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Design of Fuzzy Optimized Controller for Satellite Attitude Control by Two State actuator to reduce Limit Cycle based on Takagi-Sugeno Method

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ABSTRACT

In this paper, an algorithm was presented to control the satellite attitude in orbit in order to reduce the fuel consumption and increase longevity of satellite. Because of proper operation and simplicity, fuzzy controller was used to save fuel and analyze the uncertainty and nonlinearities of satellite control system. The presented control algorithm has a high level of reliability facing unwanted disturbances considering the satellite limitations. The controller was designed based on Takagi-Sugeno satellite dynamic model, a powerful tool for modeling nonlinear systems. Inherent chattering related to on-off controller produces limit cycles with low frequency amplitude. This increases the system error and maximizes the satellite fuel consumption. Particle Swarm Optimization (PSO) algorithm was used to minimize the system error. The satellite simulation results show the high performance of fuzzy on-off controller with the presented algorithm

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1. INTRODUCTION

The fuel saving is highly desirable in the satellite attitude control system. Two-level on-off controllers are generally used with the thrust reaction actuator for satellite attitude control. These controllers act very fast and are time independent. They control the satellite attitude with or without thrust power in minimum time.In on-off control systems, the valves operate reliably to stay open for a short time as a few milliseconds. The full opening of valves for a finite time changes the discrete angular velocity with the actuations. As a result, it's impossible to obtain zero residual angular quickness. To prevent the interaction of thrusters, a dead band is introduced between the on-off control, and the controller is shut down in this dead band region. Thus, the controlled system reaches the equilibrium point (origin) with reduced velocity or increased dampness. This generates low frequency (and amplitude) limit-cycles, and dissipates the thruster force.

Since the satellite behavior is inherently nonlinear and uncertain, it's recommended to use nonlinear control algorithms like fuzzy logic. This algorithm is independent of the accurate model of micro satellite. Stein applied three multi-input single-output (MISO) fuzzy controllers to stabilize a small (micro) satellite in low earth orbit. He proved that fuzzy controllers can erase the control limitations by choosing the best magnetic moment, polarity and switching times [1]. Satellite control system can save fuel and enhance the satellite performance. on-off attitude control by on-off and sliding mode was investigated in reference [2]. One of the problems of using sliding mode controller is that it generates a great control signal due to the system uncertainty. Fuzzy controller was used to solve this problem [3]. Fuzzy controller is an appropriate choice to control nonlinear systems. Minimizing the time required for the system to reach the steady state is an important point in fuzzy controller design. This is achieved by optimal adjustment of membership functions [4]. The controller investigated in reference [5] needs different initial values to improve the system operation and minimize the response time. But these applications are not proper to design standard linear controller. In this case, on-off controller is an appropriate option [6,7]. Reference [8] compared various controllers and concluded that the fuzzy on-off controller is the best one based on the efficiency. Fuzzy controller is a multi-level relay. It uses average least squares method for defuzzification. In the present paper, a special hardware was used to convert control signals from defuzzificator. The minimum control time of fuzzy on-off controller using a relay was presented in reference [9]. Particle swarm optimization is an optimization technique based on a population of initial responses. This technique was designed considering the social behavior of birds and fishes in bunch [10, 11]. It was widely used by the researchers and many efforts were performed to improve its efficiency in Inertia formula from different points of view. Calculating the velocity of these changes is a static agent [12]. This parameter makes equilibrium between local and overall searches in the problem space. It means that higher values of this parameter are suitable for the overall search and its lower values are appropriate for the local search. Gradual reduction of this parameter was also investigated in [13]. Its effects on the particle optimization parameters were discussed in [14]. Nonlinear reduction of this parameter due to fuzzification was described in [14]. This value was also considered in [15] except resetting times. Gradual reduction of maximum velocity was also introduced in [16]. Another interesting research area is making improvement in particle optimization through designing different vicinity models. Thus, it was assumed that nonlinear equations of satellite system are known, and its actuator is on-off thruster. The algorithm that transfers command of axis controlling moments to the thrusters is complicated for two reasons:

1. Thrusters are not linear controllers because their output is fixed. Therefore the moment generated by thrusters depends on its starting period.
2. Thrusters can only generate moment in one direction. Thus, another thruster is needed to generate moment in the opposite direction.

In this paper, a three-axis fuzzy on-off controller was presented for satellite attitude control system. It generates two levels of on-off switching on the output. Smooth operation of the control law was achieved by fuzzy laws and Mamdani fuzzy inference. There is no need to hardware limitator in the on-off controller due to using two switching plates on the output. Two linguistic variables were used in the system. These variables provide the thrusters used to orient the satellite. In order to control the attitude, one thruster was used for clockwise rotation (positive angle) and the other one was used for counterclockwise rotation (negative angle). When thruster activates, the fuel is burned at high pressure and the attitude changes.This paper includes 7 sections. After introduction, state space model of satellite is presented in section 2. Takagi-Sugeno model was described in section 3. Section 4 is an introduction to fuzzy on-off algorithm. Section 5 describes the particle swarm algorithm and using absolute error integration to reduce limit cycle on fuzzy system. The simulation results are given in section 6. Finally, the conclusions are down in section 7

2. THREE DEGREE OF FREEDOM SATELLITE STATE SPACE MODEL

The rigid satellite model with three degrees of freedom is presented in this section. The satellite model is shown in Fig. 1. Axes X_B, Y_B, and Z_B define the satellite body axis frame**,** and the origin of coordinates is considered at the centre of gravity as shown in this fig.. The roll (ϕ), pitch (θ), and yaw (ψ) angles are the satellite rotational speeds about axes X_B, Y_B, and Z_B in the body fixed frame. The non-linear state model of the satellite can be derived by partial derivatives of the model states $x = [\, p_b, q_b, r_b, \phi_I, \theta_I, \psi_I \,]^T$.

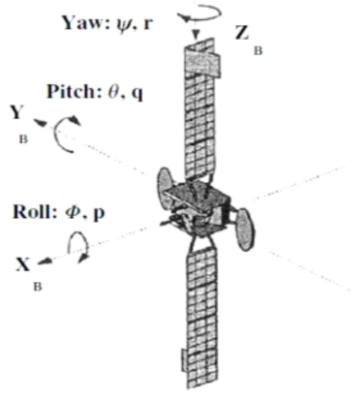

Figure 1. Satellite reference and body coordinates [17]

$$\begin{bmatrix} \dot{p}_b \\ \dot{q}_b \\ \dot{r}_b \\ \dot{\phi}_I \\ \dot{\theta}_I \\ \dot{\psi}_I \end{bmatrix} = f(x,u) = \begin{bmatrix} \dfrac{M_x - q.I_{xx}.r + r.I_{yy}.q}{I_{xx}} \\ \dfrac{M_y - r.I_{xx}.p + p.I_{yy}.r}{I_{yy}} \\ \dfrac{M_z - p.I_{xx}.r + q.I_{yy}.p}{I_{zz}} \\ p + \dfrac{(q.sin(\phi) + r.cos(\phi))sin(\theta)}{cos(\theta)} \\ q.cos(\phi) - r.sin(\phi) \\ \dfrac{q.sin(\phi) + r.cos(\phi)}{cos(\theta)} \end{bmatrix} \tag{1}$$

Table 1. Satellite Parameters [17]

Parameter	Description	Value
I_{xx}	Moment of inertia along x-axis	1.928 $kg\ m^2$
I_{yy}	Moment of inertia along y-axis	1.928 $kg\ m^2$
I_{yy}	Moment of inertia along z-axis	4.953 $kg\ m^2$
Thruster	Satellite inlet moments (M_x, M_y, M_Z)	1 $kg\ m^2$
Φ_0	Initial value of roll Euler angel	0.362 rad (20 deg)
θ_0	Initial value of pitch Euler angel	0.524 rad (30 deg)
ψ_0	Initial value of yaw Euler angel	-0.262 rad (-15 deg)
p	Body pitch roll rate	0 rad/s
q	Body yaw rate	0 rad/s
r	Body roll rate	0 rad/s
α	Dead band	0.01 rad (0.58 deg)

3. T-S FUZZY MODEL IDENTIFICATION FROM NONLINEAR MODELS [18]

With a known nonlinear model, its approximate T–S fuzzy model can be obtained by linearization about an interested operating point. Thus, the local linear models of T–S fuzzy system should be determined. In this case, the local model of T–S fuzzy model that approximates the nonlinear system model at the equilibrium can be expressed as:

$$x(k+1) = A_l x + B_l u, \tag{2}$$

$$A_1 = \frac{\partial f}{\partial x}\Big|_{x=o,u=0} \qquad B_1 = \frac{\partial f}{\partial u}\Big|_{x=o,u=0} \tag{3}$$

The next step is to determine the fuzzy membership functions for fuzzy sets about those operating points or local regions. The ideal case is to select the membership functions $\mu_l(x,u), l = 1,2,.....m$ that minimize the following modeling error:

$$E = \left\| \sum_{l=1}^{m} \mu_l(x,u)(A_l x + B_l u + a_l) - f(x,u) \right\| \tag{4}$$

This is a difficult nonlinear optimization problem. However, in many applications, simple and typical membership functions can be utilized such as triangular, trapezoid, and Gaussian functions. One of the key parameters is that the centers of these membership functions can be determined by the operating points $(x^1, u^1), l = 2,3,....., m$, and the other parameters such as the width and decay rate may be selected by the designer.

3.1. Takagi-Sugeno parameters, attitude control descriptor

Considering nonlinear expressions and their relating membership functions, there are a large number of membership functions, fuzzy laws and required subsystems to show the system behavior. Therefore, the procedure is as follows. Satellite dynamic parameters are defined according to the specific rules based on the selected operating points using the state feedback that stabilizes the response to initial conditions. Gaussian-type functions were selected as:

$$
\begin{aligned}
h_1 &= \exp\left(-\frac{x_1^2+x_2^2+x_3^2+x_4^2+x_5^2+x_6^2}{\sigma_1^2}\right)\\
h_2 &= \exp\left(-\frac{x_1^2+x_2^2+x_3^2+x_4^2+x_5^2+x_6^2}{\sigma_2^2}\right)\\
h_3 &= \exp\left(-\frac{x_1^2+x_2^2+x_3^2+x_4^2+x_5^2+x_6^2}{\sigma_3^2}\right)\\
h_4 &= \exp\left(-\frac{x_1^2+x_2^2+x_3^2+x_4^2+x_5^2+x_6^2}{\sigma_4^2}\right)
\end{aligned}
\tag{5}
$$

Where $\sigma_1, \sigma_2, \sigma_3, \sigma_4$ are the widths of the corresponding functions, respectively Then, the normalized membership functions for local models are obtained as:

$$
\begin{aligned}
\mu_1(x) &= \frac{h_1}{h_1+h_2+h_3+h_4}\\
\mu_2(x) &= \frac{h_2}{h_1+h_2+h_3+h_4}\\
\mu_3(x) &= \frac{h_3}{h_1+h_2+h_3+h_4}\\
\mu_4(x) &= \frac{h_4}{h_1+h_2+h_3+h_4}
\end{aligned}
\tag{6}
$$

In satellite nonlinear dynamic modeling, the system matrices are extracted considering the satellite dynamic equations on main coordinates system and (6). These matrices are presented in Table 2. Operating point (task point) of local linearization of dynamic satellite was selected so that the satellite operating region was covered. The above system was linearized based on Takgi-Sugeno model at four points around the equilibrium point. Four linear subsystems were derived from the satellite nonlinear model. It should be mentioned that the system B matrix was the same in all four states.

Table 2. Parameters of takagi-sugeno model

Subsystem 1 $x(1) = [0,0,0,0,0,0]^T$	$A1=\begin{bmatrix}0&0&0&0&0&0\\0&0&0&0&0&0\\0&0&0&0&0&0\\1&0&0&0&0&0\\0&1&0&0&0&0\\0&0&1&0&0&0\end{bmatrix}$ $B1=\begin{bmatrix}0.5186&0&0\\0&0.5186&0\\0&0&0.2018\\0&0&0\\0&0&0\\0&0&0\end{bmatrix}$
Subsystem 2 $x(2)=[0,0,0,0.3620,0.5240,-0.2600]^T$	$A2=\begin{bmatrix}0&0&0&0&0&0\\0&0&0&0&0&0\\0&0&0&0&0&0\\1&0.2047&0.5404&0&0&0\\0&0.9352&-0.3541&0&0&0\\0&0.4090&1.0801&0&0&0\end{bmatrix}$
Subsystem 3 $x(3)=[-0.0613,-0.0908,0.1645,0.0220,0.0429,-0.0388]^T$	$A3=\begin{bmatrix}0&-0.2581&0.1425&0&0&0\\0.2581&0&-0.0962&0&0&0\\0&0&0&0&0&0\\1&0.4420&0.0429&-0.0910&0.1628&0\\0&0.9998&-0.0220&-0.1625&0&0\\0&0.0220&1.0007&-0.0945&0.0051&0\end{bmatrix}$

Subsystem 4

$$x(4) = [0.0088, 0.0063, -0.0075, 0, -0.0100, -0.0084]^T$$

$$A4 = \begin{bmatrix} 0 & 0.0117 & -0.0099 & 0 & 0 & 0 \\ -0.0117 & 0 & 0.0138 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & -0.0100 & 0.0063 & -0.0075 & 0 \\ 0 & 1 & 0 & 0.0075 & 0 & 0 \\ 0 & 0 & 1.0000 & 0.0063 & 0.4415 & 0 \end{bmatrix}$$

4. FUZZY ON-OFF CONTROLLER

The detailed explanation of the algorithm can be found in reference [17]. A brief description is presented here. The difference is that the range of membership function changes was modified in this work to analyze the limit cycle. A fuzzy on-off controller was developed in this section. The controller was developed for only roll-axis. It's identical for the other two axes. The controller takes the advantage of Largest Maxima Defuzzification (LOM) technique to obtain on-off output directly. The following ranges were selected for simulation purposes: $\Phi(t)$ = [-1, 1] rad, $\dot{\Phi}(t)$ = [-1, 1] rad/sec and control signal $u_r = [-M_x, +M_x]$.

4.1. Linguistic Description

The input and output variables of the fuzzy controllers were explained in this section. The inputs $x_i \in \chi_i$, where χ_i, i =1, 2 is the universe of discourse of the two inputs. For linguistic input variable, $\tilde{x}_1$ = "error angle," the universe of discourse, χ_1 = [-1, 1] rad, represents the range of perturbation angle from the zero reference. For linguistic input variable $\tilde{x}_2$ = "error angle rate," the universe of discourse is χ_2 = [-1, 1] rad /sec. The output universe of discourse $\gamma = [-M_z, +M_z]$ represents the on-off output $\tilde{y} \in \gamma$. The set $\tilde{A}_i^j$ defines the j[th] linguistic value of linguistic variable $\tilde{x}_i$, defined over the universe of discourse χ_i. The control level of the system operation can be defined for input $\tilde{x}_1$ by the following linguistic values:

$$\tilde{A}_{i=1}^{j} = \tilde{A}_1^1 = LN, \tilde{A}_1^2 = SN, \tilde{A}_1^3 = Z, \tilde{A}_1^4 = SP, \tilde{A}_1^5 = LP \tag{7}$$

Similar linguistic values are selected for input $\tilde{x}_2$; i.e., $\tilde{A}_2^j \equiv \tilde{A}_1^j$. The set $\tilde{B}_1^j$ denotes the linguistic values for output linguistic variable $\tilde{y}_1$ and is defined as

$$\tilde{B}_i^j = [\tilde{B}_1^1 \rightarrow J2, \tilde{B}_1^2 \rightarrow J1] \tag{8}$$

where *J1* and *J2* are on/off commands for thrusters.

4.2. Fuzzy Rules

The rules are based on two input variables. These variables have five linguistic values. Thus, there are 25 possible rules. The rules were described in matrix form in Table 3. The rules partitions are heuristically chosen to reset the angle smoothly over the universe of discourse.

Table 3. Fuzzy Rules

$\dot{\theta}$ \ θ	LN	SN	Z	SP	LP
LN	$+M_X$	$+M_X$	$+M_X$	$+M_X$	——
SN	$+M_X$	$+M_X$	$+M_X$	——	$-M_X$
Z	$+M_X$	$+M_X$	——	$-M_X$	$-M_X$
SP	$+M_X$	——	$-M_X$	$-M_X$	$-M_X$
LP	——	$-M_X$	$-M_X$	$-M_X$	$-M_X$

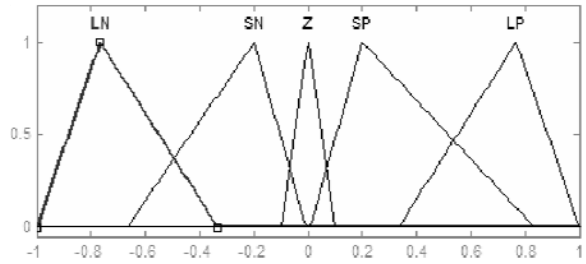

Figure 2.Membership functions of input “error angle”

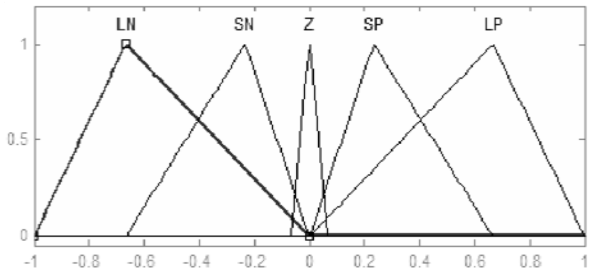

Figure 3.Membership functions of input “error angle rate”

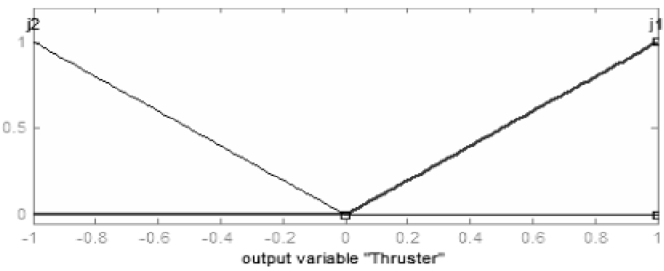

Figure 4.Output Membership functions

5. PARTICLE SWARM OPTIMIZATION (PSO) ALGORITM

Particle swarm optimization method includes a definite number of particles with random initial values. Values of attitude and velocity are defined for the particles. These values are modeled by a position vector and velocity vector, respectively. These particles move in n-dimensional space of the problem to find new options based on the optimality value as the assessment criterion. The problem space dimension is equal to the number of effective parameters in the optimization function. The best location of particles in the past and the particle with the best conditions are saved in separate memory spaces. Based on these memories, particles decide how to move in future. In the repetitions, all particles move in n-dimensional problem space. Finally, the public optimum point is found. Particles modify their velocity and location based on the local and public best solutions.

$$v_{m,n}^{new} = v_{m,n}^{old} + \Gamma_1 \times r_1 \times (p_{m,n}^{localbest} - p_{m.n}^{old}) + \Gamma_2 \times r_2 \times (p_{m,n}^{globalbest} - p_{m,n}^{old})$$
$$p_{m,n}^{new} = p_{m,n}^{old} + v_{m,n}^{new} \tag{9}$$

where $v_{m,n}^{new}$ is particle velocity, $p_{m,n}$ is particle variable, r_1, r_2 are independent random numbers with uniform distribution, Γ_1, Γ_2 are learning factors, $p_{m,n}^{localbest}$ is the best local response, and $p_{m,n}^{globalbest}$ is the best absolute solution. Particle swarm optimization algorithm updates the particles velocity vector and then adds the new velocity value to attitude or particle value. The velocity update is affected by both local and absolute best solutions. The local and absolute best solutions are the ever best solutions obtained by a particle and in the population, respectively. Constants Γ_1, Γ_2 are cognitive (perceptual) parameter and social parameter. The main advantages of particle swarm optimization are simplicity and low number of effective parameters. Also, this algorithm can optimize complex cost functions with a large number of local minimums.

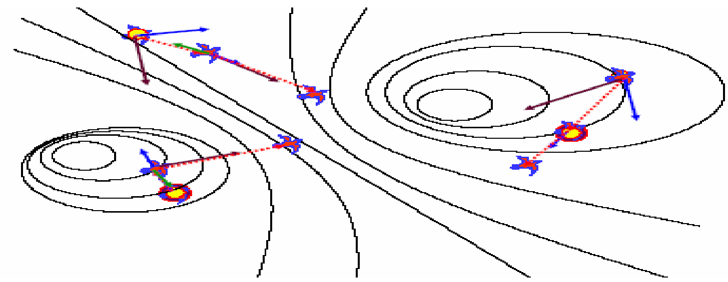

Figure 5.General structure of particle swarm algorithm

5.1. Applying particle swarm algoritm in fuzzy on-off system to reduce limit cycle

Particle swarm algorithm was used to determine the membership functions parameters of the fuzzy system inputs. The intervals of these parameters should be determined first. Thus, it's necessary to obtain the interval changes of the introduced characters. The interval change is (-1،1). Then, the membership functions parameters of all principles can be defined by analyzing the intervals. The optimization variables are fuzzy parameters selected according to the membership functions. The number of these variables is 30; therefore, a 30-dimensional space was considered to find the optimum state. Then, the factors were supposed. The minimum number of factors is twice the number of variables. 90 factors were considered in this research. These factors spread in the space. The particles move to the location with lower value of cost function. Finally, after a few trials, the optimum point was found with the minimum value of membership function. Then, the output was computed using absolute error integral technique for time range of 1000 to 2500 that is equal to 10 to 25 seconds, i.e. the time when state variables reach the steady state; in fact, the time when the state oscillates around zero and reach the steady-state. The membership function should be integrated to reduce the amplitude. Finally, the system outputs, Euler angles, were computed.

6. SIMULATION

In this section the system response to initial conditions (zero input response) was analyzed .In Figure 6, For fuzzy on-off controller, the roll angle oscillates after 18 seconds with the amplitude of 0.02 radians (1.1 degrees) with frequency of 0.028 hertz. Since rate feedback introduces damping to the system, the phase plane trajectory shows that the time response decays toward the origin where both rate and position are zero.

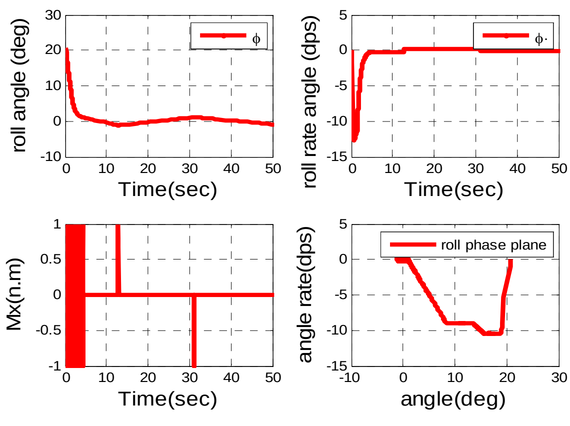

Figure 6. Roll angle operation of fuzzy on-off controller with dead band (nonlinear model)

Viewed in terms of the phase plane trajectory, a limit cycle is a closed path which is approached from a starting condition either from inside the closed path (usually with the exception of the origin), or from the outside. in the following, we used a deadband for designing controller,. When the angles approach to ± 0.01 radians (0.58 degrees), the fuzzy control leaves the orbit by a switch and comes to zero. The control signal remains zero until the angle value is in this range. This reduces the oscillations of control system and enhances the attitude control. Limit cycle performance is determined by simulation of response to small values of initial conditions for the controllers. The same value of limit cycle in the same fuzzy plate is equal to frequency of the limit cycle.

Figure 7a shows the simulation based on Takagi-Sugeno model. As shown in the simulation, the rules represent the locus of the moving line. It means that the outputs can move in output space linearly. The extent and displacement values are determined based on the inputs. Simulation results show that oscillation amplitude for the rolling angle in Figure 7a. it is very small after 9 seconds and the frequency is 0.14 hertz. Then we used particle swarm optimization algorithm to reduce the oscillation amplitude. The idea was to approximate the integrals value by discrete plurals on small intervals. Because of using discrete time to compute the integral, its maximum limit is usually considered up to three times of the summit time. So, an acceptable result is obtained for the integral. The cost function should be integrated under the optimum state to reduce the oscillation amplitude while the system state is oscillating around zero. Thus, the rolling angle was computed from 10 seconds to 25 seconds and the optimum state was shown.

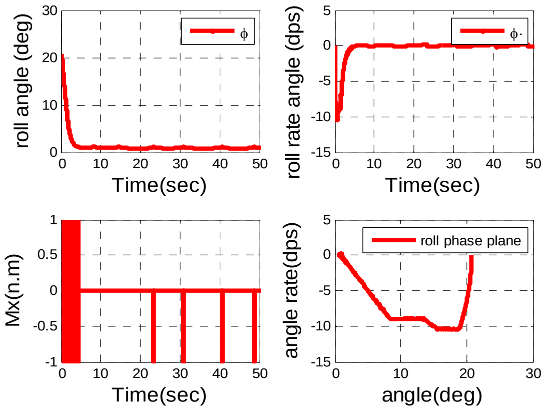

Figure 7a. Roll angle operation of fuzzy on-off controller (T-S model)

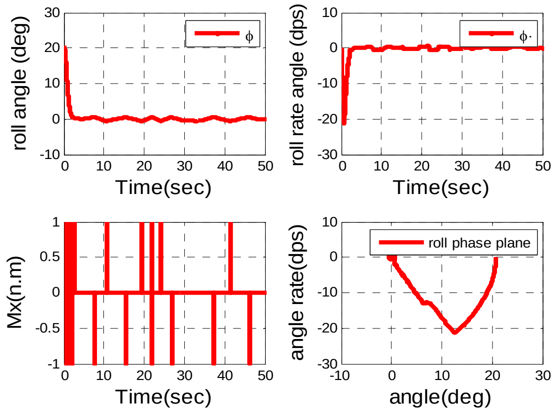

Figure 7b. Roll angle operation of optimized fuzzy on-off controller (T-S model)

As shown in Figure 7b, the oscillations of control system were reduced. This affects the output. The required control torques was reduced and the satellite power decreased at the same time. It’s clear from the simulation of optimized fuzzy in fig7b that the oscillation amplitude is near 0.001 radians (0.05 degrees) for the rolling angle after 25 seconds. Desirable factors in the fuzzy plate are smaller limit cycle and no bias (i.e. angles center should be close to zero). In fuzzy structure, the system is observed as node or oscillation around zero. According to the figure of fuzzy plate, satellite power reduces and remains near zero in a limit cycle. The difference between the optimum state and the previous one is that the circles in the optimum state reach to zero faster. In fact, the convergence was obtained faster. Absolute zero of error value in the steady-state is another benefit of the algorithm.

Figure 8 compares the solutions of zero input response at various roll angles. It is the result of fuzzy on-off with dead band (fbbdc), fuzzy on-off Takagi-Sugeno model (ts) and optimized fuzzy on-off (ts-pso). Results show that oscillation amplitude of rolling angle was reduced from. 1.1 degrees to 0.05 degrees using particle swarm algorithm. Steady-state error and system damping time were reduced using this algorithm.

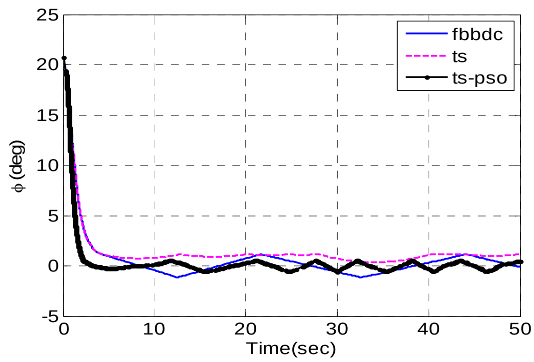

Figure 8. roll angle comparison of controllers

Table 4 shows thruster power before and after applying the particle swarm algorithm. The results denote that the power was reduced after using the algorithm and the gas consumption was also reduced in thrusters. This is favorable.

Table 4. Power consumption

controller	Roll angle(NM.S)	Pitch angle(NM.S)	Yaw angle(NM.S)
fuzzy on-off with dead band	4.464	5.222	4.346
fuzzy on-off based on T-S model	4.442	5.373	4.441
Optimized fuzzy on-off	2.791	3.17	4.299

6.1. The effects of disturbance on the controllers performance

Attitude control system was checked under disturbance and controllers resistance was checked by step disturbance operation $dis(k) = 0.5u(k-20)$. The operation was performed by step input of 10 degrees. Combination of the disturbance and the control signal affects the system state.

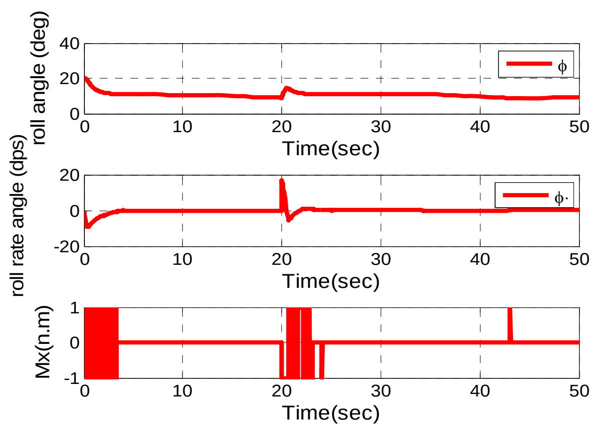

Figure 9. Roll angle Operation of fuzzy on-off controller with dead band under $dis(k) = 0.5u(k-20)$ (nonlinear model)

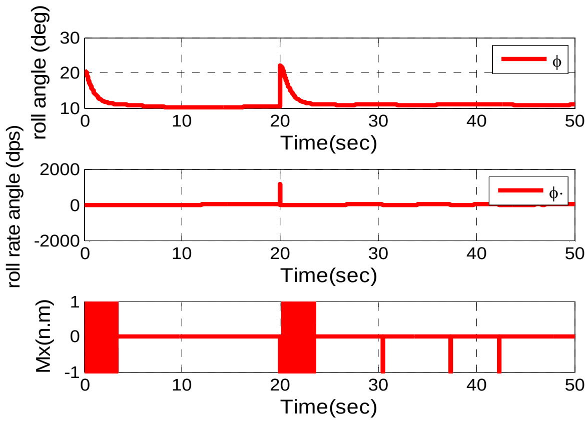

Figure 10a. Roll angle Operation of fuzzy on-off controller $dis(k) = 0.5u(k-20)$ (T-S model)

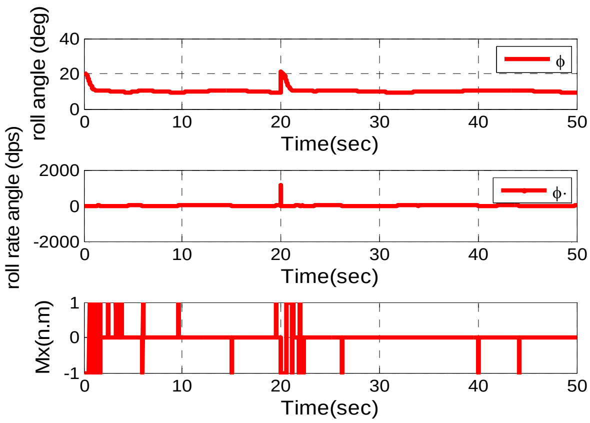

Figure 10b. Roll angle Operation of optimized fuzzy on-off controller $dis(k) = 0.5u(k-20)$ (T-S model)

As shown, in the presence of disturbance, the outputs reach to the final value without the steady-state error. Controller is also capable to remove disturbance.

7. CONCLUSION

Fuzzy on-off controller algorithm was introduced and simulated. This controller was installed on nonlinear system of a satellite and takagi-sugeno model with three degrees of freedom. The simulation results show that the present fuzzy on-off control algorithm has a good resistance against disturbance and makes the system refractory, resistant and stabilized. Particle swarm algorithm obtained from absolute error integral was used to optimize fuzzy system and reduce oscillation amplitude of limit cycle. This results in increasing fuel consumption and decreasing satellite longevity. The algorithm has a high convergence rate and requires lower number of parameters for adjustment. Based on the results, the controller finished the tracing without steady-state error using the optimization algorithm. Output oscillations amplitude was very smaller than the other controllers. The time damping system and thrusters power consumption were also reduced using this algorithm.

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