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ACO based hybrid Intelligent Controllers for Trajectory Tracking of Manipulator

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Abstract : Various sources estimate the total share of conventional controllers like PID and SMC in all the motion control controllers in industry is about 80% [1-5]. But, tuning of PID and SMC controller parameters is a tedious and time consuming job especially for the systems like manipulator. Moreover, it is well acknowledged that soft computing techniques present a helpful approach in modeling and control of non linear systems like manipulator. Hence, in this paper, an emerging optimization intelligent technique, naming ant colony optimization (ACO), is used for getting the optimized value of the constant parameters of these conventional controllers. These hybrid controllers have been applied to robotic manipulator for tracking a predefined trajectory tracking and hence checked for their effectiveness. These proposed hybrid intelligent controllers have proven themselves when compared to the basic original conventional controllers.

***IndexTerms* – Intelligent systems, ACO, Manipulator**

I. INTRODUCTION

Robot manipulators are highly complicated, dynamically coupled, time varying and non-linear systems. But, have been widely used in industrial automation. In wide range of manipulator applications, they have to track these pre-determined trajectories as close as possible. Hence, the trajectory tracking problem is one of the most significant task. The motion control problem required the knowledge of mathematical models representing the kinematics and dynamics of the robot. However, discrepancies between the models and the reality can seriously degrade the performance and often named as uncertainties.

The role of the control algorithm in the mechanical positioning systems is to assure a prescribed precision for the position control or for the velocity control. A particular control method used for motion control of the manipulator affects the manipulator's performance significantly in terms of tracking and disturbance rejection. In many practical applications, the standard linear Proportional Integral Derivative (PID) type, Sliding Mode Controller (SMC) type or linear cascade controllers are used for position control [6]. This is due to simplicity, easy implementation in hardware and software, non requirement of a precise model to start up and maintain [7-10]. This controller works well with the unrealistic assumption that the dynamics of the links are uncoupled and linear.

But, conventional classical controllers fall short of delivering high precision performance as demanded. This is due to the fact that parameter tuning in such controllers is still an art without any standardized methods [11].

Inherent parallelism in ACO makes this technique better than its peers. Also, positive feedback makes it fast to discover good solution and can be used in dynamic applications and hence it adapt to different changes. Various hard combinatorial optimization problems efficiently handled by ACO include travelling salesman problem TSP [12], quadratic assignment problem [13], graph coloring problems [14], hydroelectric generation scheduling problems [15], vehicle routing [16], sequential ordering, scheduling [17], and routing in Internet-like networks [18].

Just like other optimal parameter finding approaches of the constant parameters of controllers like PID, SMC, SVM etc; ant colony optimization may also be utilized. Ibtissem Chiha et al. proposed the tuning of PID controllers using multi objective ant colony optimization for the optimum solution of PID controller parameters by minimizing the multi objective function. It has a better control performance compared to the classical approach of tuning and the method of genetic algorithm [19].

Jagatheesan et al. described the application of an Artificial Intelligence (AI) optimization technique to design PID controller for Load Frequency Control (LFC) of single area re-heat thermal power system. In this paper the author optimized the control parameters using conventional method and ACO technique. ACO optimized technique is proved to be better even in the presence of non-linearity [20].

The ability of SMC to handle non-linear multivariate systems has made it an attractive non-linear controller. SMC is able to reject external disturbances, robust against parameter variations and model uncertainties. Lindokuhle J. Mpanza and Jimoh O. Pedro proposed a tuning mechanism for sliding mode controller used for a 2-DOF hydraulic servo system [21]. F. Allouani et al. investigated a novel approach for angel positions control of a Twin Rotor Multi input – multi output System (TRMS) with the help of SMC. Basic ACO algorithm is employed to search and select sliding surface constants and FLC input/output membership function parameters. This control method is found to have better performance in tracking error and control torque [22]. Hence, diffusion of intelligent techniques with PID [23-26] and SMC [27-31] has become a major research topic recently and achieved a lot of success in last few years.

The rest of the paper is organized as follows-Section II describes the dynamics of the robotic manipulator system, Section III explains the concepts of the ant colony optimization Section IV has the elementary concepts of the proportional integral derivative controller and the proposed hybrid ACO based PID controller followed by basics of the sliding mode controller and the proposed hybrid ACO based improved SMC controller in the Section V. Section VI has the simulation example and the discussion on the results obtained. Finally Section VII contains the conclusions drawn followed by the references.

II. Dynamics of Robotics Manipulator

The dynamics of revolute joint type n-link robot can be described by following nonlinear differential equation [32], given in (1)

$$M(q)\ddot{q} + V(q,\dot{q}) + G(q) = \tau \qquad (1)$$

with $q \in R^n$ as the join position variables,

$\tau \in R^n$ as vector of input torques,

$M(q) \in R^{nxn}$ is the inertia matrix which is symmetric and positive definite,

$V(q,\dot{q}) \in R^{nxn}$ is the coriolis and centripetal matrix and

$G(q) \in R^n$ includes the gravitational forces.

III. Ant Colony Optimization

Ant Colony Optimization (ACO) algorithms have been developed to mimic the behavior of real ants to provide heuristic solutions for optimization problems. Ant Colony Optimization Algorithms (ACO) proposed by Italian scholar Dorigo et al. [33] was inspired by the ants finding the shortest path from their nest to a food source, and vice versa. When foraging, ants leave a pheromone trail on their passed path. Because ants can smell pheromone, other randomly moving ants in the neighborhood can detect this marked pheromone trail. Numerous ants follow the pheromone-rich trail, and the probability of the trail being followed by other ants is further enhanced by increased trail deposition. This is an auto-catalytic process that favors the path along which more ants previously traversed. The ant system algorithms were based on the indirect communication capabilities of the ants. Artificial ants in the ACO algorithms are deputed to generate rules by using heuristic information or visibility, and by using the principle of indirect pheromone communication capabilities for iterative improvement of rules [34-36]. The transition probability $P'^{k}_{ij}(t)$ from city i to city j for the kth ant is as given in (2).

$$P'^{k}_{ij}(t) = \begin{cases} \dfrac{[\tau'_{ij}(t)]^{\alpha} x [\eta'_{ij}(t)]^{\beta'}}{\sum_{im\epsilon_k(i)}[\tau'_{ij}(t)]^{\alpha} x [\eta'_{ij}(t)]^{\beta'}} & ; \quad j \in j'_k(i) \\ 0 \quad ; \quad \text{others} \end{cases} \qquad (2)$$

where $P'^{k}_{ij}(t)$ is the transition probability for the kth ant at time t. i is the current city, j is the next city, $\tau'_{ij}(t)$ is the pheromone level between city i and city j at time t, η'_{ij} is the inverse of the distance between city i and city j, $J'_k(i)$ is the set of cities that remain to be visited by the kth ant positioned on city i, and α' and β' are the parameters that determine the relative importance of pheromone level versus distance. The initial pheromone concentration (τ'_0) between any two cities (from city i to city j) is set as a small positive constant: $\tau'_{ij} = \tau'_0 = (N'L')^{-1}$, where N' is the number of the total segments between all of cities, L' is the total length of all cities.

For each arrival node with every ant, formula (2) was repeated to find the passing path of every ant. The pheromone concentration on segment i and j left from the path passed by the ants is shown in formula (3),

$$\tau'_{ij}(t+1) \leftarrow (1-\rho')\tau'_{ij}(t) + \rho'\Sigma_{k=1}\tau'^{k}_{ij} \qquad (3)$$

where $0 < \rho' < 1$ is a degenerating parameter of the pheromone, (1-ρ') is evaporation (i.e., loss) rate of pheromones, the symbol ← is used to show the next iteration, and $\triangle\tau'^{k}_{ij}$ is the left pheromone concentration (from t to t+1) between cities i and j by the kth ant. If Q' is a parameter of the pheromone strength and L'^{k}_{ij} represents the length between cities i and j visited by the kth ant, $\triangle\tau'^{k}_{ij} = Q'/L'^{k}_{ij}$. In general, the Q' value is set to 100. Each ant repeats step 2 until all ants have toured all cities After this, the optimal route is updated and shortest path is selected. Obtained test stop conditions lead to the optimal results from ACO.

IV. Ant Colony Optimization Based Proportional Derivative Integral (ACO-PID) Controller

PID controller consists of three constant control parameter gains: the proportional, the integral and the derivative gains denoted as K_P, K_I and K_D respectively. Proportional gain control is required to move the process to the right direction i.e. to the desired track. Integral gain term gives the quantity of necessary reset needed to rectify an amount of error and derivative gain is the effort to see that how far a process variable has been from the set point in the past, and analyzing the point at which further rectification will be needed [37, 38]. Mathematical formulation given to PID controller is as given below in (4):

$$\tau = K_P e(t) + K_D \dot{e}(t) + K_I \int e(t) \qquad (4)$$

where K_P, K_D and K_I are the gains and represent suitable nxn positive definite diagonal matrices.

This τ is given to the manipulator for control purpose. However when the desired precision is high these controllers cannot assure satisfactory performances. Use of conventional controllers means making serious tradeoffs between feasible static accuracy, system stability, and rejection of disturbances and damping of parasitic dynamics at high frequencies. For example, one of the remedy provided to that is to increase the gain of the classical linear PID controller. This improves the control performance but with the rise in high order dynamics and noise amplification [39]. This limits the use of PID controllers as they are unable to assure an optimal performance.

ACO-PID Controller:

In the proposed ACO-PID controller, ACO algorithm is utilized to optimize the gains and the values are applied to the controller for the motion control of five bar linkage robotic manipulator. The flowchart for ACO based PID controller is shown in Fig. 1. Constant parameters of the ACO-PID controller are represented as K_{P-ACO}, K_{D-ACO} & K_{I-ACO} and the basic control law of (4) takes the form of (5).

$$\tau = K_{P-PSO}e(t) + K_{D-PSO}\dot{e}(t) + K_{I-PSO}\int e(t) \quad (5)$$

This τ is given to the manipulator for control purpose.

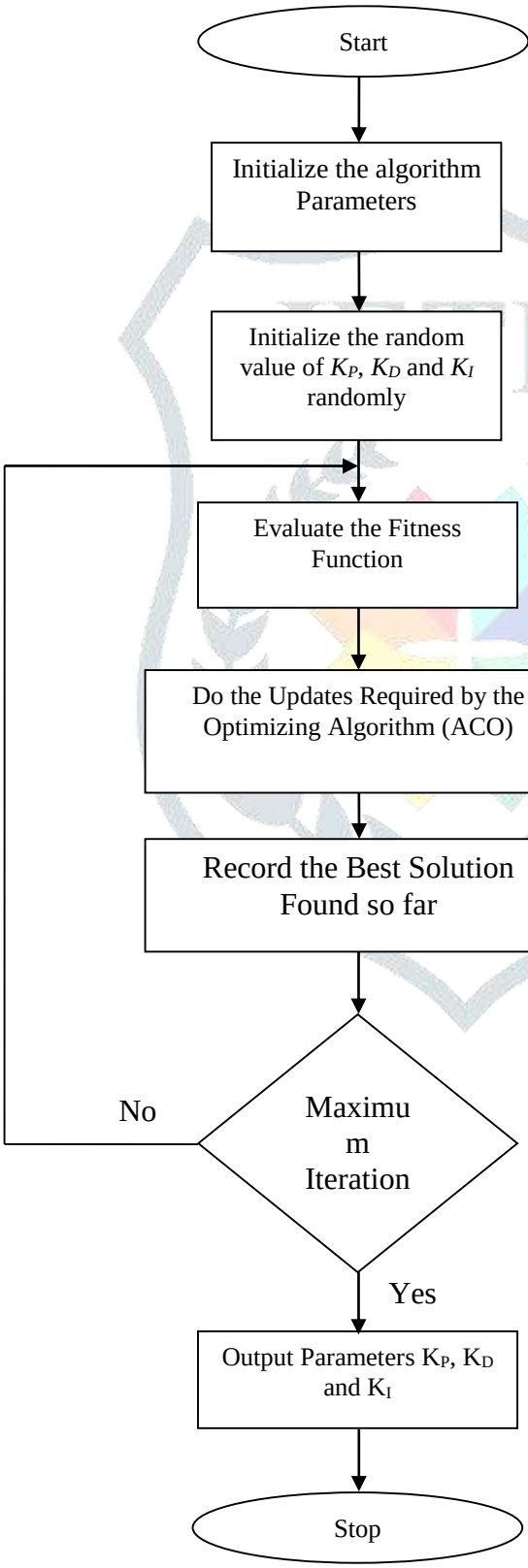

Fig.1: Flowchart Representing the Steps for Optimized PID Controller

V. Ant Colony Optimization Based Sliding Mode Controller (ACO-SMC)

A sliding mode control law is formed based on the equivalent control and in order to achieve the zero error objectives, given as following [40]:

$$\tau = \tau_0 + \tau_s \quad (6)$$

where, $\tau_0 = -\widehat{M}(\lambda_1\dot{e} + \lambda_2 e - \ddot{q}^d) + \widehat{D}\left(\dot{q}^d - \lambda_1 e - \lambda_2 \int_0^t e\ dt\right) + \widehat{G}$ i.e. nominal control input.

$$\tau_s = -As - k * sat(\xi) \text{ i.e. the sliding control input}$$

where $\widehat{M}, \widehat{D}$ *and* $\widehat{G}$ are based on nominal model and $A = diag[a_1, a_2, \ldots\ldots a_n]$, is a diagonal matrix and is positive definite, in which a_i is a positive constant, and $k = diag[k_1, k_2, \ldots\ldots k_n]$, is a diagonal positive definite matrix and it is chosen as :

$$k > |\delta|,$$

where, δ is the bound on uncertainty, which is not easy to determine in practice as uncertainties are unknown a-prior. This τ is given to the manipulator for control purpose.

To suppress chattering in SMC, the signum function in (6) gets replaced by the saturation function $sat\ (s/\delta)$, where δ is boundary layer and should be chosen as very small [41] and (s/δ) factor represents δ. Mathematically:

$$sat\ (\xi) = \begin{cases} 1, & \xi \geq 1 \\ \xi, & -1 < \xi < 1 \\ -1, & \xi \leq -1 \end{cases} \quad (7)$$

ACO-SMC Controller:

The developed SMC algorithm suffers from some problems. Firstly chattering, by which the non modeled high frequency component is excited and can cause significant disturbances. Next, earlier from initial states to the reaching stage, the system behaves as a regular feedback control and hence does not adapt to the parameter variations and the disturbances. So, robust character of the system is weakened and to improvise the quality of reaching stage, the reaching law method was proposed [42]. Moreover, the parameters of switching function and exponential reaching law affect the performance of the system. For the exponential reaching law $\tau_s = -As - k * sign(s)$; the value of A must be chosen smaller to eliminate the chattering which may affect the rapidness of the control law. On the other hand, rising k can speed up the reaching velocity with a biggish control level and chattering. For this, it is required to analyze and customize the reaching law parameter A and make it time varying with respect to sliding function. This also guarantees the state convergence and smoothening in the control input torque [43].

Consequently, an intelligently optimized SMC is developed in this section. In this proposed SMC scheme, ACO is used to optimize the switching function parameters (i.e. $\boldsymbol{\lambda_1}$ ***and*** $\boldsymbol{\lambda_2}$) and exponential reaching law parameters (i.e. $\boldsymbol{A}$ ***and*** $\boldsymbol{k}$) offline for the real time implementation of SMC. This newly developed controller will try to make the balance between favorable quality i.e. improved tracking performance and chattering of original sliding mode controller. To deal with the chattering problem of SMC, discontinuous sign function has been replaced with saturation function. This will speed up system convergence and bring better robustness in the system. Block Diagram of a generalized optimized SMC controller is given below in Fig. 2.

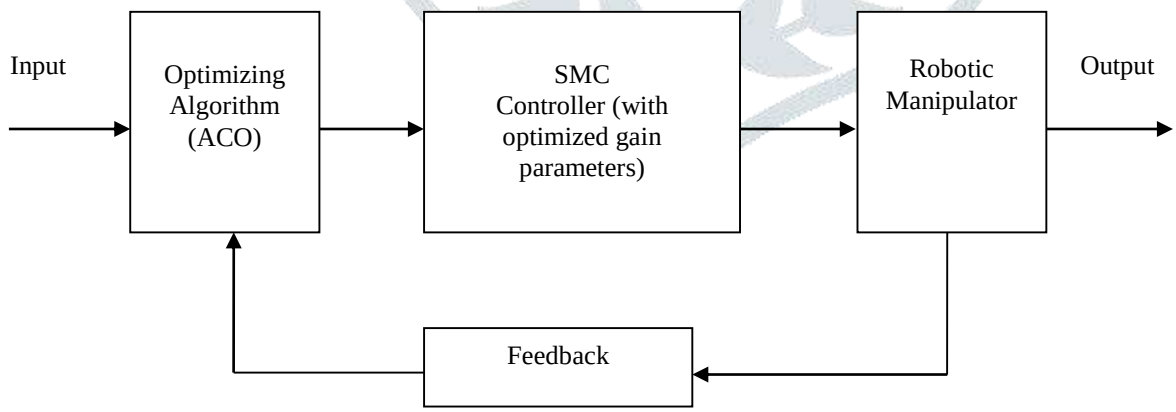

Fig. 2: Block Diagram of Generalized SMC Controller

ACO optimized SMC constant parameters are presented as $\boldsymbol{\lambda_{1ACO}}$ ***and*** $\boldsymbol{\lambda_{2ACO}}$ for switching function and $\boldsymbol{A_{ACO}}$ & $\boldsymbol{k_{ACO}}$ for exponential reaching law parameters and the control law takes the form of (8)

$$\tau = \tau_0 - A_{\text{ACO}}s - k_{\text{ACO}} * sat(\xi) \quad (8)$$

where, $\tau_0 = -\widehat{M}(\lambda_{1\text{ACO}}\dot{e} + \lambda_{2\text{ACO}}e - \ddot{q}^d) + \hat{C}\left(\dot{q}^d - \lambda_{1\text{ACO}}e - \lambda_{2\text{ACO}}\int_0^t e\ dt\right) + \hat{G}$ i.e. $A_{\text{ACO}}, k_{\text{ACO}}, \lambda_{1\text{ACO}}$ and $\lambda_{2\text{ACO}}$ are $nX1$ vector matrices obtained from ACO and all the symbols have their usual meanings. This τ is given to the manipulator for control purpose.

VI. Simulation Example and Results Discussion

To verify the performance of the proposed controller i.e. ACO-PID and ACO- 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.

a. Manipulator Dynamics:

The dynamics of a 2 DOF manipulator used in all types of controllers and satisfying (1) is given as:

$$M(q) = \begin{bmatrix} m11 & m12 \\ m21 & m22 \end{bmatrix}$$

where

$$m11 = (m_1 + m_2)a_1^2 + m_1 a_2^2 + 2m_2 a_1 a_2 \cos q_2$$
$$m12 = m_2 a_2^2 + m_2 a_1 a_2 \cos q_2 = m21$$
$$m22 = m_2 a_2^2$$
$$V(q,\dot{q})\dot{q} = \begin{bmatrix} -m_1 a_1 a_2 (2\dot{q}_1\dot{q}_2 + \dot{q}_2^2)\sin q_2 \\ m_2 a_1 a_2 \dot{q}_1^2 \sin q_2 \end{bmatrix}$$

$$G(q) = \begin{bmatrix} (m_1 + m_2) g a_1 \cos q_1 + m_2 g a_2 \cos(q_1 + q_2) \\ m_2 g a_2 \cos(q_1 + q_2) \end{bmatrix}$$

where m_1 and m_2 are the mass and a_1 and a_2 are the lengths of the links 1 & 2 respectively. Parameters of the manipulator model have been taken as: m_1=1kg; m_2=1kg; a_1=a_2=1m; g=9.8m/s^2.
This 2 DOF manipulator has been commanded to track the path shown given by (9-10) below

q^d_1= [0.3sin(0.7t-Π/2)+0.3sin(0.1t- Π/2) +0.7]; (9)
q^d_2= [0.5sin (0.9*t- Π/2) +0.5sin (0.1t-Π/2) +1.1]; (10)

b. Basic PID controller:

Values of the controller gains for PID controller by TAE are taken as

$K_p = \begin{bmatrix} 200 & 0 \\ 0 & 200 \end{bmatrix}$; $K_d = \begin{bmatrix} 60 & 0 \\ 0 & 62 \end{bmatrix}$; $K_i = \begin{bmatrix} 22 & 0 \\ 0 & 20 \end{bmatrix}$;

c. Basic SMC:

In order to acquire the desired response of the output of the manipulator sliding function constants for SMC in (6)are taken as:

$\lambda_1 = diag\{1,1\},\ \lambda_2 = diag\{20,20\}\ ,\ A = diag\{10,10\},\ k = diag\{20,10\}$

The value of boundary layer δ has been chosen as 0.1 by trial and error method.

ACO Parameters

For ACO-PID/SMC controllers, the parameters chosen for ACO are by trial and error method and are listed in Table 1.

Table 1. ACO parameters

Parameters	Value
Number of ants	50
Pheromone	0.6
Evaporation Rate	0.95
Number of Iterations	100
Range for K_p, K_d and K_i	[0-200], [0-25] & [0-50] respectively
Range for λ_1, λ_2, A and k	[0-10], [10-25], [10-40] & [0-50] respectively

Results and Discussions:
Results obtained from the simulation work carried out for this paper has been compiled in this section. Trajectory tracking results for the basic PID and the ACO optimized PID control schemes have been shown below in Figs. 3 (a) & (b) for joints 1 & 2 respectively. In both the figures, blue line represents the desired trajectory , green line represents the trajectory tracked when PID

controller is used and magenta line represents the trajectory tracked when ACO-PID controller is used. It can be clearly observed form both the figures that ACO-PID is showing the better results when compared to the basic PID controller (as it is closer to the desired trajectory as compared to the original PID).

Similarly, in Figs. 4 (a) & (b), which represents the tracking errors for the PID and ACO-PID controllers for both the joints respectively shows the supremacy of the ACO-PID controller when compared to the PID.

Further, results representing the supremacy of the ACO-SMC (magenta line) as compared to the basic original SMC (green line) are shown in Figs. 5 (a) & (b) for both the joints respectively. On the similar pattern, trajectory tracking error for SMC and ACO-SMC in Fig. 6 (a) & (b) for joint 1 & 2 respectively, represents the better performance of ACO optimized SMC by showing lesser tracking error.

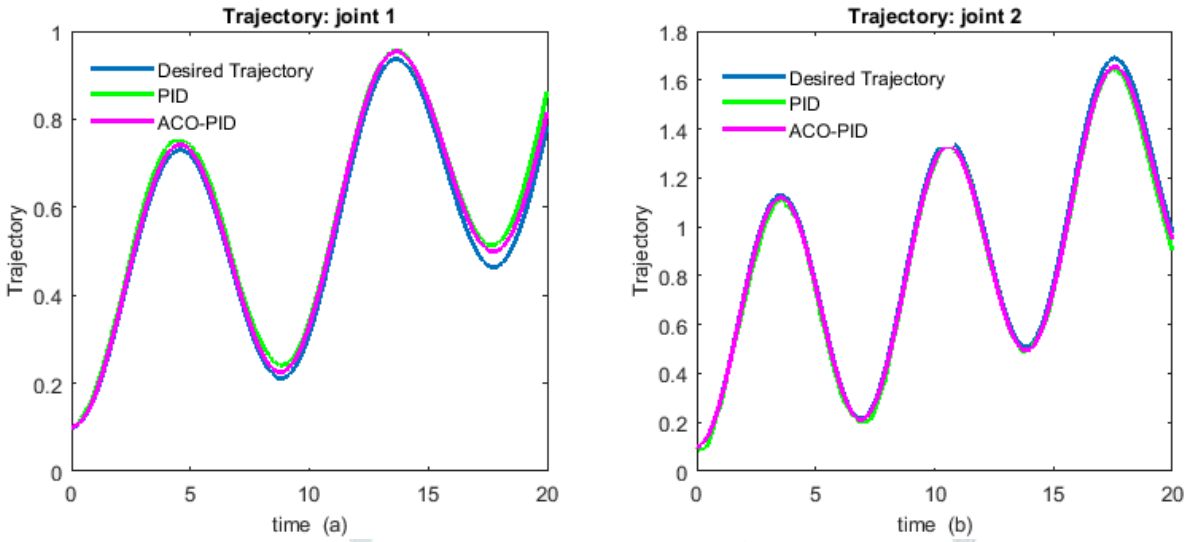

Fig. 3: Trajectory Tracking performance by PID & ACO-PID controllers for (a) joint 1 & (b) joint 2

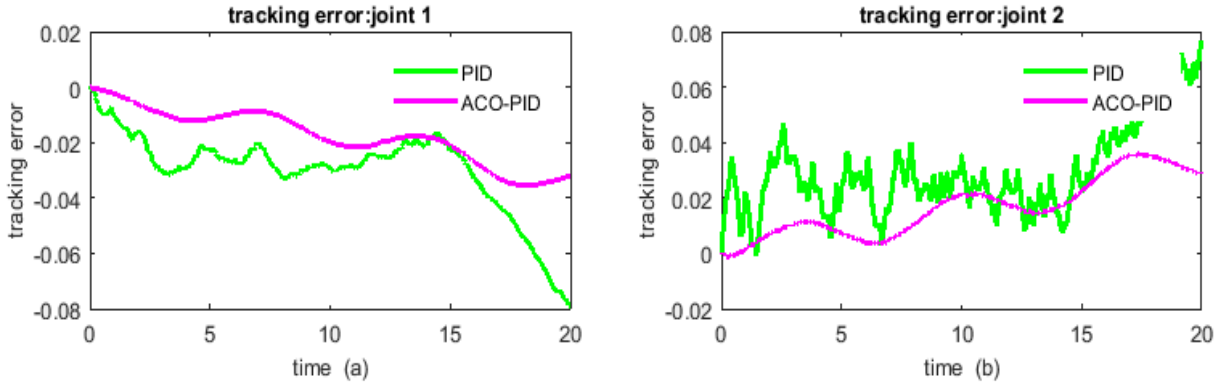

Fig. 4: Tracking errors by PID & ACO-PID controllers for joints 1 & 2 respectively

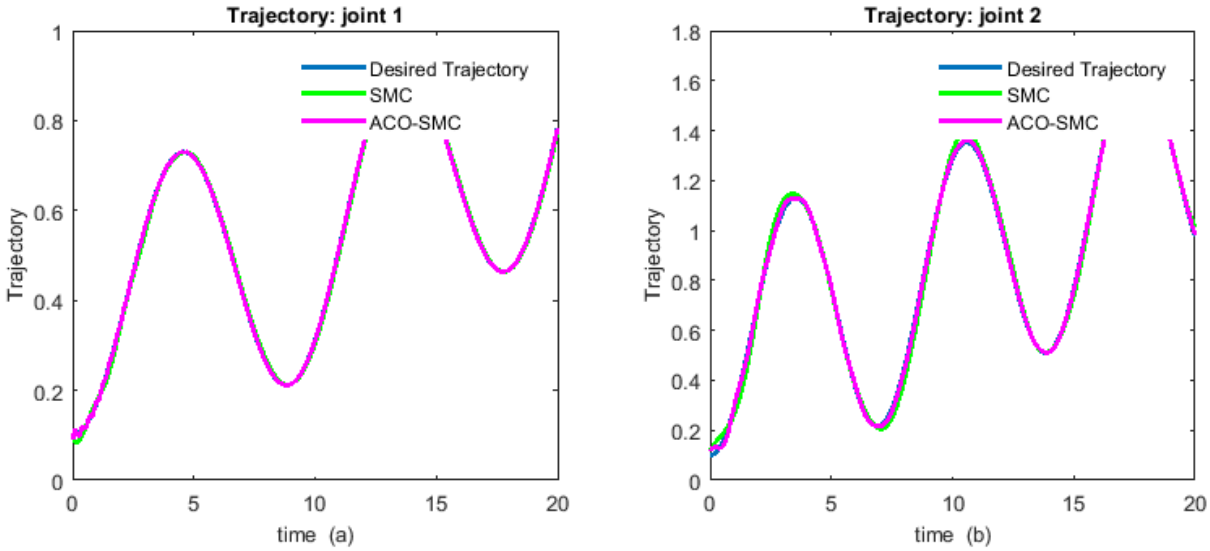

Fig. 5: Trajectory Tracking performance by SMC & ACO-SMC controllers for (a) joint 1 & (b) joint 2

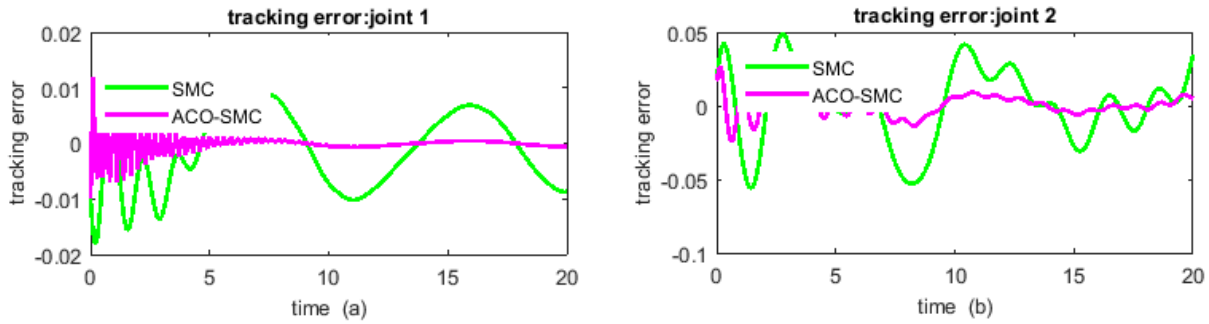

Fig. 6: Tracking errors by SMC & ACO-SMC controllers for joints 1 & 2 respectively

Quantitative analysis of the simulation performed has been compiled in the tables 2 & 3 below. Results for the various numerical factors for the PID and its optimized version have been shown in table 2. This numerical data, comparing maximum of tracking error, minimum of tracking error, mean square of tracking error and the norm (average) of the tracking error clearly shows that these quantitative numeric values of these errors reduces when basic PID constant parameters are optimized with the advance optimization technique naming, ACO.

Analysis drawn out of table 3 is again represents the advantage of hybrid of ACO with SMC. Numeric values of all the error indices of the ACO-SMC have reduced values when compared to the basic SMC. Hence, values tabulated in both tables represent the advantage of adding ACO in the basic conventional control schemes.

Table 2: Comparative Numerical Analysis for PID and Optimized PID Control Schemes

Controller	PID		ACO-PID	
	Joint 1	Joint 2	Joint 1	Joint 2
e_{max}	1.007E-04	0.0771	9.35E-06	0.0360
e_{min}	0.0793	-6.13e-04	-0.0356	0.0011
e_{mse}	0.0011	0.0011	4.03E-04	3.84E-04
norm(e)	1.5017	1.4925	0.8985	0.8797

Table 3: Comparative Numerical Analysis for SMC and Optimized SMC Control Schemes

Controller	SMC		ACO-SMC	
	Joint 1	Joint 2	Joint 1	Joint 2
e_{max}	0.0086	0.0485	0.0119	0.0259
e_{min}	0.0182	0.0558	0.01	0.0246
e_{mse}	4.67E-05	6.34E-04	4.67E-06	5.84E-05
norm(e)	0.0969	0.3572	0.0307	0.1020

VII. CONCLUSIONS

Inspite of widespread use of various conventional controllers, their practical drawbacks restricts their usage. Moreover, there is a tremendous growth in the area of intelligent controllers. Hence, this paper developed and proved hybrid controllers having ACO to optimize the constant gain parameters of the conventional most widely used PID and SMC control schemes. It can be observed form the results obtained from the simulation study carried out for the motion control problem of a robotic manipulator, that in the proposed control schemes, ACO optimized PID and SMC outperforms the basic PID and SMC controllers for the motion control problem of the robotic manipulator. Moreover, this proposed hybrid intelligent system demonstrates its feasibility and advantages, and many are used in practical applications.

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