Pertanika J. Sci. & Technol. 27 (3): 1279 - 1300 (2019)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

An Intelligent Tracking Control Scheme for Electrically-Driven Redundant Robots

Manju Rani and Naveen Kumar*

Department of Mathematics, National Institute of Technology (NIT), Kurukshetra-136119, Haryana, India

ABSTRACT

This paper deals with the trajectory tracking control problem for electrically driven redundant robot manipulators. By combining actuator dynamics with manipulator's kinematics and dynamics, a novel control scheme is proposed for the electromechanical system. In this electromechanical system, the controller is designed at the dynamic level as well as at the actuator level. In the proposed control scheme, uncertain non-linear mechanical dynamics is approximated with the model-based controller combined with the model-free radial basis function neural network based controller together with adaptive bound. The behaviour of the uncertain electrical dynamics is approximated with the help of a radial basis function neural network. The designed controller achieves both the trajectory tracking and the subtask tracking effectively. Additionally, the designed control scheme controls the direct current motors being used to provide the desired currents and torques. The errors are shown to be asymptotically converging and the control scheme is shown to be stable using Lyapunov stability theory. Finally, the simulation results are produced for the rigid link electrically driven redundant robot manipulators to show the effectiveness of the proposed control scheme.

Keywords: Actuator dynamics, lyapunov stability, radial basis function neural network, redundant manipulators, subtask tracking

ARTICLE INFO

Article history:
Received: 31 January 2018
Accepted: 13 February 2019
Published: 24 July 2019

E-mail addresses:
manjukhatri09@gmail.com (Manju Rani)
navindma@gmail.com (Naveen Kumar)
* Corresponding author

INTRODUCTION

Due to the sufficient degree of freedom in their end-effector's task space, kinematically redundant manipulators has been the main subject of study by many researchers (Hsu et al., 1989; Zergeroglu et al., 2004). The availability of the extra degree of freedom of redundant manipulators provides an infinite

ISSN: 0128-7680
e-ISSN: 2231-8526

number of motion solutions. In addition, the workspace of redundant manipulators can be increased by the presence of the joint limits. Redundant manipulators are widely utilized in the International Space Station, undersea etc.

Much research has been carried out on the trajectory tracking control of redundant robot manipulators. Moreover, most of the advanced control schemes have been delineated at the torque input level and the mechanics related to their joint actuators like electrical effects have been ignored. It has been observed by numerous researchers that the harmful consequences are blocking the high-level trajectory tracking performance and the motion development of the controller (Dawson et al., 1992; Chen et al., 1998). Therefore, supplementary advancements can be achieved by including the significance of the actuator mechanics in the control system.

For the high-level trajectory tracking performance of the rigid-link electrically driven manipulators and the redundant manipulators, a lot of progressive methods depend upon the full dynamic model of the manipulator in which the whole electro-mechanical system is assumed to be completely known. A new robust controller based on backstepping approach was reported for the trajectory tracking problem of the robot manipulator with actuator dynamics (Homayounzade et al., 2015; Soltanpour et al., 2012). A position adaptive control scheme with passivity techniques for two-link manipulator was developed (Azoui & Saidi, 2011). For the high-speed trajectory tracking objectives, a feedback linearization technique based control scheme was also developed (Fateh, 2008). In order to deal with the structured and unstructured uncertainties, an adaptive nonlinear controller with backstepping scheme was developed (Khaligh & Namvar, 2010). In addition, for the task space trajectory tracking of the end-effector of the manipulator, two adaptive control laws named RV (reference velocity) and RVS (reference velocity separation) were developed (Perumal & Natarajan, 2017). An integrator backstepping technique was developed for the motion tracking control of the robot manipulator actuated by dc motors (Chang, 2002). For the trajectory tracking in the operational space, an extended Jacobian method was used for the redundant robot manipulator (Benzaoui et al., 2010). The model based robust control schemes for the kinematically redundant robot manipulators were developed (Zergeroglu et al., 2006; Ozbay et al., 2008).

However, we observe that the above-mentioned control schemes have been worked out either by using conventional model-based control schemes or robust adaptive control schemes. Noticeably, the above model-based control schemes depend upon the exact information of the explicit parameters of the dynamic model and the performance of the designed control controller is diminished by the parametric uncertainties and the computation of the regression matrix, which further depends upon the structure of the system to be controlled and must be specified autonomously with the dynamics of the manipulator.

Therefore, for the solution of such type of problems, many of the control schemes focus on integrating the conventional control schemes with the intelligent technique based control schemes. In the present time, neural network-based technologies have been extensively used in many of the areas due to its parallel distributed structure, good learning capability, image processing and its property of approximation of any nonlinear function. Researchers have utilized model-free adaptive and robust control schemes for nonlinear systems via the neural network. A hybrid approach was developed for the tracking problem of the robot manipulator with the actuator dynamics (Jiang, 2006). In this approach, PD controller was combined with neural network based controller and simulation results were performed on an industrial manipulator Adept One XL robot. An intelligent terminal sliding mode control scheme was developed for the tracking problem (Wang et al., 2009a & 2009b). In this scheme, the non-linear dynamics was approximated by the RBF neural network. A four-layer fuzzy neural network with projection algorithm was developed for the joint position control of a two-link robot (Wai & Chen, 2006). By using the properties of the sliding mode controller, an intelligent control system for the high-level position tracking of the RLED manipulator was designed (Wai & Muthusamy, 2012). A Takagi-Sugeno-Kang type fuzzy neural network control scheme was designed for the position control of two-link RLED manipulator (Wai & Chen, 2004). Based on the neural network technique, the trajectory tracking control scheme for the electrically driven dual robot manipulator was developed (Jafarian et al., 2006). By using the backstepping method, neural network based feed-forward controller was developed (Shafiei & Soltanpour, 2009). A discrete-time robust control scheme was proposed for the RLED robot manipulators in the task space (Fateh & Azargoshasb, 2015). For the obstacle avoidance and for the trajectory tracking of a redundant manipulator, a fuzzy adaptive control scheme was developed (Benzaoui et al., 2016). By using model-free feed forward neural network based controller, Kumar et al. (2011) and Singh et al. (2012) discussed the trajectory tracking problems of the redundant manipulator. Later on, a hybrid approach was generated for the tracking problem of the redundant manipulator by the combination of the computed torque controller and RBF neural network based controller (Kumar et al., 2012; Rani & Kumar, 2016). By considering the Lyapunov-Krasovskii functional for the RLED manipulator with time delays, a newly robust adaptive neural network based tracking control system was designed (Chang, 2014). An intelligent robust tracking control problem for one-link electrically-driven manipulator was considered (Chang et al., 2008; Huang et al., 2008). Based on backstepping scheme, an adaptive three- layer neural network-based controller was developed for the trajectory tracking control problem of the electrically driven manipulator (Cheng et al., 2009). Table 1 provides the overall description of the control schemes for the trajectory tracking.

Table 1
Description of the control schemes for the trajectory tracking

References	Control Scheme	Robot Manipulator
Chang, 2002	An integrator back stepping technique	RLED Manipulator
Cheng et al., 2009	Adaptive three-layer neural network	RLED Manipulator
Wai & Chen, 2004	Fuzzy neural network control scheme	RLED Manipulator
Jafarian et al., 2006	Neural network technique	Dual robot manipulator
Wai & Chen, 2006	Four layer fuzzy neural network	RLED Manipulator
Zergeroglu et al., 2006	Model-based robust control scheme	Redundant Robot
Chang et al., 2008	Neural network based robust control scheme with time-delays	RLED Manipulator
Fateh, 2008	Feedback linearization technique	RLED Manipulator
Ozbay et al. 2008	Model-based control scheme	Redundant Robot
Shafiei & Soltanpour, 2009	Neural network based feed forward controller with backstepping approach	RLED Manipulator
Wang et al., 2009a & 2009b	An intelligent terminal sliding mode control scheme	RLED Manipulator
Benzaoui et al., 2010	Extended Jacobian method	Redundant Robot
Khaligh & Namvar, 2010	An adaptive nonlinear controller with backstepping	RLED Manipulator
Azoui & Saidi, 2011	Adaptive control scheme with passivity techniques	Two-link manipulator
Kumar et al., 2012	CT controller with RBFNN	Redundant Robot
Soltanpour et al., 2012	Backstepping approach	RLED Manipulator
Wai & Muthusamy, 2012	An intelligent technique with sliding mode control	RLED manipulator
Chang, 2014	Neural network based robust adaptive control scheme with time-delays	RLED Manipulator
Homayounzade et al., 2015	Robust controller based backstepping approach	RLED Manipulator
Benzaoui et al., 2016	Fuzzy adaptive control scheme	Redundant Robot
Rani & Kumar, 2016	Neural network based hybrid approach	Redundant Manipulator
Perumal & Natarajan, 2017	RV and RVS adaptive control laws	Robot Manipulator

In our previous work, by utilizing the partial information available about the system dynamics, the model-based control scheme was successfully combined with RBF neural network based model-free technique for the trajectory tracking of the redundant manipulators (Rani & Kumar, 2016). However, the effects due to actuators dynamics were ignored. For the particular case of high-velocity movements and high varying loads, the ignorance of the actuator dynamics has adverse effects on the trajectory tracking and the motion performance of the manipulator. Specifically, to the best of our knowledge, no research has been reported on the trajectory tracking control problem of uncertain electrically driven redundant robot manipulators considering the effects of the actuator dynamics.

The novelty of the present study is the significance of the effect of inclusion of actuator dynamics with the manipulator's dynamics for the large-scale trajectory tracking performance of the redundant manipulators. In the present study for the electromechanical system, the unknown mechanical dynamics is approximated with the model-based controller combined with the RBF neural network based model-free controller. The effects of uncertainties, external disturbances and the approximation error are effectively eliminated by using an adaptive compensator in the controller. In order to approximate the behaviour of the unknown electrical dynamics, RBF neural network is employed. With the integration of the DC motor dynamics with the robot dynamics, the actuator input voltages are the control inputs that make the overall control system more balanced.

The overall paper is structured into eight sections as follows. The kinematics, dynamics of the redundant manipulators along with the actuator dynamics are detailed in Section 2. Section 3 includes the error dynamics of the system. The structure of the radial basis function neural network is described in Section 4. Section 5 deals with the controller design at the dynamic level as well as at the actuator level. Stability analysis is detailed in Section 6. Numerical simulation results are presented in Section 7 followed by the concluding observations in Section 8.

SYSTEM DESCRIPTION

Kinematics of the Redundant Manipulator

With n link position variables $q = [q_1, q_2, ..., q_n]^T$ and m task space variables $z = [z_1, z_2, ..., z_m]^T$ of a robot manipulator, the relation between the variables z and q is defined as:

$$z = f(q) \qquad [1]$$

where $f(q)$ represents the kinematic transformation of a robot. The relationship between the joint variable velocities and accelerations with the end-effector velocities and accelerations are given as follows:

$$\dot{z} = J(q)\dot{q}$$

and

$$\ddot{z} = \dot{J}(q)\dot{q} + J(q)\ddot{q} \qquad [2]$$

where the manipulator's Jacobian matrix $J(q) \in R^{(m\times n)}$ is given as

$$J(q) = \partial f(q)/\partial q \qquad [3]$$

The pseudo-inverse of $J(q)$ is denoted by J^+ which is given as:

$$J^+ = J^T(JJ^T)^{-1} \qquad [4]$$

such that

$$JJ^{+} = I_m \quad [5]$$

where I_m denotes the identity matrix.

The matrix $J(q)$ satisfies Moore-Penrose conditions (Kumar et al., 2012).

The Dynamic Model of Redundant Manipulator Plus Actuator Dynamics

By using the Lagrangian approach, the dynamic model of a n link, revolute direct drive robot manipulator is described as (Wai et al., 2004).

$$M(q)\ddot{q} + V(q,\dot{q})\dot{q} + G(q) + F(\dot{q}) + T_d = \tau \quad [6]$$

where $M(q) \in R^{(n\times n)}$ denotes the inertia matrix, $V(q,\dot{q}) \in R^{(n\times n)}$ is the centripetal-coriolis matrix, $G(q) \in R^{n}$ is the gravity effects, $F(\dot{q}) \in R^{n}$ represents the friction effects and $\tau \epsilon R^{n}$ stands for the torque input vector. T_d represents the bounded unknown disturbances.

The robot dynamics given in [6] has some useful properties as:

Property 1: The positive definite and symmetric matrix $M(q)$ satisfies the following inequalities

$$d_1 \leq M(q) \leq d_2 \quad [7]$$

Property 2: The skew-symmetric relation between the inertia matrix and the centripetalcoriolis matrix satisfies

$$\eta^{T}(\dot{M}(q) - 2V(q,\dot{q}))\eta \quad \forall\, \eta \in R^{n} \quad [8]$$

The following useful assumptions are utilized in further analysis:

Assumption 1: $\|F(\dot{q})\| \leq b_1 + b_2\|\dot{q}\|$ for some unknown constants b_1 and b_2

Assumption 2: $\|T_d\| \leq b_3$ for some positive constant b_3

Let each joint of the robot manipulator is driven by dc motor. The actuator dynamics is described as (Dawson et al., 1992)

$$L\dot{I} + R(I,\dot{q}) + K_d = U \quad [9]$$

where $R(I,\dot{q}) = RI + k_v\dot{q}$ and

$$\tau = K_m I \quad [10]$$

where $L \in R^{(n\times n)}$ represents the positive definite diagonal matrix of armature inductance, $R(I,\dot{q}) \in R^{(n\times n)}$ is the diagonal matrix of resistance and motor back electromotive force. The electromechanical transformation between the current and the torque is described by the motor torque constant matrix $K_m \in R^{(n\times n)}$. The bounded voltage disturbance is $K_d \in R^n$ and $U \in R^n$ is the motor input voltage.

We assume that the torque transmission matrix and the inductance matrix satisfy the following relation.

$$n_1\|z_1\|^2 \leq {z_1}^T K_m z_1 \leq n_2\|z_1\|^2$$

and

$$r_1\|z_1\|^2 \leq {z_1}^T L z_1 \leq r_2\|z_1\|^2$$

where n_1, n_2, r_1 and r_2 all are bounded and positive scalar constants.

ERROR DYNAMICS

Under structured/unstructured uncertainties and external disturbances with the bounded desired trajectory tracking assumption, in this paper, we are to design RBF neural network based controller in such a way that it controls DC actuators, which will provide the desired control torque input so that the desired end-effector trajectory tracking can be achieved. In addition, the manipulator's redundancy should be utilized to execute the desired subtask trajectory tracking error objective.

We define the tracking error $e(t) \in R^m$ for the task-space as

$$e(t) = z_d - z \quad [11]$$

where $z_d \in R^m$ is the desired task-space trajectory.

We define subtask tracking error $e_N \in R^m$ similar to (Kumar et al., 2011), as

$$e_N(t) = (I_N - J^+J)(g - \dot{q}) \quad [12]$$

Here the construction of the vector function g (.) $\in R^n$ depends on the subtask objectives like obstacle avoidance and joint limit avoidance; however singularity avoidance should be its prior objective. Since vectors are mapped into the null space of J by $(I_N - J^+J)$, therefore $e_N(t) = (I_N - J^+J)(g - \dot{q})$ tend to zero. Many of the authors have considered the different selection process of the null space joint velocity for the fulfillment of the main task objective along with the other subtasks. For the desired configuration for maximum use of the manipulability of the manipulator, we define the function $f(\theta) = -\det(JJ^T)$. For the singularities avoidance, we select $g = -\Delta f$.

After the differentiation of Equation [11] and by using Equation [2] we get

$$\dot{e}(t) = \dot{z}_d - \dot{z} = \dot{z}_d - J\dot{q} = \dot{z}_d + \alpha e - \alpha e - J\dot{q} \quad [13]$$

where $\alpha \in R^n$ is a diagonal and positive definite gain matrix.

Now Equation [13] can be rewritten as

$$\dot{e}(t) = -\alpha e + J(J^{+}(\dot{z}_d + \alpha e) + (I_N - J^{+}J)g - \dot{q}) \tag{14}$$

By using Equation [14] we define the filtered tracking error $r(t) \in R^n$ as

$$r = J^{+}(\dot{z}_d + \alpha e) + (I_N - J^{+}J)g - \dot{q} \tag{15}$$

The task-space position tracking error is defined as:

$$\dot{e}(t) = -\alpha e + Jr \tag{16}$$

With the help of Equation [16], we design the control input so that the task space error and the filtered tracking error can be regulated. For this objective, we multiply Equation [15] by $(I_N - J^{+}J)$ and using the properties of pseudo-inverse of the manipulator, we get

$$e_N = (I_N - J^{+}J)r \tag{17}$$

Here Equation [17] clearly indicates that the regulation of $r(t)$ implies the regulation of $e_N(t)$.

RADIAL BASIS FUNCTION NEURAL NETWORK

Due to smooth network architecture and a good observation competence, RBF has taken much consideration, which averts the worthless and lengthy calculation. The structure of RBF is characterized in Figure 1 given below with:

Layer 1: This is the input layer in which input signal $y = [y_1, y_2, \dots, y_n]$ directly move to the next layer.

Layer 2: The second layer is the hidden layer. Each and every neuron of hidden layer is stimulated by Radial Basis function. The hidden layer output is given

$$Y_j(y) = \exp\left(\frac{-\|y - h_i\|^2}{2d_j^2}\right) \quad j = 1,2, \dots p \tag{18}$$

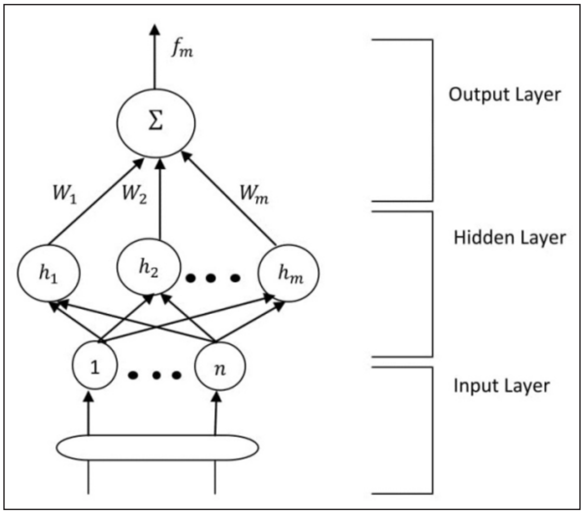


Figure 1. Radial basis function neural network

where p is the no. of hidden layers. The neural net j has the centre vector $h_i = [y_{j1}, y_{j2}, \dots, y_{jp}]$, d_j^2, the variance of the j^{th} radial basis function and Y_j denotes the Gaussian activation function for neural net j.

Layer 3: In the third layer, the output signal is a combination of linear weights such as

$$f_j(y) = \sum_{j=1}^{p} W_{ji} Y_j(y, c, d) \qquad [19]$$

CONTROLLER DESIGN

Throughout the paper, the following assumptions are used.

Assumption 3: $z_d, \dot{z}_d, \ddot{z}_d, g$ and $\dot{g}$ all are the bounded functions of time.

Assumption 4: It is assumed that all the terms in the kinematic and dynamic system such $M(q), V(q,\dot{q}), G(q), J(q)$ and $J^+(q)$ is bounded and all the kinematic singularities are always avoided.

Now, the dynamic equation in terms of the filtered tracking error can be written as:

$$M\dot{r} = -Vr - K_m I + X(y) + F(\dot{q}) + T_d \qquad [20]$$

Where

$$X(y) = M\frac{d}{dt}[J^+(\dot{z}_d + \alpha e) + (I_N - J^+J)g] + V[J^+(\dot{z}_d + \alpha e) + (I_N - J^+J)g] + G(q) \qquad [21]$$

Let us consider the current I as a fictitious control signal for the error dynamics given by the Equation [20] and we call it I_d in such a way that $e_1(t) = I_d - I$ is the error signal.

We write the Equation [20] in the form:

$$M\dot{r} = -Vr - K_m I_d + K_m e_1(t) + X(y) + F(\dot{q}) + T_d \qquad [22]$$

After the differentiation of the error signal and using Equation [9] with Equation [10], the resulting expression can be written in the form:

$$L\dot{e}_1 = H(y_1) + K_d - U \qquad [23]$$

$$H(y_1) = R(I, \dot{q}) + L\dot{I}_d \qquad [24]$$

where $H(y_1)$ is a nonlinear function of $q, \dot{q}, r,$ and I.

Now, we break the nonlinear function $X(y)$ into known dynamic part $\hat{X}(y)$ and unknown dynamic part $\tilde{X}(y)$. The dynamic part $\tilde{X}(y)$ is completely unknown and the performance of this unknown dynamic part will be learned by the RBF neural network.

$$\hat{X}(y) = \hat{M}\frac{d}{dt}[J^+(\dot{z}_d + \alpha e) + (I_N - J^+J)g] + \hat{V}[J^+(\dot{z}_d + \alpha e) + (I_N - J^+J)g] + \hat{G}(q)$$

$$\tilde{X}(y) = \tilde{M}\frac{d}{dt}[J^+(\dot{z}_d + \alpha e) + (I_N - J^+J)g] + \tilde{V}[J^+(\dot{z}_d + \alpha e) + (I_N - J^+J)g] + \tilde{G}(q)$$

Here the vector y is given by

$$y(t) = [\ddot{z}_d^T, \dot{z}_d^T, z_d^T, \dot{e}^T, q^T, \dot{q}^T, g^T, \dot{g}^T]^T$$

The approximation of the unknown dynamic part is given by

$$\tilde{X}(y) = W^T\xi(y) + \varepsilon(y) \quad [25]$$

Where $W \in R^{N\times n}$ is a neural network weight matrix and $\xi(.)$: $R^{(5m+4n)} \rightarrow R^N$ are the smooth basis functions. The neural reconstruction error is $\varepsilon(.)$: $R^{(5m+4n)} \rightarrow R^N$ and the number of the nodes is N.

For large N, $\|\epsilon(y)\| \le \epsilon_N$

Substituting Equation [25] into Equation [22] we have:

$$M\dot{r} = -Vr - K_m I_d + K_m e_1(t) + \hat{X}(y) + W^T\xi(y) + \varepsilon(y) + F(\dot{q}) + T_d \quad [26]$$

Adaptive Bound Part

By using error bound on neural network reconstruction error and the assumptions (1) and (2), we have

$$\|F(\dot{q}) + T_d + \epsilon(y)\| \le b_1 + b_2\|\dot{q}\| + b_3 + \epsilon_N \quad [27]$$

We write $\rho = b_1 + b_2\|\dot{q}\| + b_3 + \epsilon_N$ and above calculation leads to:

$$\rho = [1 \;\; \|\dot{q}\| \;\; 1 \;\; 1][b_1 \;\; b_2 \;\; b_3 \;\; \epsilon_N]^T = B^T\varphi \quad [28]$$

where $B(\|\dot{q}\|) \in R^K$ is a vector function of joint velocities $\dot{q}$ and $\varphi \in R^K$ is a parameter vector.

Step 1: For the desired objective, we design the auxiliary controller I_d as

$$K_m I_d = \tilde{X}(y) + K_1 r + J^T e + \widehat{W}^T\xi(y) + \frac{\hat{\rho}^2 r}{\hat{\rho}\|r\|+\delta} \quad [29]$$

Where $\dot{\delta} = -\gamma\delta$, $\delta(0) =$ design constant > 0 and approximate values of the parameter vector and the neural network weights are $\hat{\varphi}$ and $\widehat{W}$ respectively, which are provided by the tuning algorithm. $K_1 = K_1^T$ is a positive definite gain matrix.

After the substitution of Equation [29] into Equation [26], the error dynamics becomes:

$$M\dot{r} = -(V + K_1)r - J^T e + \widetilde{W}^T\xi(y) + F(\dot{q}) + T_d + \epsilon(y) + K_m e_1(t) - \frac{\hat{\rho}^2 r}{\hat{\rho}\|r\|+\delta} \quad [30]$$

Step 2: In this stage, we are to design the actual control input U in such a way that $e_1(t) \rightarrow 0$. However, the structure of the nonlinear term $H(y_1)$ is completely unknown and it includes $\dot{I}_d$ whose calculation is a tough task and therefore we will apply radial basis function neural network to learn the behaviour of the unknown terms in this function, we get

$$H(y_1) = W_1^T\xi_1(y_1) + \epsilon_1(y_1 \quad [31]$$

where $W_1 \in R^{(N_1\times n)}$ is a neural network weight matrix and the smooth basis functions are $\xi_1(.)$. The neural network reconstruction error is $\epsilon_1(.)$ and the number of nodes is N_I.

Substituting $H(y_1)$ from Equation [31] into Equation [23], we have

$$L\dot{e}_1 = W_1^T\xi_1(y_1) + \epsilon_1(y_1) + K_d - U \tag{32}$$

We choose the controller for the actual control input as

$$U = \widehat{W}_1^T\xi_1(y_1) + K_{d1}e_1 + \frac{\widehat{\rho}_1^2 e_1}{\widehat{\rho}_1\|e_1\| + \delta_1} \tag{33}$$

where $\|\epsilon_1(y_1)\| \leq \epsilon_{N1}$, is the approximation error for large N_I and by using adaptive bound part on bounded disturbances and on the neural network reconstruction error, we get $\rho_1 = D^T\psi$ and $\dot{\delta}_1 = -\gamma_1\delta_1$.

By using Equation [33] into Equation [32], we have

$$L\dot{e}_1 = \widetilde{W}_1^T\xi_1(y_1) + \epsilon_1(y_1) + K_d - K_{d1}e_1 - \frac{\widehat{\rho}_1^2 e_1}{\widehat{\rho}_1\|e_1\| + \delta_1} \tag{34}$$

The block diagram of the proposed control scheme is shown in Figure 2.

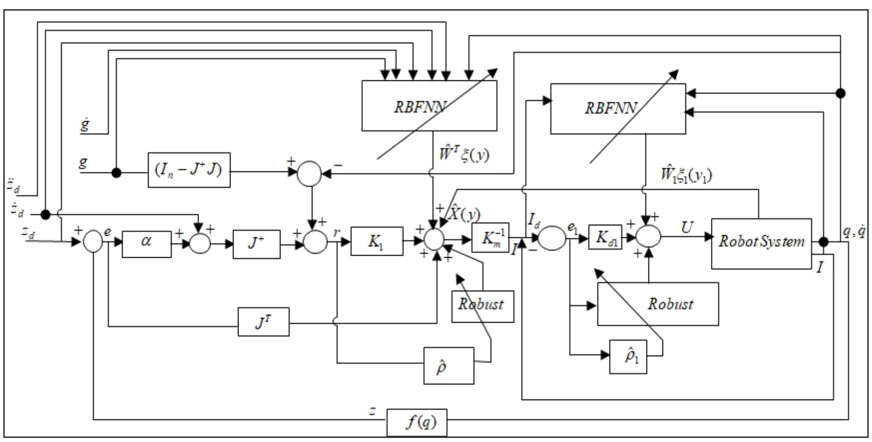


Figure 2. Block diagram of the proposed control scheme

STABILITY ANALYSIS

If the dynamics of the robot is given by Equation [6] and the control inputs given by Equation [30] and Equation [34], the adaptation laws are given by Equations [35] – [38], we are to show that the complete electromechanical system is stable and the filtered tracking error with task space error $e(t)$, subtask tracking error $e_N(t)$ and error signal $e_I(t)$ asymptotically goes to zero as $t \to \infty$.

$$\dot{\hat{W}} = \Gamma_W\xi(y)r^T \tag{35}$$

$$\dot{\hat{W}}_1 = \Gamma_{W1}\xi_1(y_1)e_1^T \tag{36}$$

$$\dot{\hat{\varphi}} = \Gamma_\varphi B\|r\| \tag{37}$$

$$\dot{\hat{\psi}} \quad = \Gamma_\psi D\|e_1\| \qquad [38]$$

where $\Gamma_W \in R^{N\times N}$, $\Gamma_{W1} \in R^{N_1\times N_1}$, $\Gamma_\varphi \in R^{K\times K}$ and $\Gamma_\psi \in R^{K_1\times K_1}$ are the positive definite matrices.

Proof: Let us define

$\widetilde{W} = W - \widehat{W}$,$\widetilde{W}_1 = W_1 - \widehat{W}_1$, $\tilde{\varphi} = \varphi - \hat{\varphi}$, $\tilde{\psi} = \psi - \hat{\psi}$, and $\beta = [r^T\ e_1^T]^T$

For the stability of the complete electromechanical system, let us assume the Lyapunov function as

$$E = \frac{1}{2}\ e^T e + \frac{1}{2} r^T M r + \frac{1}{2} e_1^T L e_1 + \frac{1}{2} tr\left(\widetilde{W}^T \Gamma_W^{-1} \widetilde{W}\right) + \frac{1}{2} tr\left(\widetilde{W}_1^T \Gamma_{W1}^{-1} \widetilde{W}_1\right)$$
$$+ \frac{1}{2} tr\left(\tilde{\varphi}^T \Gamma_\varphi^{-1} \tilde{\varphi}\right) + \frac{1}{2} tr\left(\tilde{\psi}^T \Gamma_\psi^{-1} \tilde{\psi}\right) + \frac{\delta}{\gamma} + \frac{\delta_1}{\gamma_1} \qquad [39]$$

The differentiation of Lyapunov function with respect to time gives

$$\dot{E} = e^T \dot{e} + r^T M \dot{r} + \frac{1}{2} r^T \dot{M} r + e_1^T L \dot{e}_1 + tr(\widetilde{W}^T \Gamma_W^{-1} \dot{\widetilde{W}}) + tr\left(\widetilde{W}_1^T \Gamma_{W1}^{-1} \dot{\widetilde{W}}_1\right)$$
$$+\mathrm{tr}\left(\tilde{\varphi}^T \Gamma_\varphi^{-1} \dot{\tilde{\varphi}}\right) + \mathrm{tr}\left(\tilde{\psi}^T \Gamma_\psi^{-1} \dot{\tilde{\psi}}\right) + \frac{\dot{\delta}}{\gamma} + \frac{\dot{\delta}_1}{\gamma_1} \qquad [40]$$

After simplification, the following expression is obtained

$$\dot{E} = -e^T \alpha e + e^T J r - [r^T\ e_1^T] \begin{bmatrix} K_1 & -K_m \\ 0.0 & K_{d1} \end{bmatrix} \begin{bmatrix} r \\ e_1 \end{bmatrix} - r^T J^T e + \frac{1}{2} r^T\left(\dot{M} - 2V\right) r + r^T \widehat{W}^T \xi(y)$$
$$+ r^T\left(F(\dot{q}) + T_d + \epsilon(y)\right) + e_1^T\left(K_d + \varepsilon_1(y_1)\right) + e_1^T \widetilde{W}_1^T \xi_1(y_1) - \frac{\hat{\rho}^2\|r\|^2}{\hat{\rho}\|r\| + \delta} - \frac{\hat{\rho}_1^2\|e_1\|^2}{\hat{\rho}_1\|e_1\| + \delta_1}$$
$$+ tr(\widetilde{W}^T \Gamma_W^{-1} \dot{\widetilde{W}}) + \ \ tr\left(\widetilde{W}_1^T \Gamma_{W1}^{-1} \dot{\widetilde{W}}_1\right) + tr(\tilde{\varphi} \Gamma_\varphi^{-1} \dot{\tilde{\varphi}}) + tr(\tilde{\psi} \Gamma_\psi^{-1} \dot{\tilde{\psi}}) + \frac{\dot{\delta}}{\gamma} + \frac{\dot{\delta}_1}{\gamma_1} \qquad [41]$$

By using the property (2) along with $\dot{\widetilde{W}} = -\dot{\widehat{W}}$, $\dot{\widetilde{W}}_1 = -\dot{\widehat{W}}_1$, $\dot{\tilde{\varphi}} = -\dot{\hat{\varphi}}$, $\dot{\tilde{\psi}} = -\dot{\hat{\psi}}$, $\dot{\delta} = -\gamma\delta$, and $\dot{\delta}_1 = -\gamma_1 \delta_1$, the following expression is obtained

$$\dot{E} = -e^T \alpha e - [r^T\ e_1^T] \begin{bmatrix} K_1 & -K_m \\ 0.0 & K_{d1} \end{bmatrix} \begin{bmatrix} r \\ e_1 \end{bmatrix} + r^T \widehat{W}^T \xi(y) + r^T\left(F(\dot{q}) + T_d + \epsilon(y)\right)$$
$$+ e_1^T\left(K_d + \xi_1(y_1)\right) + e_1^T \widetilde{W}_1^T \xi_1(y_1) - \frac{\hat{\rho}^2\|r\|^2}{\hat{\rho}\|r\| + \delta} - \frac{\hat{\rho}_1^2\|e_1\|^2}{\hat{\rho}_1\|e_1\| + \delta_1} - tr(\widetilde{W}^T \Gamma_W^{-1} \dot{\widehat{W}})$$
$$- tr\left(\widetilde{W}_1^T \Gamma_{W1}^{-1} \dot{\widehat{W}}_1\right) - tr\left(\tilde{\varphi} \Gamma_\varphi^{-1} \dot{\hat{\varphi}}\right) - tr\left(\tilde{\psi} \Gamma_\psi^{-1} \dot{\hat{\psi}}\right) - \delta - \delta_1 \qquad [42]$$

Now,

$$r^T\left(F(\dot{q}) + T_d + \varepsilon(y)\right) \leq \|r\|\ \|F(\dot{q}) + T_d + \varepsilon(y)\| \leq \rho\|r\| = B^T(\hat{\varphi} + \tilde{\varphi})\|r\|$$

$$e_1{}^T\left(K_d + \varepsilon_1(y_1)\right) \leq \|e_1\|\ \|K_d + \epsilon_1(y_1)\| \leq \rho_1\|e_1\| = D^T \psi \|e_1\| = D^T(\hat{\psi} + \tilde{\psi})\|e_1\|$$

Using the above inequality, the above equation can be rewritten as:

$$\dot{E} \leq -e^T\alpha e - e_{1min}\|\beta\|^2 + B^T(\hat{\varphi} + \tilde{\varphi}) - \tilde{\varphi}^T B\|r\| + D^T(\hat{\psi} + \tilde{\psi})\|e_1\| - \tilde{\psi}^T D\|e_1\|$$
$$-\frac{(B^T\hat{\varphi})^2\|r\|^2}{(B^T\hat{\varphi})\|r\|+\delta} - \delta - \frac{(D^T\hat{\psi})^2\|e_1\|^2}{(D^T\hat{\psi})\|e_1\|+\delta_1} - \delta_1 \qquad [43]$$

After simplification, we have

$$\dot{E} \leq -e^T\alpha e - e_{1min}\|\beta\|^2 - \frac{\delta^2}{(B^T\hat{\varphi})\|r\|+\delta} - \frac{\delta_1^2}{(D^T\hat{\psi})\|e_1\|+\delta_1} \qquad [44]$$

Where e_{1min} is the minimum eigen value of the matrix $\begin{bmatrix} K_1 & -K_m \\ 0.0 & K_{d1} \end{bmatrix}$.

As $E > 0$ and $\dot{E} \leq 0$, this means that the system is stable in the sense of Lyapunov and from this we conclude that $r(t)$, $\widetilde{W}$, and $\widetilde{W}_1$ hence $\widehat{W}$ and $\widehat{W}_1$ are bounded. Now by using LaSalle's extension, we can show that $r(t)$ and $e_1(t)$ go to zero as $t \to \infty$.

Also

$$\int_0^\infty \dot{E}dt \leq 0 \qquad [45]$$

The boundedness of $e(t)$ and $\dot{e}(t)$ is ensured by the boundedness of $r(t)$. The boundedness of the desired trajectory implies that z, $\dot{z}$, y and $\dot{y}$ are bounded. From Equation [44] we have $\ddot{E} \leq 0$. Since $M^{-1}(q)$, $V(q,\dot{q})$ are bounded and all terms on the right side of Equation [30] and Equation [34] justify the boundedness of $\dot{r}$, $\dot{e}_1(t)$ and $\ddot{E}$ and hence the uniform continuity of $\dot{E}$ is obtained. With time t, $\dot{E}$ goes to zero by Barbalat's Lemma and this implies that $e(t)$, $r(t)$ and $e_1(t)$ goes to zero as $t \to \infty$. Finally, Equation [17] shows that $e_N(t)$ asymptotically goes to zero as $t \to \infty$.

NUMERICAL SIMULATION RESULTS AND DISCUSSION

We execute simulation results on a 3*R* planar redundant robot manipulator, which is actuated by DC motors (shown in Figure 3). The details of the dynamical model can be referred to (Singh and Sukavanam, 2012).

The parameters for the electromechanical system are taken as L=diag (5, 5, 5)**,** R=diag (1, 1, 1)**.** The joint angles are denoted q_1, q_2, and q_3. The lengths for the links 1, 2 and 3 are l_1=0.6 m, l_2=0.4 m, l_3=0.35 m respectively. The masses of the links are taken as m_1=3.6 kg; m_2=2.6 kg and m_3=2.0 kg. The motor torque constant matrix is K_m=diag (2.0, 2.0, 2.0) ; the designed gain matrix is K_{d1} = diag (0.5, 0.5, 0.5)**,** and the voltage constant matrix is k_v =diag (0.2, 0.2, 0.2)**.** The payload mass is chosen 1 kg.

The friction terms are taken as $F(\dot{q}) = b_1 + b_2\|\dot{q}\|$.

The desired task-space trajectory is taken as:

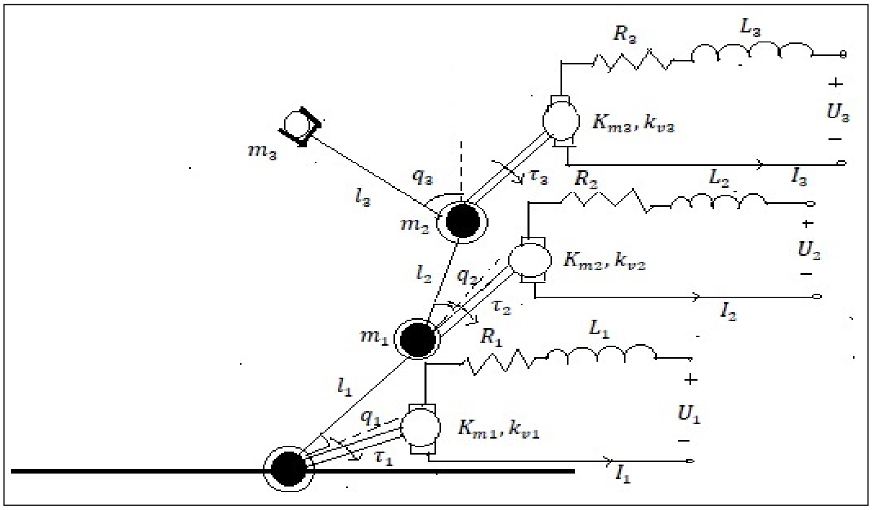


Figure 3. 3*R* planar direct-drive redundant manipulator actuated by brushed DC motor

$$x_d = \begin{bmatrix} 0.45 + 0.2\cos(0.5t) \\ 0.57 + 0.2\sin(t) \end{bmatrix} \quad [46]$$

The unknown disturbance terms are

$$T_d = \begin{bmatrix} 4\cos(2t) \\ \sin(t) + \cos(2t) \\ 2\sin(t) \end{bmatrix} \quad [47]$$

We have performed three sets of simulations with different subtask control vectors as:

In the first simulation case, we select $g(t) = 0$. For the maximization of the manipulability of the manipulator, in the second simulation case, we select

$$g(t) = \partial(\det(JJ^T))/\partial q \quad [48]$$

In the third simulation case, we select $g(t) = -2(q_3 - q_2 + 0.5q_1)[\ 1\ \ -1\ \ 1]^T$.

The above-mentioned vector function $g(t)$ is the negative gradient of the function

$$f = ((q_3 - 0.5q_2) - 0.5(q_2 - q_1))^2 \quad [49]$$

The control gains are taken as α = diag (5, 10) and K_1 = diag (100, 100,100).

The RBF neural network is composed of 5 nodes. For the Gaussians functions, the central positions are chosen from -2 to 2 and σ_i, the spread factors are taken to be 0.2. $\Gamma_W = I_5$ and $\Gamma_{W1} = I_5$ are the positive definite matrices. The parameter matrices are $\Gamma_\varphi = I_7$ and $\Gamma_\psi = I_2$. The trajectory tracking, task space tracking error and the subtask tracking errors are shown in the Figures 4-6 for the first, second and the third simulation cases respectively. These figures indicate that a satisfactory trajectory tracking, asymptotically convergent tracking error and the subtask tracking error has been achieved with a very small steady state error. The responses of the armature currents, control torque inputs and applied voltages are shown in the Figures 7-9 for the first, second and third simulation cases. The rated currents and the rated voltages for the three different simulation cases are shown in Table 2.

Table 2
The rated currents and the rated voltages

Links	$g_1(t)$		$g_2(t)$		$g_3(t)$	
	Current	Voltage	Current	Voltage	Current	Voltage
Link 1	5.9 A	70 V	5.9 A	60 V	5.7 A	75 A
Link 2	1.8 A	60 V	1.8 A	40 V	1.6 A	50 A
Link 3	2.0 A	65 V	2.0 A	35 V	2.2 A	40 A

From Table 2, it is clear that the proposed control scheme has achieved robustness to the parameter variations in both the manipulator and the motor.

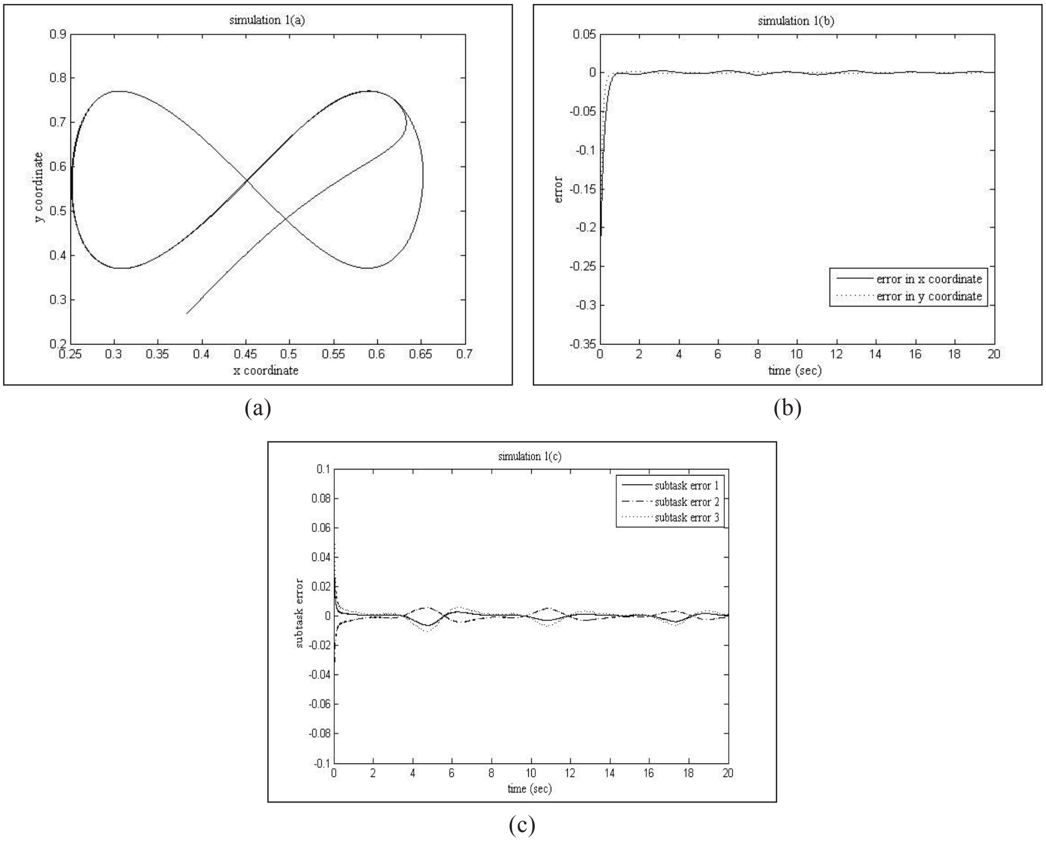
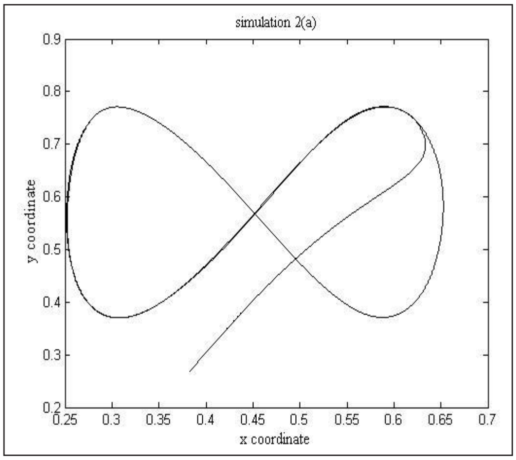
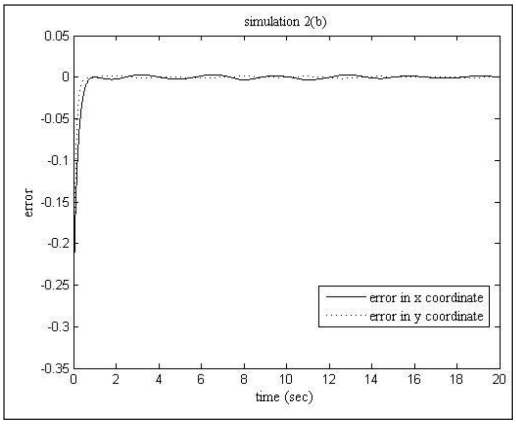


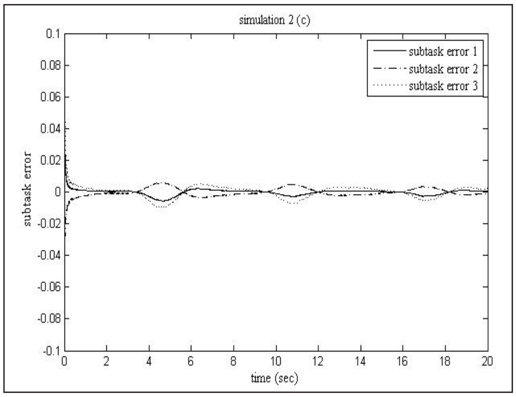
Figure 4. The performance of the proposed controller for simulation case 1 with (a) Trajectory tracking, (b) Task space tracking error, and (c) Subtask tracking error.



(a)

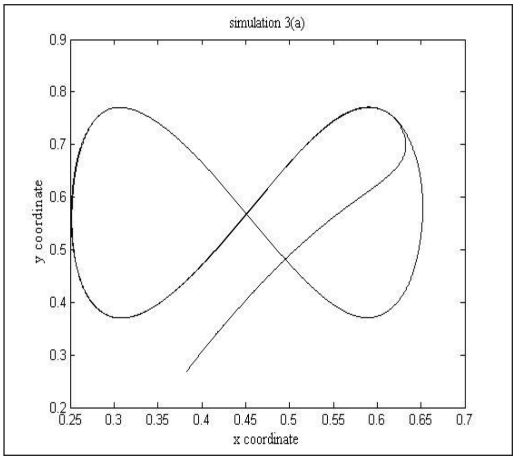


(b)

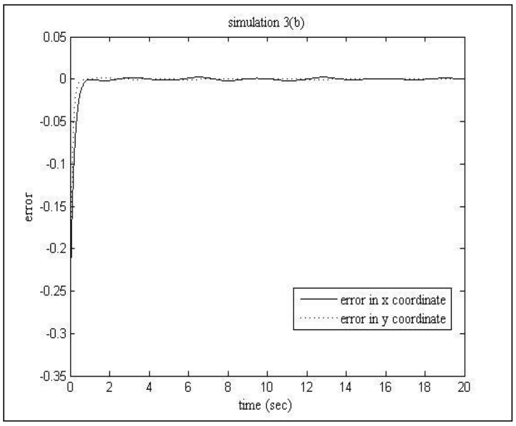


(c)

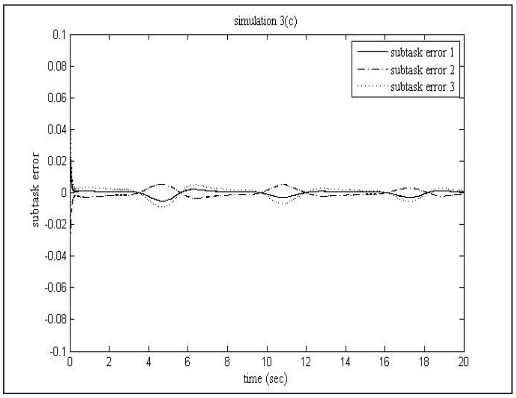
Figure 5. The performance of the proposed controller for simulation case 2 with (a) Trajectory tracking, (b) Task space tracking error, and (c) Subtask tracking error



(a)

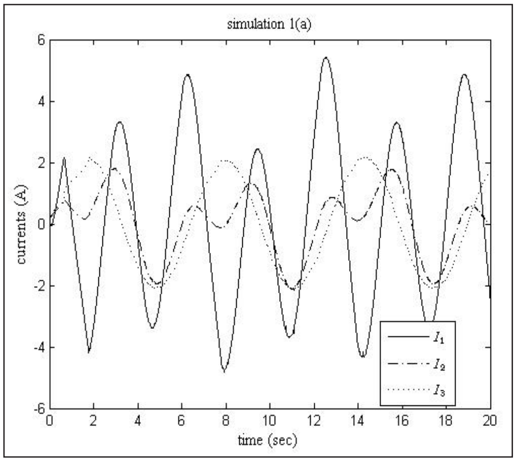


(b)

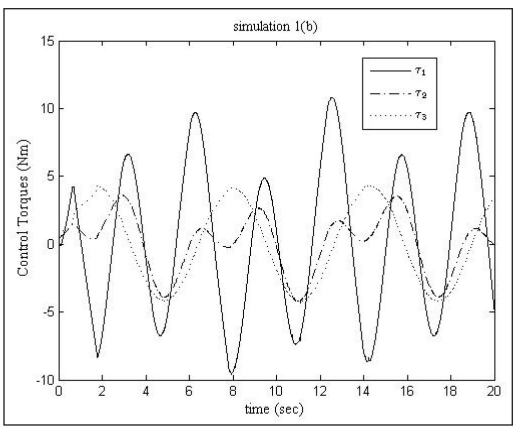


(c)

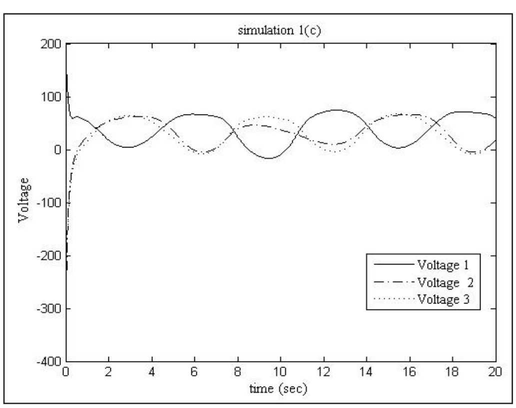
Figure 6. The performance of the proposed controller for simulation case 3 with (a) Trajectory tracking, (b) Task space tracking error, and (c) Subtask tracking error



(a)

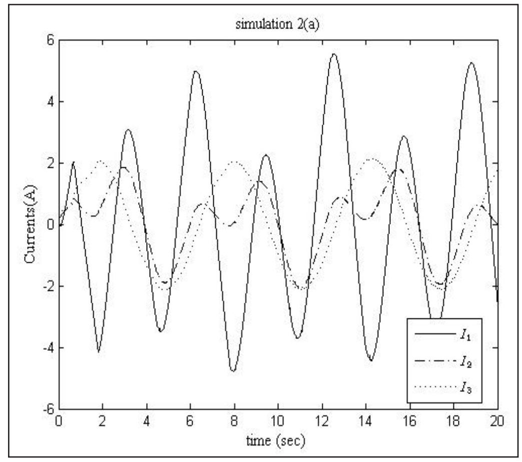


(b)

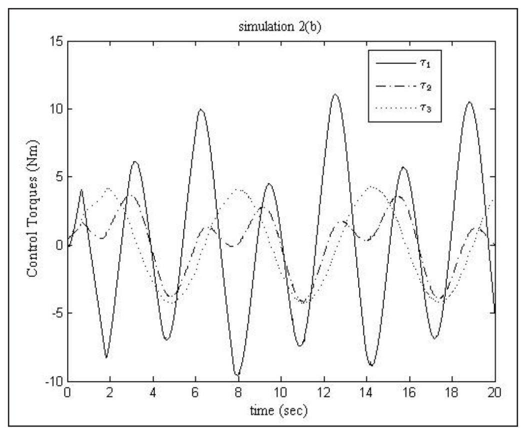


(c)

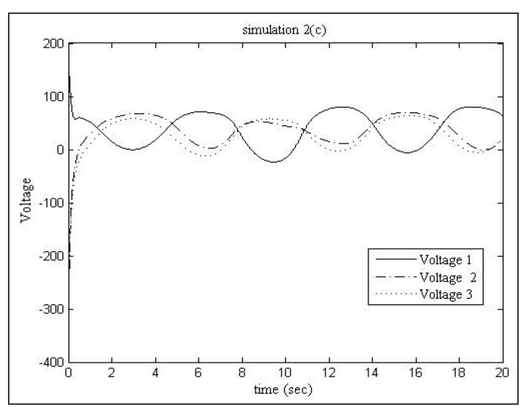
Figure 7. The performance of the proposed controller for simulation case 1 with (a) Armature current *I*(*t*), (b) Control torque input, and (c) Input voltage *U*(*t*)



(a)



(b)



(c)

Figure 8. The performance of the proposed controller for simulation case 2 with (a) Armature current *I*(*t*), (b) Control torque input, and (c) Input voltage *U*(*t*)

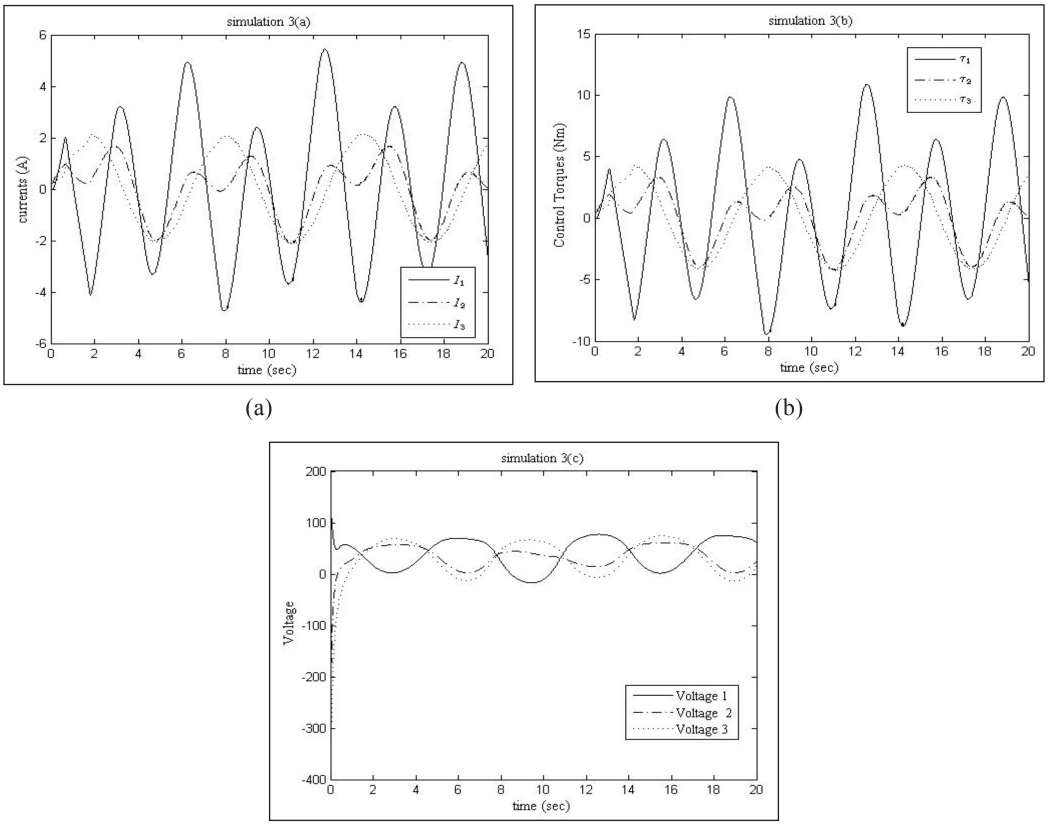


Figure 9. The performance of the proposed controller for simulation case 3 with (a) Armature current *I*(*t*), (b) Control torque input, and (c) Input voltage *U*(*t*)

For the measurement of the root mean square (the average of the tracking error), we will apply scalar valued L^2 norm for the complete curve and it is given by

$$L^2[e(t)] = \sqrt{\frac{1}{t_f - t_0}\int_{t_0}^{t_f} \|e(t)\|^2 dt} \qquad [50]$$

where the initial and the final values of the time are $t_0,\ t_f \in R^+$. To the best of our knowledge, no research has been reported on the trajectory tracking control problem of uncertain electrically driven redundant robot manipulators. However, for the comparison purpose, we have calculated the root mean square average of the tracking errors with existing approach without including the effects of the actuator dynamics (Rani & Kumar, 2016). The calculated values are shown in Table 3 for the proposed controller and Rani & Kumar (2016) controller respectively. From these tables, it is clear that the root mean square error (RMSE) of employing actuator dynamics is much less in comparison to the other existing approach without including the effects of the actuator dynamics.

Table 3
RMS Average of the Tracking Error

Vector Functions	$L^2[e(1)]$		$L^2[e(2)]$	
	Proposed controller	Rani & Kuman, 2016	Proposed controller	Rani & Kumar, 2016
$g_1(t)$	0.0354	0.5849	0.0323	0.8532
$g_2(t)$	0.0263	0.7483	0.0222	1.1624
$g_3(t)$	0.0298	0.6997	0.0279	1.0503

Hence, the validity of the proposed controller has been proven by the fact that all the existing uncertainties and external disturbances have been diminished in the RLED redundant manipulators and the satisfactory tracking of the currents, trajectory tracking, and convergent tracking errors have been achieved.

CONCLUSION

This paper discusses the trajectory tracking control problem for the RLED redundant robot manipulators. Although the tracking problem of the redundant robot manipulators has been enthusiastically studied, however there is almost no research on the trajectory tracking of the RLED redundant robot manipulators. Due to the inclusion of the actuator dynamics with the robot dynamics, the controller exhibits some important characteristics. In this paper, for the approximation of the unknown non-linear mechanical dynamics, a model-based controller has been combined with the model-free radial basis function neural network based controller. The friction term, external disturbances and neural network reconstruction error are approximated by an adaptive bound part of the controller. The behaviour of the unknown electrical dynamics is approximated with the help of RBF neural network. The superiority of the proposed control scheme has been verified by the numerical simulation results. These results indicate that the incorporated controller has satisfactory performance in dealing with the external disturbances and the motor parameter uncertainties.

ACKNOWLEDGEMENT

This work is financially supported by the University Grants Commission (UGC) Sr. No. 2121240927 with Ref No. 23/12/2012 (ii) EU-V, New Delhi, India.

LIST OF ABBREVIATIONS AND SYMBOLS

b1, b2, b3	Positive constants
CT controller	Computed torque controller
DC motors	Direct current motors
$e(t)$	Task space tracking error
$e_I(t)$	Current error signal
$e_N(t)$	Subtask tracking error
$J(q)$	The Jacobian matrix
$L^2[e(t)]$	Root mean square error
m	Number of task space variables
n	Number of link position variable
r	The filtered tracking error
RBFNN	Radial basis function neural network
RLED	Rigid-link electrically driven

REFERENCES

Azoui, N., & Saidi, L. (2011). Passivity-based adaptive control of robotic manipulators electrically controlled. *International Journal of Advanced Science and Technology*, *34*, 45-54.

Benzaoui, M., Chekireb, H., & Tadjine, M. (2010, June 23-25). Redundant robot manipulator control with obstacle avoidance using extended Jacobian method. In *Proceedings of 18th Mediterranean Conference on Control and Automation* (pp. 371-376). Marrakech, Morocco.

Benzaoui, M., Chekireb, H., & Tadjine, M. (2016). Tracking with obstacle avoidance of redundant manipulator based on fuzzy interference systems. *Neurocomputing, 196*, 23-30.

Chang, Y. C. (2002). Adaptive tracking control for electrically-driven robots without over parameterization. *International Journal of Adaptive Control and Signal Processing*, *16*(2), 123-150.

Chang, Y. C., Yen, H. M., & Wu, M. F. (2008). An intelligent robust tracking control for electrically-driven robot systems. *International Journal of Systems Science*, *39*(5), 497-511.

Chang, Y. C. (2014). Robust adaptive neural tracking control for a class of electrically driven robots with time delays. *International Journal of Systems Science*, *45*(11), 2418-2434.

Chen, B. S., Uang, H. J., & Tseng, C. S. (1998). Robust tracking enhancement of robot systems including motor dynamics: A fuzzy-based dynamic game approach. *IEEE Transactions on Neural Networks*, *6*(4), 538-552.

Cheng, L., Hou, Z. G., & Tan, M. (2009). Adaptive neural network tracking control for manipulator with uncertain kinematics, dynamics and actuator model. *Automatica, 45*(10), 2312-2318.

Dawson, D. M., Qu, Z., & Carroll, J. J. (1992). Tracking control of rigid-link electrically driven robot manipulators. *International Journal of Control*, *56*(5), 991-1006.

Fateh, M. M. (2008). On the voltage-based control of robot manipulators. *International Journal of Control, Automation and Systems*, *6*(5), 702-712.

Fateh, M. M., & Azargoshasb, S. (2015). Discrete time robust control of robot manipulators in the task space using adaptive fuzzy estimator. *Journal of AI and Data Mining*, *3*(1), 113-120.

Homayounzade, M., Keshmiri, M., & Ghobadi, M. (2015). A robust tracking controller for electrically driven robot manipulators: stability analysis and experiment. *International Journal of Automation and Computing*, *12*(1), 83-9

Hsu, P., Hauser, J., & Sastry, S. (1989) Dynamic control of redundant manipulators. *Journal of Robotic Systems, 6*(2), 133-148.

Huang, S. N., Tan, K. K., & Lee, T. H. (2008). Adaptive neural network algorithm for control design of rigid-link electrically driven robots. *Neurocomputing*, *71*(4-6), 885-894.

Jafarian, H., Eghtesad, M., & Tavasoli, A. (2006, July 24-26). Network control of two electrically driven cooperating 6 DOF robot manipulators. In *2006 World Automation Congress* (pp. 1-6). Budapest, Hungary.

Jiang, Z. H. (2006). Trajectory control of robot manipulators using a neural network controller. In A. Jinenez & B. M. Al-Hadithi (Eds.), *Robot Manipulators Trends and Development* (pp. 361-377). Rijeka: InTech.

Khaligh, Y. S., & Namvar, M. (2010, May 3-7). Adaptive control of robot manipulators including actuator dynamics and without joint torque measurement. In *2010 IEEE International Conference on Robotics and Automation* (pp. 4639-4644). Anchorage, AK, USA.

Kumar, N., Panwar, V., Sukanavam, N., Sharma, S. P., & Borm, J. (2011). Neural network- based nonlinear tracking control of kinematically redundant robot manipulators. *Mathematical and Computer Modelling*, *53*(9-10), 1889-1901.

Kumar, N., Borm, J., Panwar, V., & Chai, J. (2012). Tracking control of redundant robot manipulators using RBF neural network and an adaptive bound on disturbances. *International Journal of Precision Engineering and Manufacturing*, *13*(8), 1377-1386.

Ozbay, U., Sahin, H., & Zergerogl, E. (2008). Robust tracking control of kinematically redundant robot manipulators subject to self-motion criteria. *Robotica, 26*(6), 711-728.

Perumal, S. K. J., & Natarajan, S. K. (2017). Investigation of adaptive control of robot manipulators with uncertain features for trajectory tracking employing HIL simulation technique. *Turkish Journal of Electrical Engineering and Computer Sciences*, *25*(3), 2513-2521.

Rani, M., & Kumar, N. (2016, October 14-16). A hybrid approach for trajectory tracking control of redundant robot manipulators. In *2016 2nd International Conference on Next Generation Computing Technologies (NGCT)* (pp. 299-305). Dehradun, India.

Shafiei, S. E., & Soltanpour, M. R. (2009). Robust neural network control of electrically driven robot manipulator using back stepping approach. *International Journal of Advanced Robotic Systems*, *6*(4), 285-292.

Singh, H. P., & Sukavanam, N. (2012). Neural network based control scheme for redundant robot manipulators subject to multiple self-motion criteria. *Mathematical and Computer Modelling, 55*(3-4), 1275-1300.

Soltanpour, M. R., Khalilpour, J., & Soltani, M. (2012). Robust nonlinear control of robot manipulator with uncertainties in kinematics, dynamics and actuator models*. International Journal of Innovative Computing, Information and Control*, *8*(8), 5487-5498.

Wai, R. J., & Chen, P. C. (2004). Intelligent tracking control for robot manipulator including actuator dynamics via tsk-type fuzzy neural network. *IEEE Transaction on Fuzzy Systems*, *12*(4), 552-559.

Wai, R. J., & Chen, P. C. (2006). Robust neural-fuzzy-network control for robot manipulator including actuator dynamics*. IEEE Transactions on Industrial Electronics*, *53*(4), 1328-1349.

Wai, R. J., & Muthusamy, R. (2012). Fuzzy-neural-network inherited sliding-mode control for robot dynamics. *IEEE Transactions on Neural Networks and Learning Systems*, *24*(2), 274-287.

Wang, L., Chai, T., & Zhai, L. (2009a) Neural-network-based terminal sliding mode control of robotic manipulators including actuator dynamics. *IEEE Transactions on Industrial Electronics*, *56*(9), 3296-3304.

Wang, L., Chai, T., & Fang, Z. (2009b). Neural-network-based two-loop control of robotic manipulators including actuator dynamics in task space. *Journal of Control Theory and Applications, 7*(2), 112–118.

Zergeroglu, E., Dawson, D. M., Walker, I. W., & Setlur, P. (2004) Nonlinear tracking control of kinematically redundant robot manipulator. *Mechatronics, 9*(1), 129-132.

Zergeroglu, E., Sahin, H., Ozbay, U., & Tektas, U. (2006, October 4-6). Robust tracking control of kinematically redundant robot manipulators subject to multiple self-motion criteria. In *Proceedings of the IEEE International Conference on Control Applications* (pp. 2860-2865). Munich, Germany.