

OPTIMIZATION OF FUZZY LOGIC CONTROLLER USING GENETIC ALGORITHM FOR SATELLITE ATTITUDE CONTROL

¹AdunolaFataiOlatunde, ²Dr S.M.Sani, ³Dr D.S.Nyitamen, ⁴ Dr I.I. Alabi

Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna

Abstract: The design of fuzzy logic controllers (FLC) is largely influenced by the choice of parameters like membership functions, number of rules, scaling factors, universe of discourse, and fuzzification and defuzzification methods. If these parameters are varied by trial and error method, an infinitely large population of values will be involved, and at the end, an optimal fuzzy controller is not assured. This study presents a technique to optimize fuzzy logic parameters based on genetic algorithm. This approach is applied to control the attitude of a satellite model with reaction wheel as actuator. The genetic algorithm is used to tune simultaneously, the membership functions, fuzzy rules and scale factors in order to achieve optimal value for these parameters. The results show that the optimized fuzzy controller gives better performance than a conventional fuzzy controller in terms of rise time, settling time and peak percent overshoot. This means that whenever the satellite loses its orientation, it will be regained very fast and available for communicating with the ground station.

I. INTRODUCTION

Today, orbiting satellite are used for various space missions such as remote sensing, weather forecasting, data and image capturing. These applications depend largely on high accuracy and reliability of attitude control of satellite system. The satellite in the orbit does encounter different forms of disturbances that make them loose orientation and as such cannot effectively communicate with the ground station. The inbuilt actuator(s) is designed to generate torque that can bring it back to a desired orientation within the shortest possible time. Satellite is known to be inherently nonlinear system and uncertain *Rezanezhad*(2014).

Nonlinear controller like fuzzy controller is recommended for attitude control. Fuzzy logic technique is used to solve a number of problems due to the flexibility in some of its parameters. Designing fuzzy logic system contains two things such as:

(a) Structure which consists of:

- Specification of input(s) and output(s),

- Selection of shape of membership function (MFs) for both input and output, and tuning the MFs and
- Collation of rules,

(b) Determination of system parameters which involve:

- (i) Universe of discourse,
- (ii) Number of partition in input and output,
- (iii) Firing strength of rules,
- (iv) Defuzzification method
- (v) Selection of scaling factors.

The problem of tuning controller's parameters is a complex exercise. Many techniques such as Fuzzy logic gain scheduling, Model reference adaptive system, Fuzzy self-tuning regulator and Dual control were reported in *Guanrong and Trung* (2001). Others are neural network, Self-organizing control and Numerical optimization.

Generally, the conventional techniques shown in Figure 1 Lappas (2006) require a large amount of computation, gradual convergence and invariably time consuming. At the end, the result obtained may not be optimal. Therefore, there is the need to search for alternative method of optimizing fuzzy parameters. Genetic algorithm is widely used for solving optimization problems in different fields due to its robustness and ability to provide optimal solution. Therefore, genetic algorithm is proposed to optimize the fuzzy logic controller so as to achieve better performance indices shown in Figure 2.

Genetic algorithms are search methods based on the Darwinian principle of the survival of the fittest. Because one of the essential limitations of a fuzzy system is due to the imprecision of membership functions definition. GA can be applied to fuzzy system with good results.

In literature, there are control systems that employ various combinations of artificial intelligent. The target of such hybrid-techniques is to reduce the timing control parameters. In other words, settling time, rise

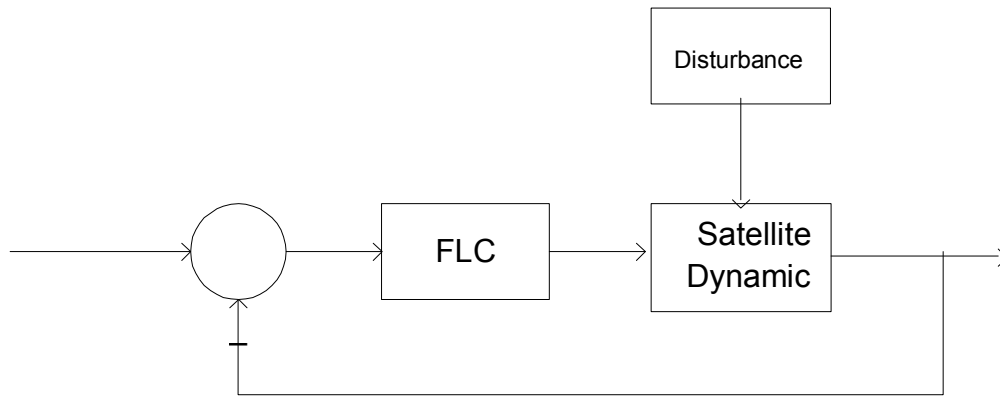


Figure 1: Conventional technique of Fuzzy Logic Controller for Satellite Attitude Control **Lappas (2006)**

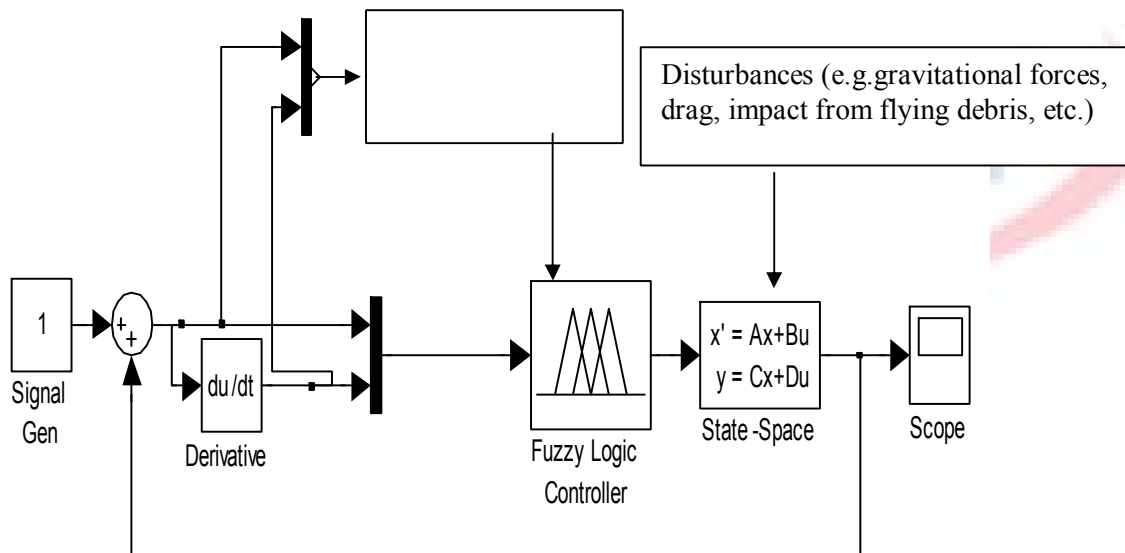


Figure 2: Optimized Fuzzy Logic Controller Technique for Control of Satellite Attitude

time, and overshoot must be as small as possible, to guarantee a good control procedure **Danilo Pelusi (2011)**. He attempted to combine intelligent techniques such as fuzzy logic, genetic algorithms and neural networks to obtain optimal control performances. The membership functions of the fuzzy controllers were optimized through Genetic Algorithms. The results show that there was an improvement on the timing performances of the controllers. The drawback is that it is difficult to examine all the inputs – output data of a complex system to find the optimal membership function for a fuzzy system. A further improvement is possible by working on the tuning method of rule base, particularly on the weights of fuzzy rules. Likewise, **Gomes and Rocco (2012)** designed and applied a fuzzy proportional-integral-derivative (PID) controller to satellite attitude control system equipped with reaction wheels. An analysis of the scaling factor was developed to verify its influence during attitude maneuver. The results showed that adequate selection of scaling factor contributes to the improvement of control results. However, the authors only considered scaling factor for one of the inputs i.e. error rate instead of the two inputs. A better result is possible if the two inputs are considered.

Rezanezhad (2014) designed a fuzzy controller based on Takagi-Sugeno satellite dynamic model and optimized with Particle Swarm Optimization (PSO) algorithm. The simulation results show that fuzzy on-off control algorithm has a good resistance against disturbance and makes the system refractory, resistant and stabilized. It also resulted in increasing fuel and decreasing satellite longevity. Applying many fuzzy rules can better output response would be assured which would have reduced fuel consumption.

Hosseini et al (2016) designed a fuzzy-quaternion controller for attitude control of a satellite, then the fuzzy memberships are tuned in an intelligent way by using particle swarm optimization (PSO) algorithm. The simulation results show that designed controller can accurately control the satellite attitude in severe and large maneuvers in desirable time.

II. FUZZY MODELLING OF SATELLITE ATTITUDE DYNAMIC

Figure 3 is the schematic diagram of satellite model with fuzzy logic controller presented by Adunola et al (2016). Table 1 is the Nigeriasat -1 Satellite properties / parameters used in the model. It was modified with MATLAB function and scale factor blocks. The modification to the model is in respect of the identified

parameters i.e. adjusting the fuzzy rules and selection of scaling factors for the two inputs. It should be remembered that people select this scaling factor by trial and observation approach which of course is time consuming and the operator might not yet have obtained the best value at the time he became exhausted. The adequate selection of the scaling factor contributes to the improvement of control results. Writing script and running it in Matlab / Simulink environment will automatically select the best value for each of the gain i.e. scale factor and also generate the best fuzzy rules that give the optimal value.

Table 1: Nigeriasat -1 Satellite properties / parameters **Ogunbadewa (2008) and NASRDA:**

PROPERTIES	VALUE
Weight	129Kg
Inertia matrix	$I_x=9.8194,$ $I_y= 9.7030,$ $I_z = 9.7309 \text{ Kgm}^2$
Orbit	686 km 10:30 AM – 10:30 PM Sync. Low Earth Orbit
Orbit period	97.7min
PARAMETERS	INITIAL VALUE
Angular velocity	$\omega_a = [0 \ 0 \ 0]^T$
Euler Angles[$\phi \ \theta \ \psi$]	[0 0 0]
Desired Euler Angles [$\phi \ \theta \ \psi$]	[20 40 60]
ω_n	0.02

The following equations (1), (2), and (3) **Kaplan (2006) and Adunola et al (2016)** represent satellite dynamics and kinematics. The satellite is assumed to be a rigid body using reaction wheel that provides torques about three mutually perpendicular axes. These are spacecraft control law, relating the derivative of vector part of the quaternion which depend on satellite angular velocity of the body with respect to orbital frame ($\dot{\epsilon}_i$), moment of spacecraft inertial matrix, reaction wheel torque and orbital rate.

$$\dot{\epsilon}_1 = (1 - k_x)\omega_o \dot{\epsilon}_3 - 4k_x\omega_o^2 \epsilon_1 + \frac{L_{rx}}{2I_x} \quad (1)$$

$$\dot{\epsilon}_2 = -3k_y\omega_o^2 \epsilon_2 + \frac{L_{ry}}{2I_y} \quad (2)$$

$$\dot{\epsilon}_3 = -(1 - k_z)\omega_o \dot{\epsilon}_1 - k_z\omega_o^2 \epsilon_3 + \frac{L_{rz}}{2I_z} \quad (3)$$

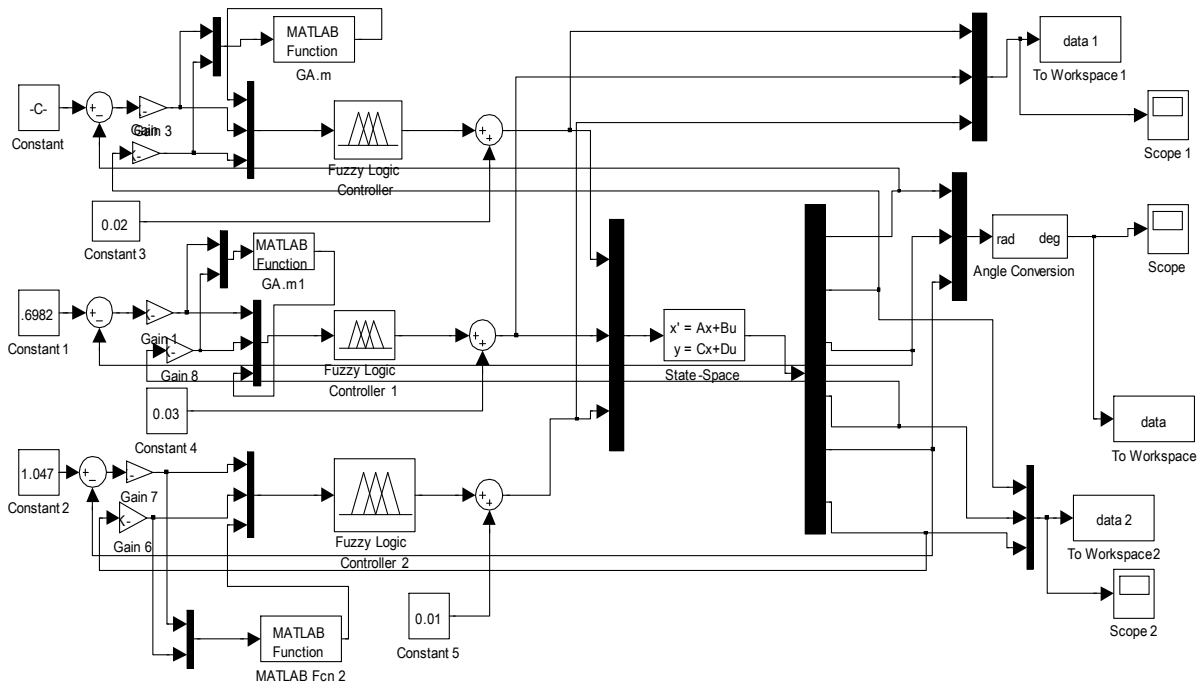


Figure 3: Model for optimal Fuzzy Logic controllers Through GA

where $k_x = \frac{I_y - I_z}{I_x}$, $k_y = \frac{I_x - I_z}{I_y}$, and $k_z = \frac{I_y - I_x}{I_z}$, I_x, I_y , and I_z are inertial matrix, $[L_{rx} L_{ry} L_{rz}]^T$ is the moment vector of reaction wheel and ω_o is the angular velocity. These satellite dynamic equations (1) to (3) can be modeled in fuzzy way by fuzzy IF – THEN rules which represent local linear input and output relations of a nonlinear system. The continuous fuzzy system can be expressed as:

If $Z_1(t)$ is M_{ij} and $Z_n(t)$ is M_{in} , then

$$\dot{x}(t) = A_i x(t) + B_i u(t) \quad i = 1 \dots r \quad (4)$$

$$y = Cx(t)$$

Where M_{ij} is the fuzzy set, $j = 1 \dots n$, $Z_n(t)$ is the premise variable, r is the number of model rules, n is the number of premise variable, $x(t)$ is 6×1 state vector = $[\varepsilon_1 \dot{\varepsilon}_1 \varepsilon_2 \dot{\varepsilon}_2 \varepsilon_3 \dot{\varepsilon}_3]$, $u(t)$ is 3×1 control input

$$\text{vector} = \begin{bmatrix} L_{rx} \\ L_{ry} \\ L_{rz} \end{bmatrix},$$

A_i is 6×6 system matrix and B_i is 6×3 control matrix defined in equation

$$A_i = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ -4k_x \omega_o^2 & 0 & 0 & 0 & 0 & (1 - k_x) \omega_o \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & -3k_y \omega_o^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & -(1 - k_z) \omega_o & 0 & 0 & -k_z \omega_o^2 & 0 \end{bmatrix} \quad (5)$$

$$B_i = \begin{bmatrix} 0 & 0 & 0 \\ \frac{1}{2I_x} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & \frac{1}{2I_y} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \frac{1}{2I_z} \end{bmatrix} \quad (6)$$

The fuzzy model is then constructed according to the weighting of each linear model given as follows:-

$$\dot{x}(t) = \sum_{i=1}^r h_i[z(t)] \{A_i(t)x(t) + B_i u(t) + D_i w(t)\} \quad (7)$$

$$y = Cx(t)$$

Where the membership functions

$$h_i[z(t)] = \frac{\prod_{j=1}^n M_{ij}[z_j(t)]}{\sum_{i=1}^r w_i[z(t)]} \quad (8)$$

$M_{ij}[z_j(t)]$ is the grade of membership of $z_j(t)$ in the fuzzy set M_{ij} , $w_i(t)$ is the weight of each membership function. The $h_i[z(t)]$, $i = 1, \dots, r$, hold a convex sum property **Xihai and Ming (2012)**:

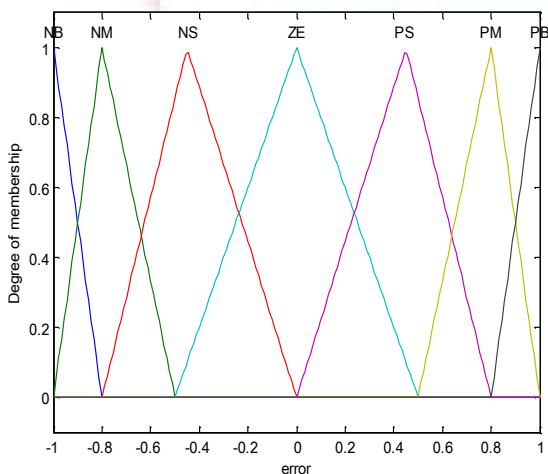
$$\sum_{i=1}^r h_i[z(t)] = 1, \quad h_i[z(t)] \geq 0, \quad i = 1, \dots, r \quad (9)$$

III. FLC OPTIMIZATION

Most authors optimize fuzzy controller by considering only one parameter out of the above mentioned in section 1 which may result in suboptimal solution. More so there is not much literature or work has being done using selection of scale factor to optimize fuzzy logic controller. In this study, two parameters are combined simultaneously to optimize fuzzy logic controller:-

- (i) *Tuning the MFs and adjusting the fuzzy rules.*
- (ii) *Selection of scaling factors.*

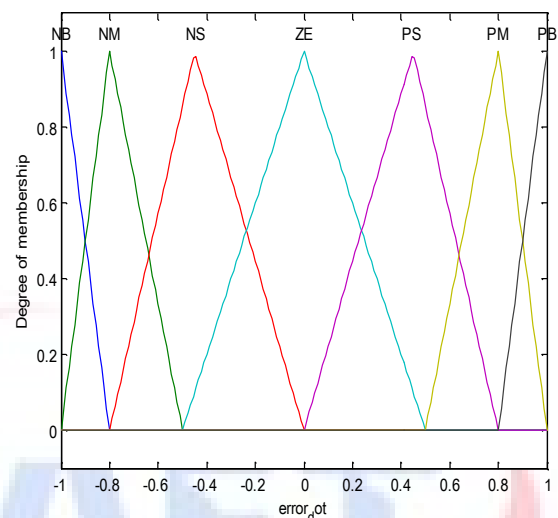
A fuzzy set is completely characterized by its MF which may be determine by the knowledge of human experts to specify the membership function in a particular domain or from the data collected from various sensors (Ajit K.M, 2006).



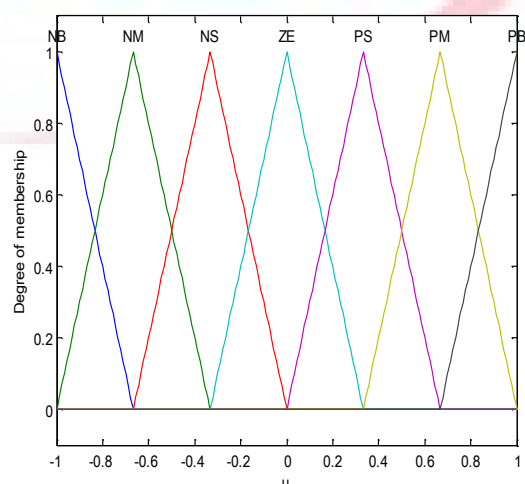
(i)

The first step in the design of FLC is to choose the number and distribution of membership functions (MFs) for the inputs and the output. In this work, seven normalized membership functions with triangular shapes are considered, Figure 4. The linguistic labels

used to describe the fuzzy sets are Positive Big (PB), Positive Medium (PM), Positive Small (PS), Negative Big (NB), Negative Medium (NM), Negative Small (NS), and Zero (ZE). The popular triangular membership function which can be stored with minimum use of memory and manipulated efficiently is chosen. Both the inputs and outputs are all normalized in a universe of discourse $[-1, 1]$. The membership functions are shown in Figure 4.



(ii)



(iii)

Figure 4: (i) Membership function for error, (ii) Membership function for error rate, and (iii) Membership function for output u.

The second step is formulation of fuzzy rules relating membership functions which are presented in Table 2 for inputs and output. These rules are extracted from fundamental knowledge and human experience about the process. The rules contain the input / output relationships that define the control strategy. If the number of membership function be n_1 , so that there will be for every value of error and error rate an n_1 -dimensional vector of membership values (M_{error} and $M_{error\ rate}$ respectively). There will also be $n_1 \times n_1$ rules. Firing these rules will generate a set of clipped fuzzy sets describing the output as shown in table 2.

Table 2: Standard Rule set for 49 rules (Omizegba et al, 2003) & (WillerlandEvandro, 2012).

U		\dot{e}						
		NB	NM	NS	ZE	PS	PM	PB
e	NB	NB	NB	NS	NB	NM	NS	ZE
	NM	NB	NB	NS	NM	NS	ZE	PS
	NS	NB	NB	NS	NS	ZE	PS	PM
	ZE	NB	NM	NS	ZE	PS	PM	PB
	PS	NM	NS	ZE	PS	PM	PB	PB
	PM	NS	ZE	PS	PM	PB	PB	PB
	PB	ZE	PS	PM	PB	PB	PB	PB

Where e is the error, \dot{e} is the error rate and u is the output.

The values inside the Table indicate rule consequents. The rules are interpreted from the Table 2 as: IF error is NB AND error rate is NB THEN output is NB.

The third step is procedure of normalizing the input and denormalizing the output by means of scaling factors is considered among the parameters for optimizing the fuzzy logic controller. The scaling factors and play the role of mapping the domain of inputs onto the domain of the output.

The fourth step is to tune these three parameters (MF, rules and scaling factor) through a search algorithm based on Genetic Algorithm. This technique assures that at least a good local optimum can be discovered.

IV. USING GENETIC ALGORITHM TO OPTIMIZE FUZZY LOGIC CONTROLLERS

In order to apply GA to optimize FLC, a means of evaluating different parameters mentioned in section 3 is required. The evaluation of these parameters is

performed relatively quickly as GA should be able to process large numbers of different combinations of parameters. GA called evaluation function from the (GAOT i.e. genetic algorithm optimization toolbox) to calculate the fitness of a set of parameters. After the processes, it returns a value corresponding to how well the parameters performed the task at hand.

The first function extracts the relevant parameters from the chromosome passed in. This will perform some error checking, the parameters are then used to create fuzzy inference system (FIS) and set the appropriate scaling factors with the second function.

Then the Simulink model in Figure 3 is called, from which the attitude of the satellite to be control is monitored on the oscilloscope as simulation progress. At the end of any iteration, a value is recorded and then the simulation is returned. Table 1 show the properties and properties of Nigeriasat-1 used in this model. Table 3 gives the parameters used for GA. The desired attitude for the satellite to communicate with the ground station is [20 40 60]. The two inputs: error in the angle and the error rate are scaled by the appropriate gains which are set by the GA. This is listed in the second function below. The universe of discourse for the result lies in the range -1 to 1. These inputs are fed into the FLC and FLC's outputs are then scaled by another gain. Once the satellite loses its orientation i.e. deviated from the desired attitude, this acts as the input to the system. The controller, actuators and other appendages directs the satellite back to the desired attitude for it to continuing communicating with the ground station.

In the Simulink model, there is also a disturbance torque introduced at each of the attitude as the satellite does encounter it in the orbit. This disturbance perturbs the satellite enough to make controlling the system a sufficiently challenging task.

Table 3: Parameters used for GA

Parameter	Value
Number of Generation	20
Population Size	20
Type of Crossover	Arithmetic
Type of Mutation	Uniform
Termination method	Maximum Generation

V. FORMULATION OF FITNESS FUNCTION

It is important at this point to determine the consequents of the FLC rules, membership functions parameters and scaling factors that will propel the performance of satellite to be optimum according to a chosen fitness function. These parameters modify the central point and shape of membership function. The output of the fuzzy controller is adjusted by the gain block in the figure 6.

The outputs of this block direct the orientation of the satellite to the desired angle of orientation. Such value is compared with the reference and the model computes the error and the derivative error (error rate). The new inputs are sent to the fuzzy controller and process begins again. The ranges of scaling factors are also determined. To evaluate the performance of the controller, it is necessary to define an objective function.

The target of our controller is to control the attitude of a disorient satellite to desire angle (i.e. roll, yaw, pitch) for it to continuing communicating with the ground station within the shortest time possible. The objective function is therefore defined as:-

$$f(e) = \min \sum_1^s (F[(\phi_o - \phi_{in}), (\theta_o - \theta_{in}), (\psi_o - \psi_{in})]) \tag{10}$$

Where s - number of chromosome,
 ϕ_o - Output of roll angle, ϕ_{in} - input of roll angle,
 θ_o - Output of yaw angle
 θ_{in} - Input of yaw angle, ψ_o - Output of pitch angle,
 ψ_{in} - input of pitch angle

Considering the above mentioned FLC parameters for the optimization i.e. rules, membership functions parameters and scaling factors. Each FLC has two inputs and n membership functions for each input. Therefore, for each FLC, there are n^2 rules which are chosen. Each FLC inputs have its scaling factor.

GA is used to find the best solution or individual according to the GA terminology. In this problem, the solution contains two types of data: integers and real numbers. The integer is then n^2 rules i.e. 7^2 integers for the fuzzy rules where integer mutation and crossover operations will be applied.

The real numbers contain 27 real numbers for parameters of the membership function and scaling factors where real crossover and mutation will be applied. The selection process will be applied for the individual as a whole. This is represented as:-

$$z = \left\{ \begin{array}{l} \text{Real} \left\{ \begin{array}{l} MF \text{ for error 1 (roll angle)} \left\{ \begin{array}{l} a_1 \\ \cdot \\ a_7 \end{array} \right\} \\ MF \text{ for error 2 (yaw angle)} \left\{ \begin{array}{l} a_1 \\ \cdot \\ a_7 \end{array} \right\} \\ MF \text{ for error 3 (pitch angle)} \left\{ \begin{array}{l} a_1 \\ \cdot \\ a_7 \end{array} \right\} \end{array} \right. \\ \text{Scaling factor} \left\{ \begin{array}{l} G_1 \\ \cdot \\ G_6 \end{array} \right\} \\ \text{Integers} \left\{ \begin{array}{l} \text{Rules} \left\{ \begin{array}{l} r_1 \\ \cdot \\ r_{49} \end{array} \right\} \end{array} \right. \end{array} \right. \tag{11}$$

And summarized as:

$$\min f(z) \quad z \in R^{76} \tag{12}$$

The GA algorithm is executed according to the flow diagram shown in figure 5.

The optimal value in this case is when the satellite is communicating with the ground station at desired orientation for roll, pitch and yaw.

The difference from the set angle after encounter any disturbance must be brought to minimum. For example, if the desired angles for roll, pitch and yaw are [20 40 60], the angle varied as soon as the satellite experience disturbance i.e.

$$(\phi_o - \phi_{in}) \cong 20, (\theta_o - \theta_{in}) \cong 40, (\psi_o - \psi_{in}) \cong 60 \tag{13}$$

For this Flow chart is given below

Flowchart for Tuning Fuzzy Controller using GA.

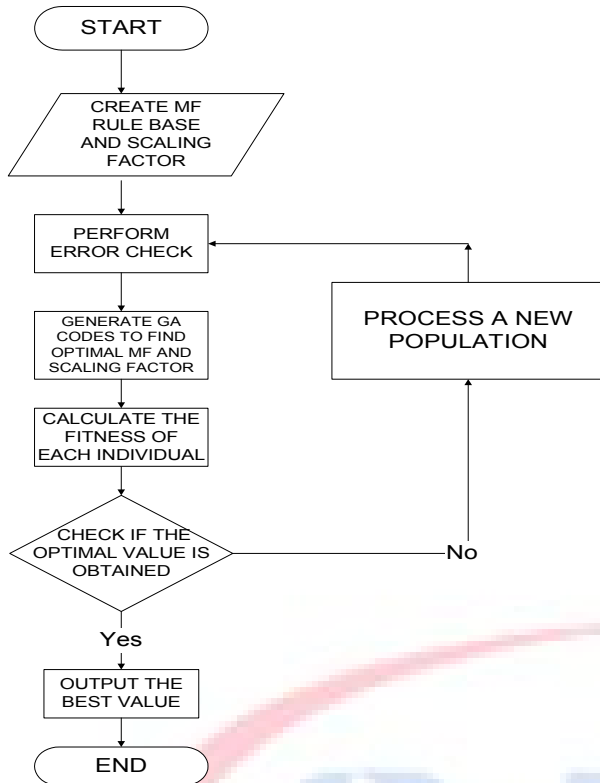


Figure 5: Flowchart for Tuning Fuzzy Controller using GA.

VI. SIMULATION RESULTS

The results of simulations carried out based on the implementation of solution methodologies outlined in the preceding sections are presented and discussed here.

6.1 Optimization of Membership Function

The tuning approach employs the use of fuzzy logic toolbox, genetic algorithm optimization toolbox (GAOT) have been appropriately modified, scripts were written and implemented in using Matlab codes to meet simulation needs. This system is continuously modified to find an optimal solution. The rule mat that gives optimal response of membership function and fuzzy rules are interpreted in Tables 4 and 5.

Table 4: Encoding system for optimize fuzzy output.

Membership function	Corresponding value
NB	1
NM	2
NS	3
ZE	4
PS	5
PM	6
PB	7

Table 5: The best generated rules.

Output		Rate of change of error						
		NB	NM	NS	ZE	PS	PM	PB
Error	NB	NB	NB	NM	NM	NM	NS	PS
	NM	NB	NM	NM	NS	NS	PS	PM
	NS	NB	NM	NS	NS	ZE	PS	PM
	ZE	NM	NM	NS	ZE	PS	PS	PS
	PS	NM	NS	ZE	PS	PS	PS	PB
	PM	NM	NS	PS	PS	PM	PM	PB
PB	NS	PS	PM	PM	PM	PB	PB	

The membership functions for the two inputs, and output is shown in figures 7, 8, and 9.

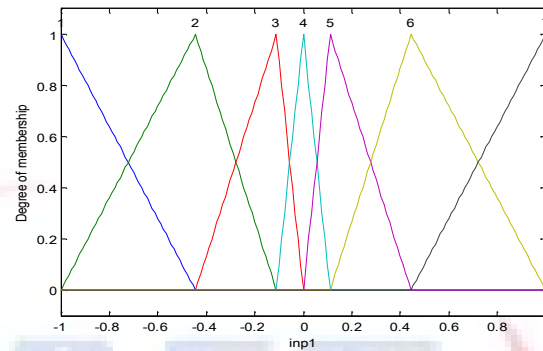


Figure 7: Optimal membership functions of error variable.

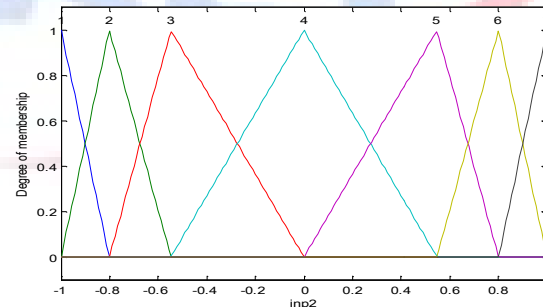


Figure 8: Optimal membership functions of error rate.

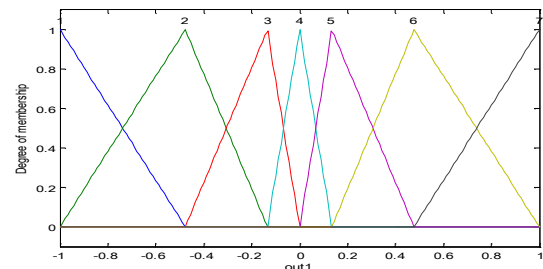


Figure 9: Optimal membership functions output

The tuning approach employed the use of MATLAB M-files and functions to manipulate the selection of the best scaling factor within the range 1.10 to 2.50 for error variable and -9.4 to -8.7 error rate. At the end of simulation, Table 6 is obtained for the three error variable inputs labeled G1, G2, G3, three error rate inputs labeled G4, G5 and G6, and the best fitness function. Figure 10 and 11 shows the best attitude response when MFs, fuzzy rules and scaling factor are optimized.

Table 6: The best scale factors and fitness function

G1	2.4276
G2	2.4685
G3	2.4793
G4	-9.3508
G5	-8.8512
G6	-9.3167
Best Fitness Function	216.0762

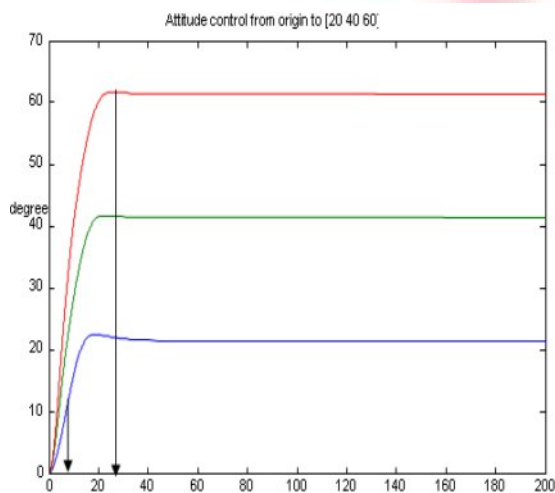


Figure 11: The best Attitude response i.e. attitude angle (degree) against time (s).

From Figure 11, the performance indices recorded is in Table 7. The first arrow indicates the rise time while the second arrow indicates the settling time.

Table 7: Performance indices

Rise time (sec)	Settling time (sec)	% Overshoot
7s	23s	--

Comparing this Table 7 with Table 8 which are data obtained by Adunola et al (2016), the values obtained

for rise time and settling time in Table 8 are better than what was obtained in Table 7 for Optimized FLC.

Table 8: Performance indices.

	Rise time(sec)	Settling time (sec)	Percent overshoot (%)
Conventional FLC by Adunola et al (2016)	8	30	45
Optimized FLC (this work)	7	23	---

Figure 12 shows the progress of GA that found the best fitness. The upper curve represents the maximum fitness while the lower curve represents the mean fitness.

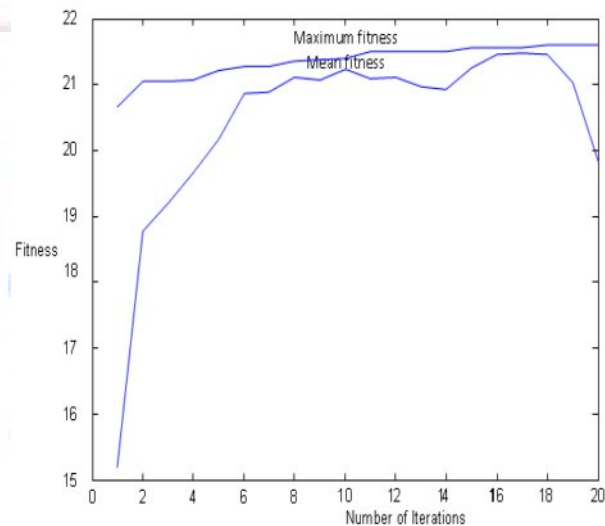


Figure 12: Progress of GA that found the best fitness.

VII. DISCUSSION OF RESULTS

Details of the optimized FLC found by the GA are presented in Tables 4 to 8 and Figures 7 to 12. For FLC with two inputs and seven (7) membership functions for each input, there are forty nine (49) rules which should be chosen. The consequent of each rule can take any of the output fuzzy variables. To be able to include the linguistic rules in the optimization process, Table 4 shows the integer encoding system used to refer to the output fuzzy variables. Table 5 shows the best generated rules. Figures 7 to 9 shows the best membership function distribution. For error variable

and output, the membership functions are compressed towards the center, while they were compressed at the extremes for the error derivative. Figure 11 shows the optimal attitude response of the satellite with no overshoot in the least. Table 8 compared the result obtained from Figure 11 with conventional FLC obtained by Adunola et al (2016). The rise time and settling time for conventional FLC are 8s and 30s respectively with 45% overshoot. In this optimized FLC, the rise time and settling time are 18s and 23s respectively with 0% overshoot. It is clear from these results that the algorithm was able to generate an optimal FLC with a very good performance. Table 6 present the best value selected for the six (6) gains i.e. scale factors with the best fitness. This lead to final optimized attitude response in Figure 11 with rise time, settling time and percent overshoot to be 7s, 23s and 0% respectively shown in Table 8. This shows that a better optimization is achieved when the two factors i.e. membership function and scale factors are optimized and Figure 12 shows the progress of GA that found the best fitness.

VIII. CONCLUSION

In this study, genetic algorithm was applied to obtain optimal membership functions, the best rules and the best scale factors are selected. These drive the fuzzy logic controller to adequately control the attitude of satellite whenever it lost its orientation.

The results show that the optimized fuzzy controller gives better performance than a conventional fuzzy controller in terms of rise time, settling time and percent overshoot. In other words, the tuning design approach offers a fast way of designing an optimal fuzzy controller.

The tuning approach through genetic algorithm assures a fast and good definition of fuzzy rules. Moreover the simulation shows that the optimized fuzzy controller gives better performance than a conventional fuzzy controller in terms of rise time, settling time and percent overshoot. The termination condition for GA occurs when the maximum generation number is reached (20 in this case).

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