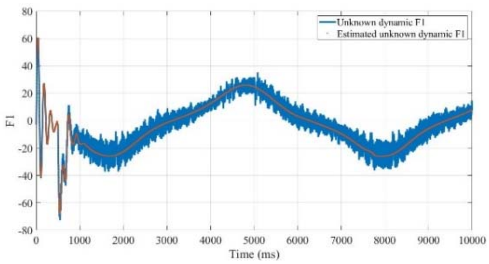

Fig. 5. Estimated dynamic unknown function F_1.

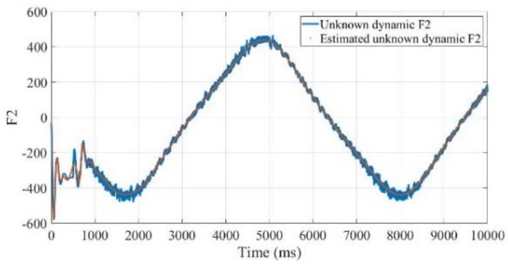

Fig. 6. Estimated dynamic unknown function F_2.

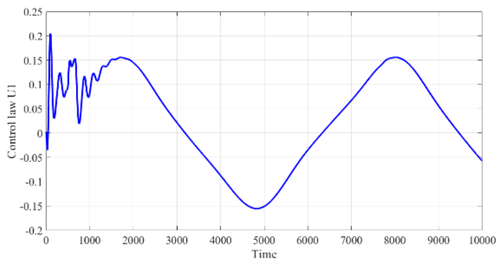

Fig. 7. The control law u_1 generated using the dynamic functions estimates.

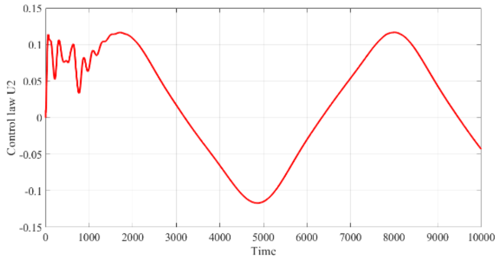

Fig. 8. The control law u_2 generated using the dynamic functions estimates.

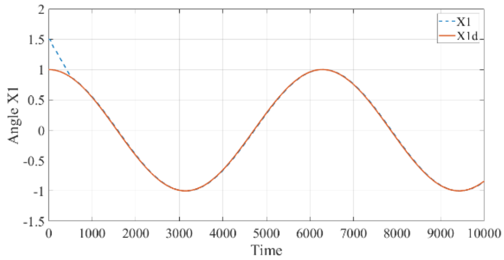

Fig. 9. Desired trajectory x_{1d} and estimate trajectory x_1.

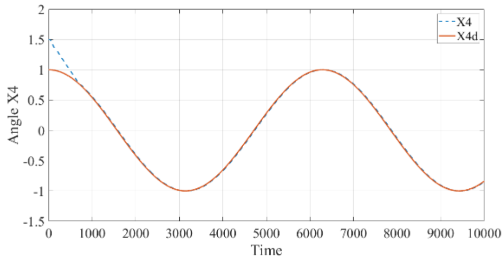

Fig. 10. Desired trajectory x_{4d} and estimate trajectory x_4.

4.2. Simulation 2

Now, let's take the parameter gain values λ_1 = 12.5, λ_2 = 1000, λ_3 = 10, and λ_4 = 750 of the sliding manifold, then we find the following results (Figs. 11-16).

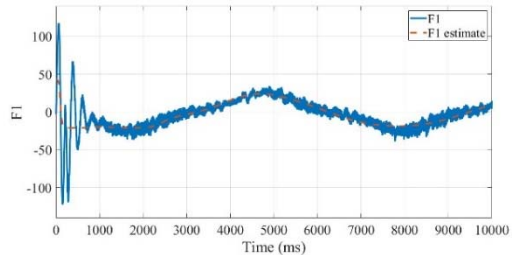

Fig. 11. Estimated dynamic unknown function F_1.

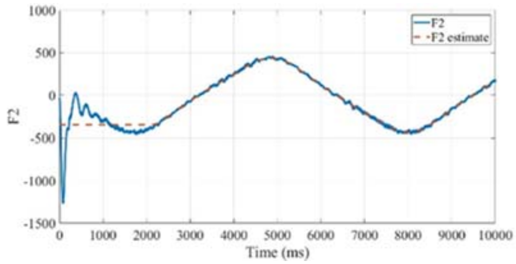

Fig. 12. Estimated dynamic unknown function F_2.

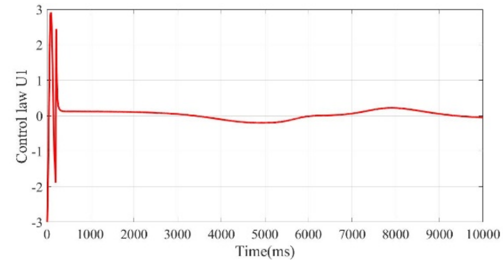

Fig. 13. The control law u_1 generated using the dynamic functions estimates.

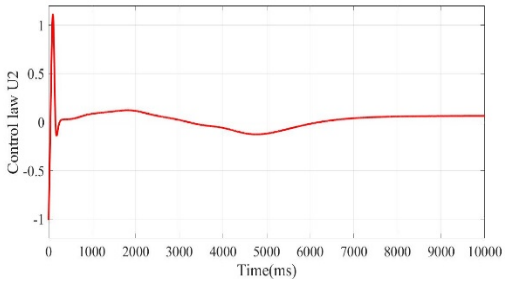

Fig. 14. The control law u_2 generated using the dynamic functions estimates.

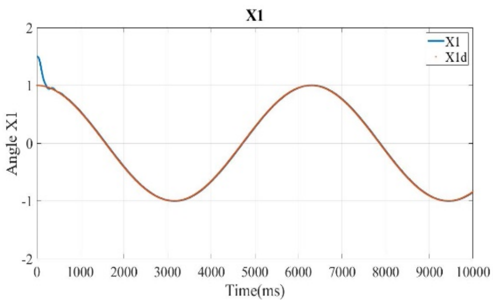

Fig. 15. Desired trajectory x_{1d} and estimate trajectory x_1.

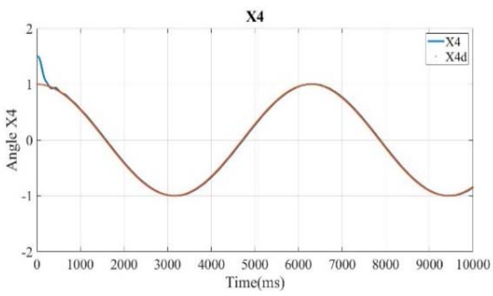

Fig. 16. Desired trajectory x_{4d} and estimate trajectory x_4.

4.3. Simulation 3

Now, let's take the same parameter gains as simulation 2, with $x_{1d} = 2\cos(t)$ and $x_{4d} = 2\cos(t)$ being the new desired trajectory, then we find the results (Control laws and estimate trajectories) as following (Figs. 17-20).

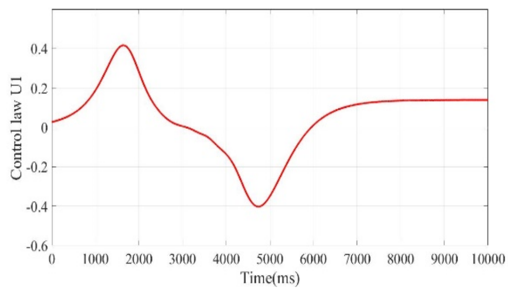

Fig. 17. The control law u_1 generated using the dynamic functions estimates.

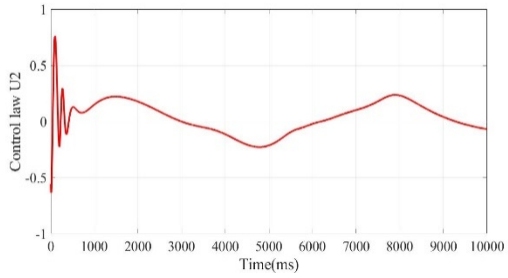

Fig. 18. The control law u_2 generated using the dynamic functions estimates.

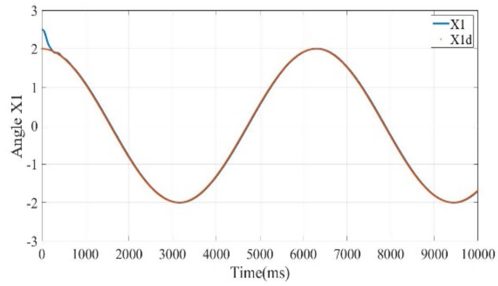

Fig. 19. New desired trajectory x_{1d} and estimate trajectory x_1.

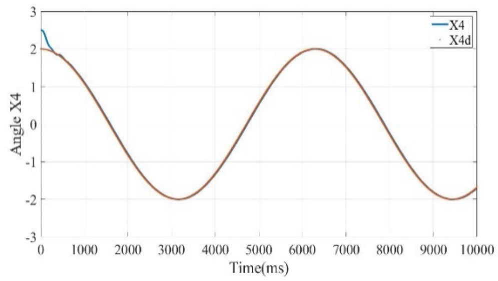

Fig. 20. New desired trajectory x_{4d} and estimate trajectory x_4.

5. Conclusions and Perspective

The paper presents a controller that estimates the dynamic functions of the two-link robot with two control laws using SMC and radial basis function neural networks. This newly designed controller performs well in terms of time convergence and stability, as illustrated by the simulation as in [8] and

[12]. To get the greatest outcomes for this task, we will attempt to improve it by utilizing new and more relevant methods in future works.

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