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PSO tuned SVM-SMC Controller for the Trajectory Tracking of a Five Bar Linkage Manipulator System

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Abstract
Remarkable advantages of SVM make it one of the most widespread and successfully used estimating techniques of the era, especially for the non-linear systems like robotic manipulators. Control system used in trajectory tracking problems of robotic manipulator is of great importance and hence, accuracy in tracking of manipulator is directly associated to the improvement in the quality of the controller engaged. So, to improve the control performance of the SVM based control technique, it is very important to select the optimal values of its three interdependent free parameters. Hence, in this paper, PSO has been used to get optimal values of these SVM parameters. Performance of the proposed PSO optimized SVM controller has been validated by checking its performance on a five-bar linkage robotic manipulator system having uncertainties. From validity checking point, simulation results have been compared with the results of the GA optimized SVM and the basic SVM. In last, suitable conclusions have been drawn from the study performed and it has been found that the PSO is showing its supremacy over conventional GA and the PSO optimized SVM based controller is performing best out of the three.

Keywords: *Support vector machines, particle swarm optimization, hybrid intelligent controllers, manipulators*

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INTRODUCTION
A robot is the main component of automation industry these days, although other areas where a robot finds its applications may include restaurants, homes, banks, offices etc. Robotic manipulator is considered to be highly reliable equipment which meets today's requirements of being very accurate and cost effective. Conventional controllers such as proportional-derivative (PD) or proportional-integral-derivative (PID) enjoy their wide acceptance amongst manipulator applications, in the automation industry due to easy operation and satisfactory results given by them. But these controllers require higher control gains to give better tracking results which provide undue pressure on the system and should be avoided [1, 2]. Sliding Mode Controller (SMC) is very good at disturbance rejection and can be applied under parameter fluctuations but at the cost of increased chattering in the output produced [3–8]. Many solutions to the problem of chattering have been suggested by researchers in the literature, some of them include continuous approximation method [9], second and higher order SMC [10], boundary layer solutions [11] etc.

These conventional controllers fail to address the practical problems of trajectory tracking which include uncertainties and disturbances present in the system. The accurate knowledge of these unwanted components is a must to address these problems. Hence, there arises a strong need for intelligent controllers which do not necessarily need the knowledge of mathematical models of uncertainties and still these controllers give better results when compared to conventional ones. Neural Networks (NN) and Support Vector Machines (SVM) have shown great learning capability among intelligent controllers as these techniques can effectively handle the unknown situations.

SVM was actually invented for pattern recognition and classification [12]. SVM suggested by Vapnik has proved to be a better scheme which offers better generalization and easier to find global optimal solutions when compared to neural networks with less number of training data [13–15]. The performance of SVM based methods has shown great performance in regression and time series prediction applications [16]. Proper selection of free parameters of SVM can ensure better results. Tuning of these parameters can be done by trial and error (TAE) method [17], expertise knowledge or prior knowledge. Yuan and Wang used mutative scale chaos optimization algorithm to find the best value of the SVM parameter [18], and Luo *et al*. employed quantum inspired evolutionary algorithm for the tuning of SVM parameter [19].

For the non-linear complex systems like robotic manipulator, applying optimization techniques like genetic algorithm (GA) and particle swarm optimization (PSO) can be one of the appropriate solutions of getting optimal parameters of SVM. GA and PSO are the intelligent techniques which do not necessarily require a smooth objective function to locate the global optima, so these can perform with a discontinuous objective function. Being most advanced techniques among present ones, these optimization methods would make best choice for comparing their performance to find the optimum values of SVM parameters [20]. In this paper, SMC is collaborated with the GA and PSO optimized SVM and are named as GA-SVM-SMC and PSO-SVM-SMC.

Next part of the paper covers the preliminaries; part afterwards focuses on the support vector machines; the proposed control scheme (GA/PSO-SVM-SMC); simulation study; and lastly the conclusion of the paper.

PRELIMINARIES

Dynamic Model of Five Bar Linkage Manipulator

Parallel manipulators have been very popular amongst researchers in industrial applications in the recent years due to their dual role of robot manipulators as well as machine tools [21]. Parallel manipulators constitute multiple kinematic chains which connect a fixed base with a moving platform. Motion of this kind of manipulator is controlled due to the parallel forces produced due to actuated joints. The load of the manipulator is shared by different actuators in different chains which results in high stiffness and high load bearing capacity in these parallel manipulators. The balancing act of joint errors in these manipulators gives higher accuracy in positioning of the load.

A five bar linkage manipulator is a special class of manipulators with a minimum of two kinematic chains controlling the motion of end-effectors. The central strategies for all multi-link manipulators are verified by the five bar linkage manipulator. In this manipulator one link less than the total links (N-1) move in a vertical plane with the help of two prismatic or revolute motors. The examples of this class of manipulators include elbow, spherical and cylindrical manipulators. Figure 1 shows the schematic diagram of a five bar linkage manipulator.

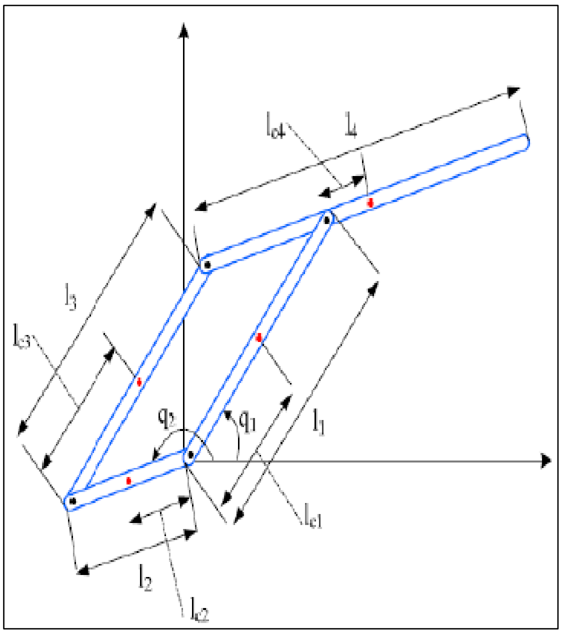

***Fig. 1**: Five Bar Linkage Manipulator.*

The angular motion in link 1 and link 2 of this manipulator is induced by two servomotors, which rotate about revolute joints q1 and q2. In this two DOF mechanism, q3 and q4 are represented as functions of q1 and q2. The dynamic model of the mechanism is derived from the reduced model method for closed chain mechanism.

The system equations of the dynamics of five bar linkage manipulator are represented below in Eq. (1)–(4) [22]:

$$\tau_1 = (M_{11} + I_h^1)\ddot{q}_1 + M_{11}\ddot{q}_2 + \frac{\partial M_{12}}{\partial q_2}\dot{q}_2^2 + g(m_1 l_{c1} + m_3 l_{c3} + m_4 l_1)cos(q_1)$$

$$\tau_2 = (M_{22} + I_h^2)\ddot{q}_2 + M_{12}\ddot{q}_1 + \frac{\partial M_{12}}{\partial q_1}\dot{q}_1^2 + g(m_2 l_{c2} + m_3 l_2 - m_4 l_{c4})cos\,(q_2) \quad (1)$$

Where,

$$M_{11} = I_{11}^1 + I_{11}^3 + m_1 l_{c1}^1 + m_3 l_{c3}^2 + m_4 l_1^2 \quad (2)$$

$$M_{22} = I_{11}^1 + I_{11}^4 + m_2 l_{c2}^1 + m_4 l_{c4}^2 + m_3 l_2^2 \quad (3)$$

$$M_{12} = M_{21} = (m_3 l_{c3} l_2 - m_4 l_{c4} l_1)cos(q_1 - q_2) \quad (4)$$

Where, q_i is the joint variable; τ_i and I_h^i are torque and hub inertias respectively. $I_i, l_i, l_{ci} and\, m_i$ represent the inertia matrix, link length, distance of center of gravity and mass of the link respectively. M is the inertia matrix of the entire manipulator. In all of the equations, the index i displays the i^{th} motor.

Uncertainties

Payload and the friction are the two most common uncertainties present in the manipulator system. A brief description of these uncertainties has been given in authors' previous paper [15]. Payload change in mass of link 4 is given as:

$$m_4 = m_{4o} + \Delta m_4 \quad (5)$$

Where, m_{4o} is the nominal mass of link 4 and Δm_4 is the payload change in m_4. Here in this case Δm_4 is taken as 30% of m_4.

The classical model for friction incorporates coulomb and viscous friction models. The static model of friction considered in this paper is given below [23]:

$$F = F_v\dot{q} + F_c sgn(\dot{q}) \quad (6)$$

Where, F_v is a diagonal matrix with diagonal elements as static friction constants and F_c is a diagonal matrix representing coulomb friction constants, $\dot{q}$ is joint angle velocity for each link of the manipulator. Value of friction model is defined by the constants as$F_v = 2$ &$F_c = 2$.

Genetic Algorithm

Genetic algorithm is the most popular evolutionary computational technique. GA finds the best population among the initial random population members. The outcome is a high quality individuals and each one of them will present an optimum solution for the problem under consideration. The length of the chromosomes defines the number of variables that has to be optimized. The procedure of finding the optimal solution to a particular problem initiates from a population of individuals, generated randomly. Evolution process takes place through a number of generations and each generation improves from its parent generation with respect to their inherent qualities; this process through generations gradually approaches fitness function.

Three basic genetic operators i.e. selection, crossover and mutation are sequentially applied to each chromosome during each generation. The performance of GA is highly affected by the choice of fitness function, individuals represented and the values of various GA parameters such as threshold of fitness value, population size, mutation and crossover rate.

Particle Swarm Optimization (PSO)

Particle Swarm Optimization was first introduced by Kennedy and Eberhart in 1995 [24]. PSO has proved with an excellent performance record in some nonlinear and constrained problems [25]. PSO simulates the social behaviour of animals such as flocking of birds, fish schooling etc. PSO starts with population of random individuals available in search space and gives out the optimum solution. Every member is excited to occupy the best neighboring position while moving towards global best position. Each new position is represented by Eqs. (7) and (8).

$$vel_i = \omega * vel_{i-1} + c_1 \in_1 (best_{\chi p} - \chi_p) + c_2 \in_2 (best_{\chi gbest} - \chi_p) \quad (7)$$

Where, ω is the inertia weight, c_1&c_2 are the acceleration constants that permits that how far individuals can fly from each other, and $\in_1 \& \in_2$ outputs a random number between 0 and 1,

$$\chi_p = \chi_{pp} + vel_i \quad (8)$$

vel_i is the present velocity, vel_{i-1} is the previous velocity, χ_p is the current location of the particle, χ_{pp} represents the previous location of the particle, and *i* being the particle index. The coordinates $best_{\chi p}$ and $best_{\chi gbest}$ are used to drag the particles towards the global minimum.

Value of ω is given in Eq. (9)

$$\omega = (\omega_{max} - \omega_{min})(\frac{maxiter - iter}{maxiter}) + \omega_{min} \quad (9)$$

SUPPORT VECTOR MACHINES (SVM)

SVM is a prediction tool that uses the fundamental of machine learning to maximize the accuracy while simultaneously avoiding the overfitting of data. SVMs were earlier developed for classification problems, later on, the regression problems have been successfully solved by them [26]. It is a statistical tool that creates association between the input and output of the system. The main objective of regression is to predict a function from a given set of samples.

Considering N data points$\{x_i, y_i\}(i = 1 \dots k)$, with input $x_i \subset R^n$ and output $y_i \subset R^n$ where k denotes the size of the training data. The support vector regression solves an optimization problem:

$$min(\frac{1}{2}\|w_s\|^2 + C\sum_{i=0}^{k} (\xi_i + \xi_i^*)) \quad (10)$$

subject to,

$$y_i - \langle w_s, x_i \rangle - b \leq \varepsilon_i + \xi_i$$

$$\langle w_s, x_i \rangle + b - y_i \leq \varepsilon_i + \xi_i^* (11) \; \xi_i, \xi_i^* \geq 0$$

Where, x_i is mapped to a higher dimensional space by the function Φ, $\|w_s\|$ is the Euclidean norm of weights representing model complexity and ε is the tolerance loss function; $C>0$ is the cost factor that determines the tradeoff among model complexity and empirical loss function; $\xi_i, \xi_i^*$are the slack variables representing upper and lower constraints on output of system subject to the ε insensitive tube $y_i - \langle w_s, x_i \rangle + b \leq \varepsilon$.

Three parameters naming cost of error *C*, mapping function Φ and the width of the tube ε affect the quality of regression. The constraints imply that most data x_i is put in the tube $y_i - \langle w_s, x_i \rangle + b_s \leq \varepsilon$. The error ξ_i or ξ_i^* which requires to be minimized in the objective function if x_i is not in the tube.SVM performs well by training data by minimizing the training error $C\sum_{i=0}^{k}(\xi_i + \xi_i^*)$ and regularization term $\frac{1}{2}\|w_s\|^2$.Width of the tuneε is always zero and data are not mapped into higher dimensional spaces for traditional least square regression. Hence, SVM proves to be best technique to deal with regression problems. The radial basis function (RBF) outperforms among several kernel functions in SVM for rainfall runoff modeling [27]. The centralized feature of RBF can be utilized to model the regression process more effectively [28].

Radial Basis Kernel

Radial basis functions are the most commonly used function and have Gaussian form as given in Eq. (9).

$$K(x_i, x_j) = exp(-\gamma\|x_i - x_j\|^2) \quad (12)$$

Where, γ is the RBF kernel breadth.

PROPOSED CONTROL SCHEMES (GA/PSO-SVM-SMC)

In SVM-regression with RBF kernel, the three main parameters to be estimated accurately are cost factor (C), gamma (γ) and epsilon (ε).

The value of parameter C plays a vital role as it may result in the imbalance between empirical risk minimization (ERM) and model complexity minimization (MCM), therefore, its value is a tradeoff between the extent to which greater deviations than ε are allowed and model complexity. Parameter ε controls the width of $\varepsilon -$ insensitive zone. Significance of the three parameters is as: an inappropriate value of C can lead to an imbalance between model complexity minimization (MCM) and empirical risk minimization (ERM). Hence, value of parameter C is the trade-off between the model complexity and the degree to which deviations larger than ε are tolerated. Parameter ε controls the width of the $\varepsilon-$ insensitive zone. Large value of ε allows greater margins in the insensitive to include data points which results in flat and unacceptable regression estimates. The parameter σ is the width of RBF kernel and a too small value will make SVM to over fit the training data and a too large value makes SVM less flexible for the problems of complex function approximation. Hence the performance of SVM controller highly affected due to these parameters and are also interdependent i.e. change in the value of one changes others also. A general flowchart representing the GA/PSO optimized SVM is given in Figure 2. Flowchart represents that the output obtained from it is the optimized parameters of SVM. Further, this SVM (using these optimized parameters) is used in collaboration with the SMC. Mathematically, the equation of the GA/PSO optimized SVM-SMC is as given in Eq. (13):

$$\tau = -M(\Lambda_1 \dot{e} + \Lambda_2 e - \ddot{q}^d + \dot{\beta}) + V(\dot{q}^d - \Lambda_1 e - \Lambda_2 \int_0^t e\, dt) + G - A\sigma - K_{GA/PSO-SVM-SMC} \quad (13)$$

Where, $A = [a_1, a_2, \ldots. a_n]$, a_i is a positive constant, and

$$K_{GA/PSO-SVM-SMC} \quad (14)$$

is the output from the GA/PSO optimized SVM.

k is a positive constant representing the discontinuous constant gain and all other symbols have their usual meaning [15]. In this research work, fitness function or the objective function to be minimized is mean square error (MSE).

SIMULATION STUDY

To verify the performance of the proposed controller i.e. PSO-SVM based SMC, it has been validated on one of the most emerging non-linear control problem of motion control of robotic manipulator for tracking a given trajectory. In this case, robotic manipulator chosen is a five bar linkage robotic manipulator and two types of trajectories i.e. cosine and exponential trajectories have been tracked.

Manipulator Dynamics

Numeric values of the parameters of the manipulator dynamics chosen are listed in Table 1.

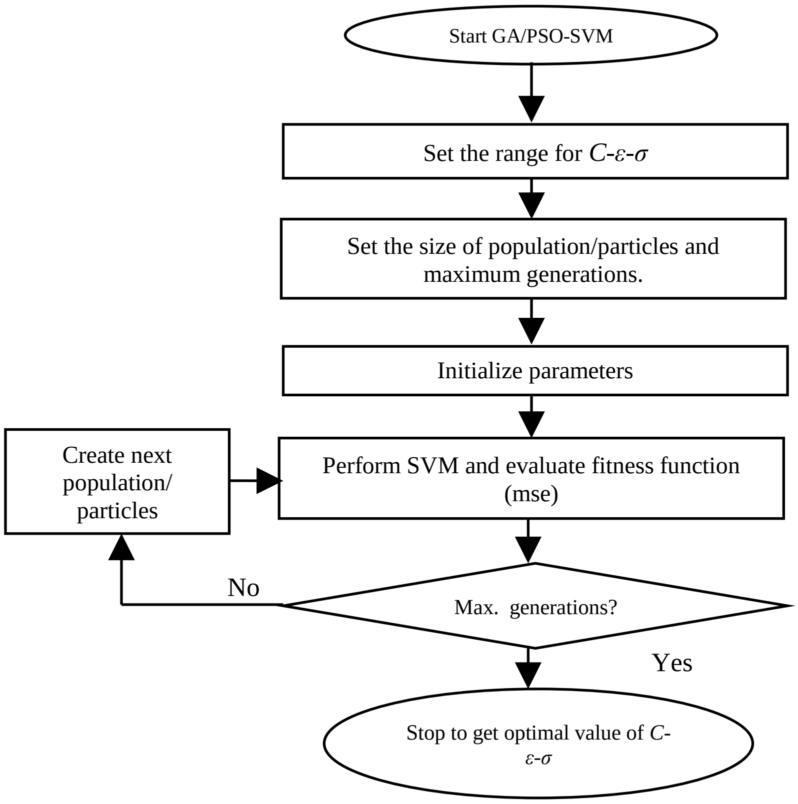

***Fig. 2**: Flowchart Representing the GA/PSO Optimized SVM Parameters.*

GA-SVM

Parameters of GA to find the SVM constant parameters i.e. cost factor (C), gamma (γ), epsilon (ε) are tabulated in Table 2. Range for search in GA in taken as: for γ=[1 20], C=[100 1000] and ε=[1 4].

PSO-SVM

PSO parameters to find the SVM constant parameters i.e. cost factor (C), gamma (γ), epsilon (ε) have been tabulated in Table 3. Range for search in PSO is same as in GA.

RESULTS

Results obtained from the various simulation studies carried out in the present study have been given below. Two types of trajectories, cosine and exponential, have been taken here. Tracking results for cosine trajectory have been shown graphically in Figures 3–7. Figure 3 represents the trajectory tracking results for all the three controllers i.e. SVM, GA-SVM-SMC and the proposed PSO-SVM-SMC. Figure 4 gives the tracking results in zoomed form. These figures represent the supremacy of the proposed PSO optimized SVM controller for the trajectory tracking problem. It can also be observed in the figures given that the GA optimized SVM is giving better performance than the SVM but is poorer in performance when compared to the PSO-SVM-SMC. Similarity in the pattern of results can been observed in the case of tracking error results which are given in Figure 5. It can be seen in Figure 5 that the tracking error is minimum in PSO based SVM controller followed by GA optimized SVM controller and then followed by basic SVM.

Table 1: *Parameters of the Parallel Manipulator.*

$S.No.$	$Mass$ $m_i(kg)$	$Link$ $l_i\ (m)$	$Mass\ Centre$ $m_i\ (m)$	**Inertia** $I_i(\ 10^{-2}\ kg/m^2)$
1	0.91	0.080	0.006	0.847
2	0.28	0.100	0.028	0.630
3	0.38	0.250	0.125	4.002
4	0.38	0.250	0.125	4.002
5	-	0.250	-	-

Table 2*: GA Parameters.*

Parameters	**Value**
Mutation type and rate	Uniform type and 0.06
Population size	25
Crossover type and fraction	Single point/2 point and 0.9
Elite count	1

Table 3*: PSO Parameters.*

Parameters	**Value**
Acceleration Coefficients (c1, c2)	(2,2)
Population Size	25
Inertia Weight (w)	Varied Linearly; Range (0.4–0.9)

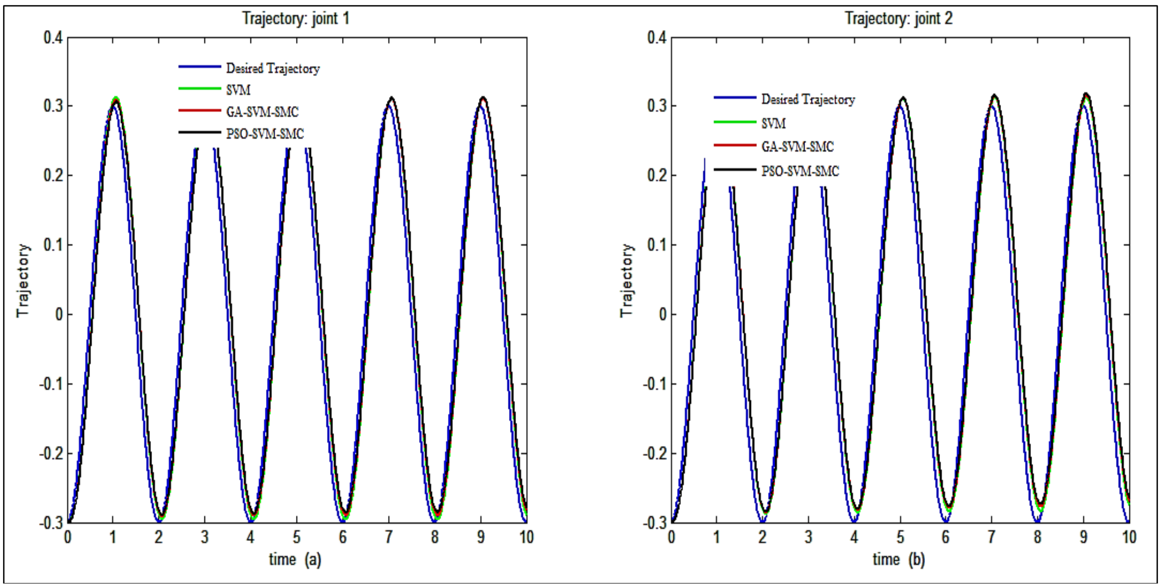

Fig. 3*: Trajectory Tracking for Cosine Trajectory for* ***(a)*** *Joint 1 and* ***(b)*** *Joint 2.*

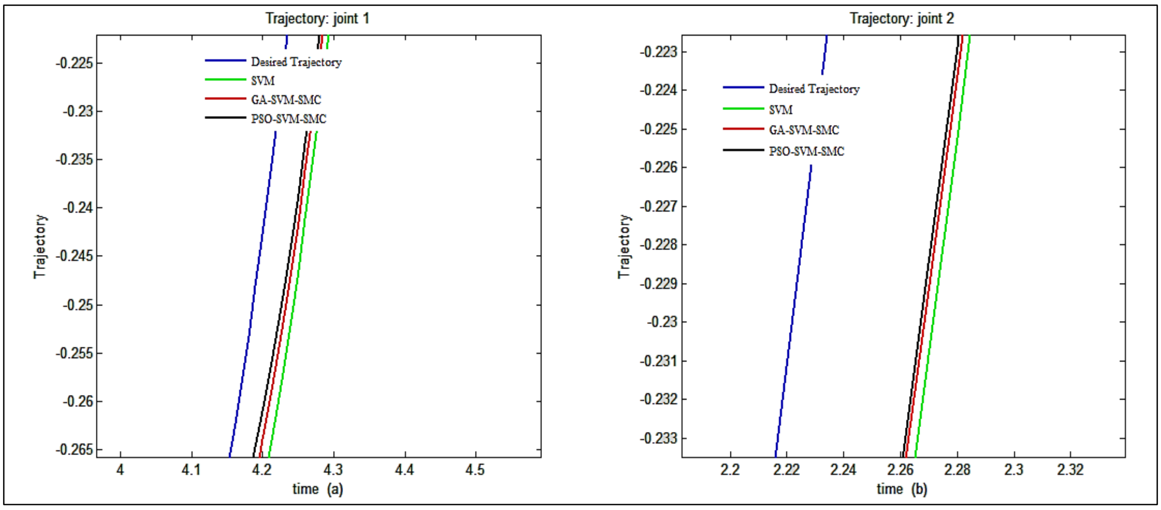

***Fig. 4**: Trajectory Tracking for Cosine Trajectory for **(a)** Joint 1, and **(b)** Joint 2 (Zoomed).*

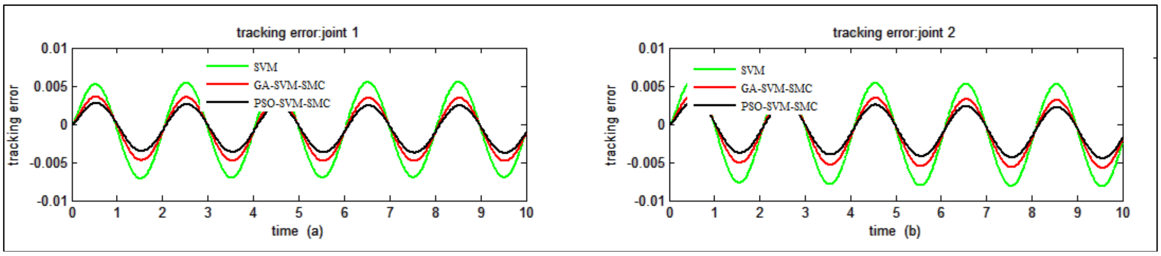

***Fig. 5**: Tracking Error for Cosine Trajectory for **(a)** Joint 1, and **(b)** Joint 2.*

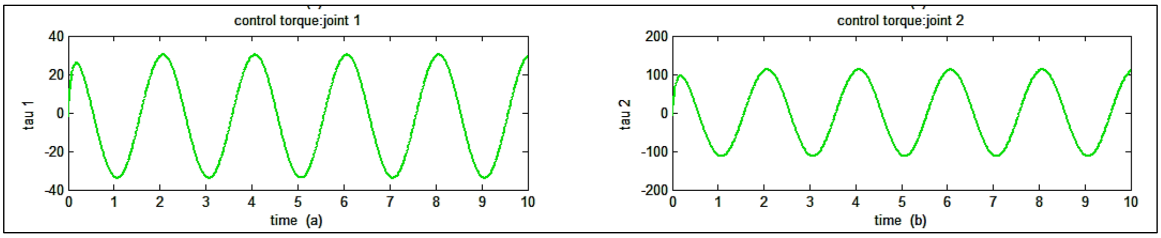

***Fig. 6**: Control Torque for Cosine Trajectory for **(a)** Joint 1, and **(b)** Joint 2 in PSO-SVM-SMC.*

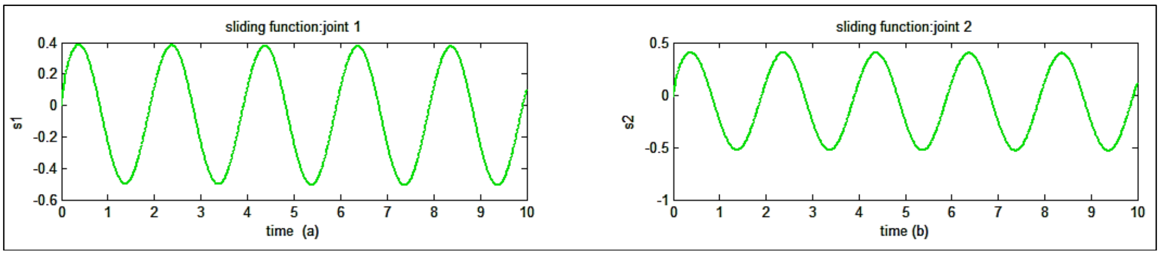

***Fig. 7**: Sliding Function for Cosine Trajectory for **(a)** Joint 1, and **(b)** Joint 2 in PSO-SVM-SMC.*

Further, Figure 6(a & b) gives the control torque of the proposed PSO-SVM-SMC for joint 1 and 2 respectively. Figure 7 represents the sliding function of the same proposed controller for joint 1 and 2. Both Figures 6 and 7 clearly show that the control torque and the siding function are chattering free for both the joints. Also, the control input torque and the sliding function for the other two controllers are found to have the similar type of chattering free pattern and hence have not been shown here. Moreover, for the other trajectory i.e. exponential trajectory, similar types of results have been found and hence not shown here.

A quantitative analysis of the above shown tracking results have been tabulated in Tables 4 and 5 for cosine trajectory and in

Tables 6 and 7 for exponential trajectory. It can also be clearly observed in the tables that with and without uncertainties PSO based control scheme is showing the minimum norm of tracking error and the control torque followed by GA based control scheme and then followed by the basic SVM. It can also be seen in the tables that for both the trajectories in both the cases (with and without uncertainties) in both the joints chattering is eliminated. Hence, it can be said that PSO-SVM-SMC is a better controller than both the other controllers of the paper.

CONCLUSIONS

In this paper, advantages of three widely used, proficient techniques naming sliding mode, PSO and SVM have been integrated for the trajectory tracking problem of the robotic manipulator. In the basic SVM, optimal value of SVM kernel constants has been obtained using PSO and GA. PSO has shown its supremacy as compared to the GA based controller and the original SVM. This controller has been tested for motion control of a robotic manipulator incorporating uncertainties in the system. Even in presence of uncertainties, simulation results of the proposed control scheme proves it when compared with a standard SVM and GA-SVM-SMC in terms of tracking performance, 2-norm of error and 2-norm of control effect. In last, it can be said that the controller proposed is robust and performs best in uncertain conditions too. In spite of a numerous number of advantages, this control technique is complex. Further, this proposed controller can be used in many other control problems and forecasting areas like load, weather forecasting etc.

Table 4: *Performance Evaluating Factors for the Controllers for Cosine Trajectory (without Uncertainties).*

Control Schemes	2-Norm of Tracking Error		2-Norm of Control Torque		Chattering in Torque	
	Joint 1	Joint 2	Joint 1	Joint 2	Joint 1	Joint 2
SVM [15]	0.1905	0.1894	709.30	2.501e+3	0.0073	0.2161
GA-SVM-SMC	0.0854	0.1089	700.09	1.982e+3	0.0002	0.0892
PSO-SVM-SMC	0.0674	0.0956	657.23	0.999e+3	0.0045	0.0543

Table 5: *Performance Evaluating Factors for the Controllers for Cosine Trajectory (with Uncertainties).*

Control Schemes	2-Norm of Tracking Error		2-Norm of Control Torque		Chattering in Torque	
	Joint 1	Joint 2	Joint 1	Joint 2	Joint 1	Joint 2
SVM [15]	0.1919	0.1910	715.65	2.535e+3	0.0069	0.2155
GA-SVM-SMC	0.1234	0.1098	705.45	2.122e+3	0.0987	0.1245
PSO-SVM-SMC	0.0987	0.0249	698.98	1.077e+3	0.0006	0.1090

Table 6: *Performance Evaluating Factors for the Controllers for Exponential Trajectory (without Uncertainties).*

Control Schemes	2-Norm of Tracking Error		2-Norm of Control Torque		Chattering in Torque	
	Joint 1	Joint 2	Joint 1	Joint 2	Joint 1	Joint 2
SVM	0.1110	0.1212	1010.01	987.03	0.0034	0.0879
GA-SVM-SMC	0.099	0.1004	987.09	809.00	0.0011	0.0765
PSO-SVM-SMC	0.067	0.0869	960.66	798.98	0.0008	0.0986

Table 7: *Performance Evaluating Factors for the Controllers for Exponential Trajectory (with Uncertainties).*

Control Schemes	2-Norm of Tracking Error		2-Norm of Control Torque		Chattering in Torque	
	Joint 1	Joint 2	Joint 1	Joint 2	Joint 1	Joint 2
SVM	0.1289	0.1280	1321.2	1001.0	0.0089	0.0876
GA-SVM-SMC	0.1209	0.1109	1007.09	910.00	0.0001	0.0059
PSO-SVM-SMC	0.609	0.1060	989.9	800.98	0.0098	0.0698

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