Comparison of ABC and Ant Colony Algorithm Based Fuzzy Controller for an Inverted Pendulum

Anita Khosla, Leena G. M. K. Soni

***Abstract:** Fuzzy logic is a practical, robust, economical and intelligent alternative for controller design of complex systems. Choosing appropriate fuzzy rules is essential for a fuzzy logic controller to perform at the desired level. Various evolutionary algorithms are used to find an optimal set of fuzzy rules in the literature. In this paper, an artificial bee's colony (ABC) optimization algorithm and Ant colony algorithm are used to optimize the fuzzy membership functions to control the deviation in pendulum angle and velocity. The proposed control techniques are implemented in MATLAB/Simulink platform and the control performances are evaluated. With the ABC based fuzzy, the inverted pendulum is remaining in the steady position with less error.*

***Keywords:** Inverted pendulum, angle, velocity, integrated control, ABC algorithm, fuzzy controller, Ant colony algorithm.*

I. INTRODUCTION

Inverted Pendulum is a well established benchmark problem that produces many challenges to a control engineer. It is a nonlinear, unstable, nonminimum phase and under actuated systems [1]. One reason behind the extensive studies of the pendulum is that many important engineering systems can be approximately modeled as pendulum like pitch dynamics of rocket, bipedal dynamic walking, wheeled motion and balancing mechanisms [2].

Fuzzy logic is a practical, robust, economical and intelligent alternative for controller design of complex systems. Some of the recent research works on control of the inverted pendulum system using fuzzy controller are provided in [2-8]. As fuzzy rules and the fuzzy sets are very crucial in the performance of fuzzy logic controller, choosing the right rules and fuzzy sets becomes very important.

Finalizing the fuzzy rules and sets is mainly based on the control experience of operator. But sometimes converting the experience into if-then rules is difficult and usually the rules are incomplete and show conflict of knowledge. Evolutionary optimization algorithms have been appealing because they allow adaptation and optimization of fuzzy systems without human intervention[9-10].Many approaches have been effective to design fuzzy logic controller such as Genetic algorithm[11], partial feedback linearization and integrator back stepping approach [12]. However the local search capability and search efficiency of GA is not so appreciable. ABC algorithm is one of the swarm intelligence based optimization algorithm introduced by Karaboga [13]. This approach is motivated by the intelligent behavior of honey bees.

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Since the ABC optimizing technique combines local search methods carried out by employed and onlooker bees with global search methods managed by scouts, the approach attains global or near global optima. It is used for optimizing the inputs of fuzzy controller. The objective function of ABC algorithm is developed by the control output of fuzzy. So, the conventional fuzzy system is converted into adaptive and the control performance of the fuzzy controller is improved. The paper is organized as follows: Section 2 describes the inverted pendulum. Section 3 presents the fuzzy controller based on ABC algorithm. The model is simulated in Matlab/Simulink platform and the results are given in Section 4. Section 5 provides the conclusions.

Ant colony algorithm first introduced by M. Dorigo [18] is a new metaheuristic approach inspired by the foraging behavior of real ants. The basic ant colony algorithm idea is that a set of cooperating artificial ants searching the solution space in parallel simulates real ants searching their environment for food. The ant colony algorithm offers a number of advantages: it can explore and exploit the parameter space without trapping in Local optima. But little has been done for the search in continuous-spaces. To break through the limitations of the basic ant colony algorithms, we propose an adaptive ant colony algorithm (AACA) for solving continuous optimization problems. By dividing the space of solution into subdomains and dynamically adjusting the strategy of selection of the paths and the strategy of the trail information updating, the algorithm can find the subdomain in which the solution is located, and then determines the specific value of the solution within the subdomain. To prove the validity of AACA, it is applied to a suite of benchmark functions, and compared with ABC algorithm. Simulation results show that AACA can seek out the global optimum with considerably fast convergence. AACA is used to design a fuzzy Logic controller for real-time control of an inverted pendulum. In order to avoid the combinatorial explosion of fuzzy rules, state variable synthesis scheme is employed to reduce the number of fuzzy control rules greatly [20]. Simulation results show that the designed controller can control the inverted pendulum successfully.

II. MODELING OF INVERTED PENDULUM

The inverted pendulum is a classical nonlinear control problem and is frequently found in literature [14] as a benchmark test for control technique. It consists of an inverted beam (pole) on a moving cart as shown in Fig.1. The task of the controller is to stabilize the pole angle (θ) and the cart position (x) by applying the force (F). The configuration and the free body diagram are illustrated in Fig.1 and Fig.2 respectively.

$$ml\frac{d^2x}{dt^2}=\left(I+ml^2\right)\frac{d^2\phi}{dt^2}-mgl\phi \qquad (1)$$

$$\left(M+m\right)\frac{d^2x}{dt^2}+b\frac{dx}{dt}-ml\frac{d^2\phi}{dt^2}=F \qquad (2)$$

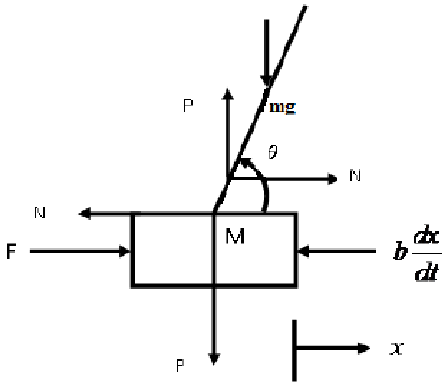

Fig.1 Configuration of Inverted pendulum

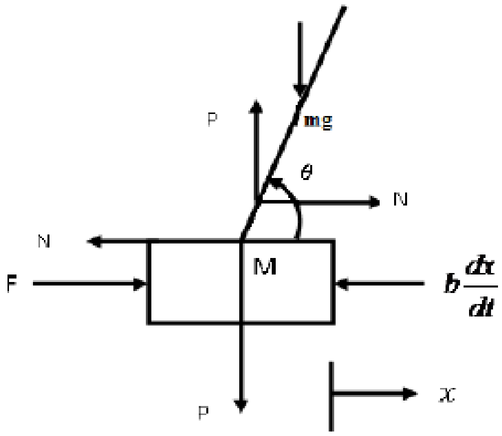

Fig. 2 Free body diagram

where F is the control (applied force), x is the displacement of the cart, θ is the angle of the with respect to the vertical axis, ϕ indicates the pendulum deviation position from the equilibrium position i.e. $\theta=\pi+\phi$; g = 9.8m/s^2 is gravity acceleration. Other parameters are the mass of the cart M = 0.455Kg, mass of the pole m=0.21 Kg; the friction coefficient b = 0.1N/m/sec ;distance to pole centre of mass l = 0.3m; the inertia of the pole I =.0035Kg.m^2 ; The proposed optimal fuzzy logic controller as shown in Fig. 3 is used for controlling the angle and the velocity of the pendulum. An artificial bee's colony (ABC) algorithm is used for optimizing the input membership function of fuzzy inference system.

III. FUZZY CONTROLLER AND ABC ALGORITHM

The inputs of the fuzzy system are the change of angle and change of velocity of the inverted pendulum. The output of the fuzzy system is the controlled output of the pendulum. The control action of fuzzy depends on the change of angle $(\Delta\theta)$ and the change of velocity (Δv) of the pendulum. The change of angle is calculated by difference between the current and previous error. Similarly, the change of velocity of the pendulum is evaluated. These, change of angle and change of velocity are applied to the input of fuzzy system and the control output is determined. The inputs of the fuzzy system are optimized by ABC algorithm and the optimized membership function is generated based on the optimized output of ABC algorithm. The objective function of ABC algorithm depends on the control output of the fuzzy system.

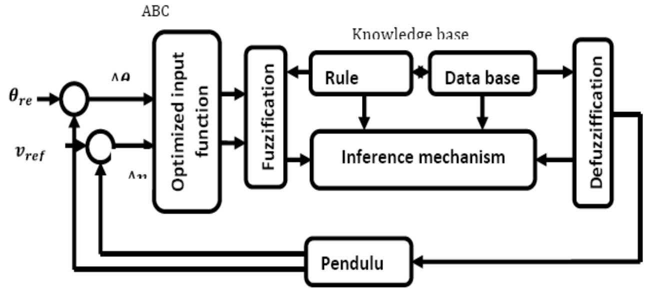

Figure 3: Structure of proposed controller

A. ABC algorithm for optimizing fuzzy input

ABC algorithm is a swarm intelligence based optimization technique [13] used to optimize the change of angle and velocity of the pendulum. In ABC algorithm, the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. The employed bee provides the neighborhood of the source in its memory which stays on a food source. Onlooker bee gets the information of food sources from the employed bees in the hive and select one of the food source to gathers the nectar. The scout is responsible for finding new food, the new nectar, and sources. The random number of the population is $x_i\in(\Delta\theta_i,\Delta v_i)$, where $\Delta\theta_i=1,2,3....SN$ and $\Delta v_j=1,2,3....SN$, SN is the size of population.

The probability for selecting the food source by the artificial onlooker bee depending on the probability value associated with that food source. The expression used to calculate the food source is expressed as follows:

$$P_i=\frac{fit_i}{\sum_{n=1}^{SN} fit_n} \qquad (3)$$

Where, fit_i is the fitness of the solution i, which is proportional to the nectar amount of the food source in the position i . $fit_i=\min(\Delta\theta_i,\Delta v_i)$ (4)

The main steps of the algorithm for the proposed approach are described as follow:

Step 1: Initialize population size of change of pendulum angle and velocity.

Step 2: *Repeat*

Step 3: Place the employed bees on the corresponding population.

Step 4: Place the onlooker bees on the pendulum parameters depending on their nectar amounts.

Step 5: Send the scouts to the search area for discovering new solution.

Step 6: Memorize the best solution found.

Step 7: *Until* requirements are met as equation (4).

From the output of ABC algorithm, the optimized input of fuzzy controller developed.

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The fitness value of equation (4) is selected so as to provide less change of angle and velocity deviation of pendulum.

B. Optimal fuzzy inference system

For stabilizing the inverted pendulum model, the fuzzy logic controller with triangular member ship function is used. The artificial intelligence system [15] consists of three steps that are categorized as fuzzification, inference mechanism and defuzzification. The detailed explanation of the steps are described as following them, *Fuzzifications:*

During fuzzification, the crisp variables of input $\Delta\theta$ and Δv are converted into fuzzy variables. In fuzzification, the change of angle and change of velocity are mapped to the linguistic labels of fuzzy sets. The membership functions of these fuzzy sets are associated to every label with triangular shape which consists of two inputs and one output. The following linguistic labels NB, NM, NS, ZE, PS, PM, PB have been used in this paper. All of the inputs and output have membership function among all these seven linguistics.

Inference mechanism:

The data base rule base inference mechanism involves defining the rules which represented as IF-THEN rules statements leading the relationship between input and output variables in terms of membership function. In the stage, the input variables $\Delta\theta$ and Δv are progression by the inference mechanism which executes 49 rules characterized in rule table I. For considering the first rule, it is represented as IF change of angle is NB and change of velocity is PB, THEN the pendulum control output will be Z.

Table I: Fuzzy control rules.

Δv / $\Delta\theta$	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NM	NS	NS	Z
NM	NB	NM	NM	NM	NS	Z	Z
NS	NM	NM	NS	NS	Z	Z	PS
Z	NS	NS	Z	Z	Z	PS	PS
PS	NS	Z	Z	PS	PS	PM	PM
PM	Z	Z	PS	PM	PM	PM	PB
PB	Z	PS	PM	PM	PL	PB	PB

Defuzzification:

The defuzzification is the reverse process of fuzzification. Here the center of area (COA) defuzzification method is used to produce fuzzy set value for the output fuzzy variable. The control output of the inverted pendulum is determined by the defuzzification process. The control output of the pendulum is denoted as ΔC. The COA expression with universe of discourse can be written as follows;

$$\Delta C = \frac{\sum_{i=1}^{n} \Delta C_i \mu_{out}(C_i)}{\sum_{i=1}^{n} \mu_{out}(\Delta C_i)} \qquad (5)$$

Where, $\mu_{out}(\Delta C_i)$ is the union of all the contribution of rules with the degree of completion greater than zero. Then, the defuzzified control output of fuzzy system is applied to inverted pendulum.

C. Results and discussion

In the paper, ABC algorithm based optimized fuzzy controller is proposed for controlling the velocity and angle of inverted pendulum. In Fig.3, the input of the fuzzy controller is change of velocity and change of angle of the pendulum. The change of velocity and change of angle is optimized by ABC algorithm and the optimal inference system is developed. The input and output membership function with respect to the change of angle, change of velocity and control output are shown in Figure 4.a, b and c respectively. The proposed controller was implemented in MATLAB/simulink working platform (version 7.12). The simulink configuration of the proposed ABC-fuzzy controller is illustrated in Fig. 5. With the ABC-fuzzy controller the angle, velocity and cart position are shown in Fig.6, 7and 8 respectively.

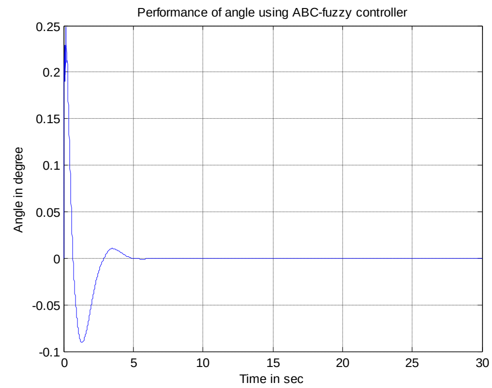

Fig. 6 Pendulum angle with ABC fuzzy controller

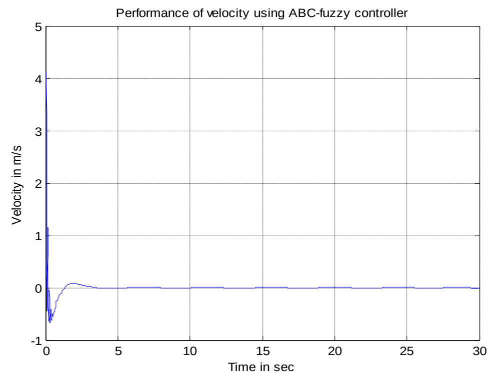

Fig. 7 Pendulum velocity with ABC fuzzy controller

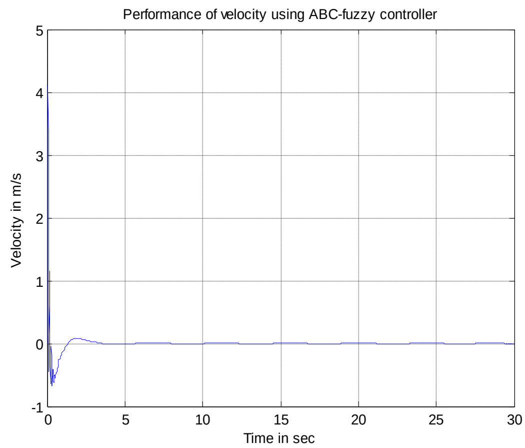

Fig. 8 Cart position with ABC fuzzy controller

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IV. FUZZY CONTROLLER AND ANT COLONY ALGORITHM

A fuzzy Logic controller is used to control the inverted pendulum system. The inputs of the fuzzy Logic controller are the 4 state variables of the inverted pendulum: x ,θ,x˙,θ˙. The multivariable inputs would result in combinatorial explosion of fuzzy control rules, and the number of fuzzy control rules would become very large. In order to avoid this phenomenon, state variable synthesis scheme is employed (see Fig. 9). State variables x and θ are synthesized as the synthesis error e, and x˙ and θ˙ are synthesized as the synthesis error change ec. Thus, the fuzzy Logic controller (FLC) has only 2 inputs, and the number of fuzzy control rules is reduced.

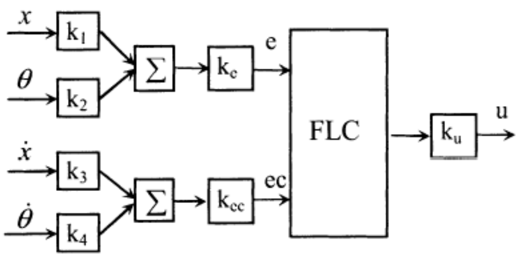

Fig. 9 State variable synthesis frizzy Logic controller

The synthesis coefficients k_1, k_2, k_2,k_3, k_4 can be calculated by solving Riccati equation. First, the dynamic equations of the inverted pendulum system are linearized near r = θ = r˙ = θ˙ =0 and the linear state equations are obtained.

X=AX+Bu

Y=CX (6)

Then, utilizing the state equations above, the following Riccati equation is solved.

$PA+A^TP- PBR^{-1}{}'B^TP+C^TQC = 0$ (7)

Finally, the synthesis coefficients can be calculated as$[k_1,k_2,k_2,k_3,k_4]=R^{-1}{}'B^TP$=[IO00.00,167.65,56.50,31.37] (8)

The input and output universes ofdiscourse for the fuzzy Logic controller are all normalized in the range -1 to 1 by scaling factors k_e ,k_{ec} and k_u. Assume E and EC are the fuzzy linguistic variables of e and ec, and each linguistic variable has 3 linguistic values, i.e., "Positive", "Zero" and "Negative". Thus, the fuzzy Logic controller with 9 fuzzy control rules (3x3) can be obtained. The table of fuzzy control rules is shown in Table 1.

Table 2. The table of fuzzy control rules

E EC	N	Z	P
N	P	P	Z
Z	P	Z	N
P	Z	N	N

The fuzzy control rules in Table 2 are symmetrical because of the symmetrical characteristic of the inverted pendulum system. Moreover, the membership functions for each linguistic variable are also symmetrical. Hence, if the membership function is Gaussian function, then the membership functions for each linguistic variable can be determined by 3 parameters, i.e., the center and variance of membership function for linguistic value "Positive" and the variance of the membership function for linguistic value "Zero". The center ofthe membership function for linguistic value "Zero" is always 0. Therefore, there are 3x3 = 9 parameters for membership functions and 3 scaling factors needed to be determined. It is difficult to give these parameters appropriately according to the human's experience. In this paper, an adaptive ant colony algorithm is used to design these parameters automatically.

A. ADAPTIVE ANT COLONY ALGORITHM

A. Basic principle of ant colony algorithm

Ant colony algorithms were inspired by the observation of real ant colonies. Real ants are capable of finding the shortest path from their nest to a food source without using visual clues by exploiting a chemical substance called pheromone,which records the information on distance. While walking,ants deposit pheromone on the path, and follow, in probability, pheromone previously deposited by other ants.While more and more ants are walking to the food source, the shorter path accumulates the more pheromone. This in turn increases the number of ants choosing the shorter path, with a positive feedback effect. Finally the ants will find the shortest path.

This phenomenon has inspired artificial ant colony algorithm, in which a set of artificial ants cooperate to the solution of a problem by exchanging information via pheromone deposited on graph arcs. Ants make use of the amount of the pheromone deposited by other ants as their parameters of choosing path. The more pheromone is on the arc, the higher probability is the arc to be chosen with. The update strategy of pheromone is that the shorter arc should get the more pheromone. Searching for better route through this positive feedback is the basic theory of the ant colony algorithm.

B. Adaptive ant colony algorithm

In order to introduce AACA, we consider the following continuous-space optimization problem:

$$\begin{cases} min/\max j = f(x_{1,x_{2,\dots\dots x_n)}} \\ x_{ij} \le x_i \le x_{iu} \quad (i = 1,2, \dots.n) \end{cases} \qquad (9)$$

where f is a non-linear function.

As the first step to solve the continuous space problem by using AACA, the definition field should be divided to N sub-spaces.

Let the total number of ants be m .We use n vertices to represent the n components (variables). There are N edges between vertex i and vertex i+1 to represent the candidate values of component i, a path from the start vertex to the last vertex represents a solution vector whose n edges represent n components. We denote the jth edge between vertices i and i+1 as (i,j) and its intensity of trail information at time t as τ_{ij} (t) .

The procedure for AACA is described as follows.

Step 1: For every variable x_i, we divide the domain of x_i into N equal parts. The length of each subdomain is:

$$h_{i=}\frac{x_{iu}-x_{il}}{N} \quad (i = 1,2 \dots\dots n) \qquad 10)$$

Step2: (initialize).

For every edge (i,j), set an initial value τ_{ij} =constant; place the m ants on the N subdomains of start vertex on random.

Step3: If max (h_l,h_2,...h_n,)<ε, finish the process. The optimal solution is $x_i = x_{il} + x_{iu}/2$ (i1,i2....n) otherwise return to Step 4.

Step4: Set counter of internal circulation S ←0

Step5: For all m ants, each ant selects the jth subdomain on the ith variable according to pseudorandom proportional rule given by

$$j = \begin{cases} \arg\max \mathrm{r}_{ij} \mid 1 \le j \le N\} \ if\ q \le q_0 \\ J \quad otherwise \end{cases} \quad (11)$$

where q is a random variable distributed in [0,1], $q_0(0 < q_0 < 1)$ is a parameter, and J is a random variable selected according to the probability distribution given by

$$p_{ij}\ (t) = \tau_{ij}\ (t) / \sum_{s=1}^{N} \mathrm{r}_{is}(t)$$
(12)

Step6: (local pheromone updating).

Update the amount of pheromone on the jth subdomain of the ith variable according to formula:

$$\tau_{ij}=(1-\varepsilon).\ \tau_{ij}+\varepsilon\tau_o \quad (13)$$

$$\tau_{o} = \min\{\mathrm{r}_{ij} \mid 1\le\tau\le N\}$$

where $\varepsilon(0\le\varepsilon\le1)$ is a parameter

Step7: For the current ant, let

$$x_i = x_{i1}+ (2j -1)h_i /2. \quad (14)$$

Step8: If all ants have completed the solution, go to next step; otherwise go to Step 5.

Step9: Calculating the value f_k of fitness function of the ant k, let f_{ib} denote the iteration-best solution in the current iteration.

Step 10: (global pheromone updating).

If the optimal solution in current iteration smaller or equal to the optimal solution in the last iteration, the pheromone level on the iteration-best solution is updated by applying the global

updating rule:

$$\tau_{ij}\ (t + 1) = 1 -\rho(t)) * \tau_{jj}\ (t) +\rho\ (t)\ \Delta\tau_{ij}$$

$$\Delta\tau_{ij} = \begin{cases} \frac{Q}{a+f_{ib}}, if\ (i,j) \in iteration - best\ solution \\ 0 \\ 0 \end{cases} \quad (15)$$

otherrwise

$$\rho(t) = max(1 - \frac{log(t)}{log(t+b)}, \rho_{min}$$

where $\rho(0 < \rho < 1)$ is the pheromone evaporation rate, a and b are constant, ρ min is the lower bound of ρ which can prevent the rate of convergence of algorithm from decreasing.

Step 11: Let

$$\tau_{ij} = \begin{cases} \tau_{min}, if\ \tau_{ij} < \tau_{min} \\ \tau_{ij}, if\ \tau_{ij} \in [\tau_{min}, \tau_{max}] \\ \tau_{max}, if\ \tau_{ij} > \tau_{max} \end{cases} \quad (16)$$

where τ_{min} and τ_{max} are the lower bound and the upper bound for the amount of pheromone.

Step 12: Let S ←S+1. If S<T, where T is a fixed positive integer, go to Step5; otherwise we find out the index vector (m_l, m_2,. .,m_n), where

$$m_i = \arg\max\{\tau_{ij} \mid \le j \le N\} \quad (17)$$

Then the scope of variable x_i is reduced according to the formula:

$$x_{it} \leftarrow \max(x_{ij,}x_{il} + (m_i -\Delta)h_i) \quad (18)$$

$$x_{it} \leftarrow \min(x_{ij,}x_{il} + (m_i +\Delta)h_i)$$

where Δ is a constant, let S←0; return to Step1.

V. BDESIGN OF FUZZY LOGIC CONTROLLER BY AACA

The AACA is used to design the fuzzy Logic controller in Fig. 9 for real-time control of the inverted pendulum. The scaling factors and membership functions of the fuzzy Logic controller are needed be tuned. Compared with the membership functions, the 3 scaling factors have drastic effects on the overall system behavior. Modification to the scaling factors leads to an expansion or contraction of the operating range, which in tum decreases or increases the sensitivity of the system for that variable. Hence, the 3 global parameters are tuned early before the membership functions are fine-tuned locally. The membership functions are fixed. The fixed membership functions are shown in Fig. 2. For all linguistic variables, the center and variance of the membership functions for linguistic value "Positive" are 0.7 and 0.45 respectively, and the variance of the membership functions for linguistic value "Zero" is 0.35.

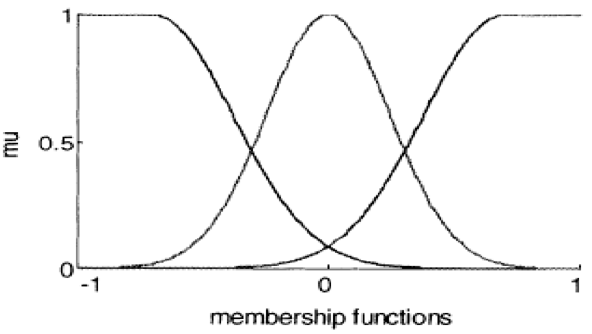

Fig. 10 The membership functions for all linguistic variables

In the following , we use AACA to tune the 3 scaling factors (k_e k_{ec}, k_u) , where k_{ec} ε[0,1] , k_{ec}ε [0,1] , and k_u ε[1, 150] Each possible value of vector (k_e k_{ec}, k_u) expresses a controller. The quadratic performance index is used to evaluate the performance of controller:

$$J = \sum_{k=1}^{N} X^T(k)QX(k) + u^T(k)Ru(k)$$

Where J is the performance index of the controller; Q=diag(10,1,0,0) and R=0.001 are weight matrixes; $X^T(k)$ = [x(k), θ (k), x·(k), θ ·(k)] is state vector; u(k) is the output of the controller, and N is the simulation length.

The parameters of AACA are: m=25, q_o =0.7,ξ =0. 2, ρ_{min} =0.1, Q=10, a=10, b=250, ε=0.00l ,the maximum iterative time 100.

Then the scaling factor with the smallest value of J is taken as the designed scaling factors. The designed scaling factors k_e k_{ec},and k_u are 0.0107, 0.0112 and 81.0969 respectively.

After the scaling factors are obtained, AACA is used to tune the membership functions. There are 3 x 3 = 9 parameters for membership functions needed to be determined. The center of membership function for linguistic value "Positive" is defined on [0.3, 1]. The variance of the membership function for linguistic value "Positive" and "Zero" is defined on [0.1, 0.8].

AACA is given the same parameters above. Then the best individual is taken as the membership functions designed, which are shown in Table 3.

Table 3. The designed membership functions

		Negative	Zero	Positive
e	Center	-0.4712	0	0.4712
	Variance	0.5658	0.4396	0.5658
cc	Center	-0.3774	0	0.3744
	variance	0.5581	0.4175	0.5581
u	Center	-0.8621	0	0.8621
	variance	0.1944	0.1000	0.1944

The designed fuzzy Logic controller is used to drive the cart to a target position and simultaneously stabilize the inverted pendulum. The sampling interval is 0.006s.The initial state is x = -0.3,6 = 0.3, x = 0, 0= 0, and then the cart is pushed to 0. Im at 1.8s. The target position of cart is set to 0m.

The simulation results are shown in Fig. 3. It can be seen that the controller can successfully stabilize the pendulum at the upright position and drive the cart to the target positions. The simulation results demonstrate the usefulness of the designed fuzzy Logic controller in handling the unstable nonlinear system.

VI. RESULTS AND DISCUSSION

An adaptive ant colony algorithm is proposed in this paper. The algorithm has novel search mechanism that dynamically adjusts the strategy of selection of the paths and the strategy of the trail information updating. The simulation results of function optimization show that AACA has nice performance. It is used to design a fuzzy Logic controller for real-time control of an inverted pendulum system. The simulation results verify the effectiveness of the designed controller

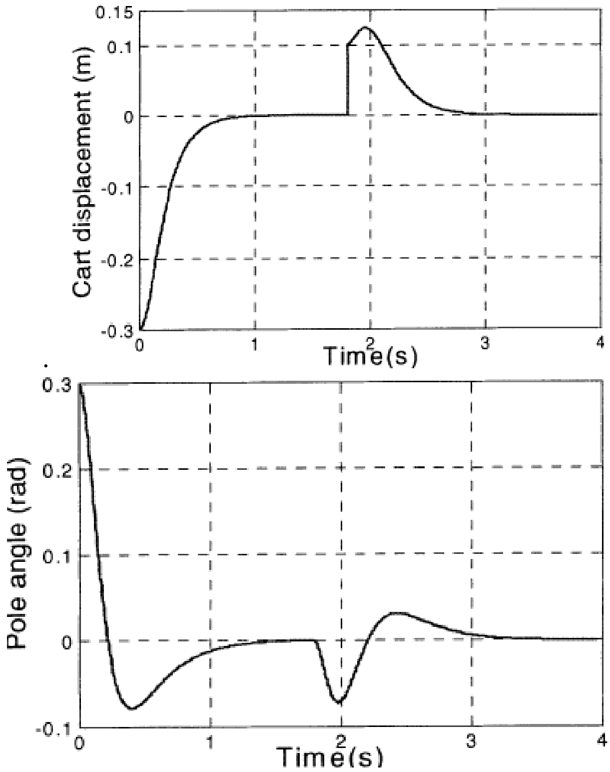

Fig 11. Results of simulation of cart displacement,pole angle of controller

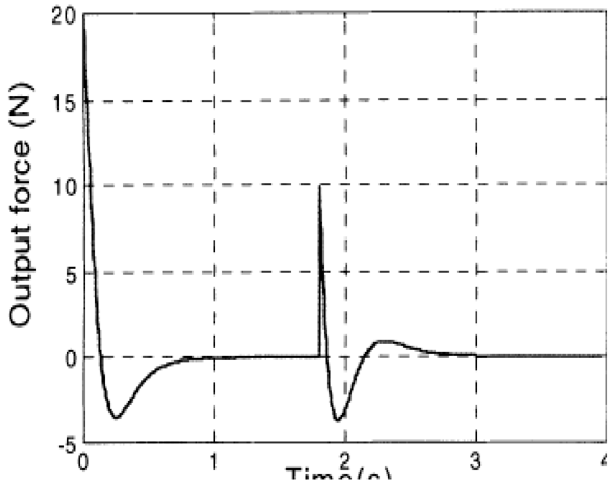

Fig 12. Results of simulation of output force of controller

VII. CONCLUSION

A fuzzy controller based on ABC and ACA algorithm for inverted pendulum-cart system has been compared in this paper. A nonlinear model of the inverted pendulum-cart system has been considered to develop the controllers. The fuzzy controller is proved to be effective and feasible in angle control of pendulum at upright position. Hence fuzzy controller based on ABC algorithm is better than other controller. It gives better performance as compared to the other combination of fuzzy based controller for inverted pendulum. These responses are shown in Fig6-8 and Figure11-12.

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