Influence of the membership functions number of fuzzy logic controller on the performances of dynamic systems

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Abstract: The aim of this work is to study the influence of the number of membership functions (MF) of fuzzy logic controller (FLC) on the temporal performances of dynamical systems. A second contribution to this idea is the introduction of the disturbance signal as an additional input to the FLC and this makes it possible to deliver a command taking into account the values of this undesirable signal. In order to illustrate the influence of the number of membership functions of an FLC, the angular position in a linear model of an Autonomous Underwater Vehicle (AUV) will be controlled around a given reference. The simulation results show that it is sufficient to limit the number of membership functions to a maximum of 5 MF and this is interpreted by the boundary fuzzy decision surface of the fuzzy control because there is no influence, in the case of adding other supplementary MFs, on the performances of the system.

Keywords: Fuzzy logic controller, Membership functions, Fuzzy rules, Autonomous underwater vehicles, Temporal performances.

1. Introduction

Fuzzy control is an intelligent control technology that has been used to achieve promising results for many applications that are difficult to handle with conventional techniques. This type of control covers several applications in fields such as the environment, medical, electronics and automation. This command has shown its efficiency and robustness with respect to their membership functions and fuzzy rules (Ying et al., 1988; Ying, 2002). Although classical control methods are based on the quantitative analysis of the mathematical model of the system, fuzzy controls serve as a linguistic description of the control procedure (Driankov & Hellendoorn, 1995; Yeh & Chen, 1997);

The concept of fuzzy sets was introduced in 1965 by Lotfi Zadeh as a means of representing fuzziness in applications. He suggested a modified set theory in which an individual can have a value that varies over a set of values instead of being 0 or 1, fuzzy set theory is an extension to traditional theory, and fuzzy logic is the logic corresponding to the manipulation of fuzzy sets (Ijima et al., 1995; Seising, 2018). Through fuzzy logic, a system can not only represent imprecise concepts such as fast, large, etc., but also, through a set of sound mathematical principles, it can also use these concepts to make inferences about the system. Fuzzy logic aims to model imprecise or common-sense reasoning for uncertain, ill-defined, and complex processes that do not require a high level of precision (Fortes et al., 2013; Torres-Garcia et al., 2022).

The essential basis of FLC is the use of relations and linguistic elements as functions and variables. A fuzzy rule of inference or a fuzzy relationship is often expressed by the conditional 'if-then' logic structure. Several researchers have been part of developing the reasoning of the FLC especially the use of optimization methods in order to choose the expressed fuzzy rules and those not effective (Bouarroudj et al., 2017; Kacimi et al., 2020).

The FLC law is characterized by a nonlinear hypersurface in the product space of controller inputs and controller outputs.

The question that arises: does the increase in the number of membership functions improve the temporal performance of a system controlled by an FLC? And also, if a disturbance signal is injected as an additional input to the FLC, does this affect stability or other characteristics?

To answer these questions, an application of the fuzzy logic controller on the linear model of an autonomous underwater vehicle (AUV) is designed. The rest of paper is organized as follows:

Section 2 includes a related works to the paper, it presents similar solutions based on other

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researchers proposals and also showcases the limitations of other solutions and the opportunities for the current research. Some notions on fuzzy logic control are briefly discussed in Section 3 and 4. In Section 5, general modelling of autonomous under-water vehicle is detailed. In Section 6, the fuzzy logic controller is applied to stabilize an AUV and the paper will be concluded in Section 7.

2. Related works

The impact of the number of membership functions on the performance of the Fuzzy Logic Controller regulator refers to how changes in the number of membership functions used in a Fuzzy Logic Controller affects its ability to regulate a system. A higher number of membership functions can provide more precise control over the system, while a lower number can simplify the control process and reduce computational complexity. The influence of the number of membership functions on the performance of the Fuzzy Logic Controller regulator is an area of ongoing research, with different solutions and proposals being proposed to optimize the system's performance. Some related works to this subject are detailed as follows:

In the reference (Simo et al., 2022), two propositions of fuzzy rules number are used but the authors do not explain which one is? adequate. The authors in (Azizi et al., 2020) detail the use of different optimization methods for an FLC controller without judging what maximum or minimum number of membership functions is necessary in order to improve the performance of controlled systems. In (Aras et al., 2011), changes are made either to the number of the fuzzy partitions or to the mapping of the membership function when the results are not as desired and then the system can be tested again. The authors in (Herman et al., 2009) show the importance of the accurate membership functions which is selected by optimization but these methods possess one common weakness where conventional FLC use membership function generated by human operators. In the research paper (Aras et al., 2017), the tuning process is made either to the number of fuzzy partitions or the mapping of the membership function so that the results can follow the desired set point, but in this case the authors do not determine any limit to the number. Fuzzy membership functions of the fuzzy controller are optimized using Firefly Algorithm (FA) in (Farajdadian Hosseini, 2019) to generate the proper duty cycle. Unfortunately, all these methods are limited because of not determining the optimal number of membership functions. On the other hand, the present work in this paper specifies the number of membership functions at 5 MFs for improving the performance of controlled systems.

3. Fuzzy membership functions and inference rules

A fuzzy rule of inference or a fuzzy relationship is often expressed by the conditional "if-then" logic structure. They are of the form "If A then B", where A and B are fuzzy sets characterized by appropriate membership functions. These rules tend to account for the imprecision of human reasoning when it comes to making a decision in an environment of uncertainty and imprecision. For example, a fuzzy rule for controlling the current in the compressor inside an air conditioner might be written as follows: "If the temperature is high and the humidity is low, then supply a moderate amount of current". The "If" condition is called the antecedent and "Then" is called the consequence. Such rules are generally obtained from system knowledge and reflect the experience and know-how of human experts. Another form of fuzzy rules, proposed by Takagi and Sugeno, shows the involvement of fuzzy sets only in the premises part. An example of a fuzzy rule using Takagi and Sugeno's fuzzy inference rule can be given by small algorithm (1):

Begin

V=speed; F=force;

if the ***V*** is ***high*** then (1)

F= k *V;

End

where a linguistic value represented by a membership function is raised in the antecedent part. The result is a non fuzzy equation, i.e. the output variables being numeric. For the computer implementation of a fuzzy rule, low and moderate values must be associated with numerical values. The theory of fuzzy sets makes it possible to define these terms by means of membership functions and to attribute these qualitative values to fuzzy sets (Ben-Ari & Mondada, 2018; Valmohammadi & Dehbasteh, 2019).

Fuzzy sets defined on the linguistic variables will be presented as triangular membership functions, as shown in Figure 1.

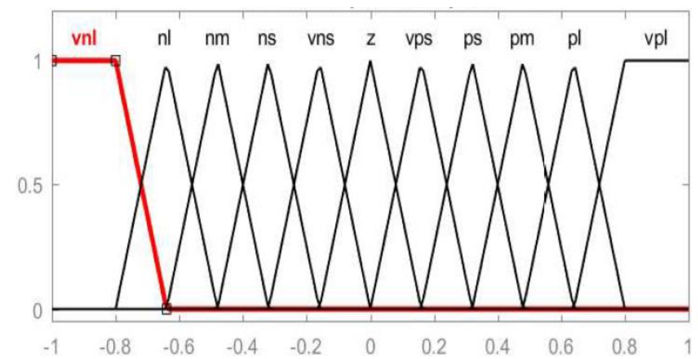


Figure 1. Membership functions plots

For the change in the control action, the designer does not need in a fuzzy controller to define correspondent fuzzy sets (as it does not have a chain of rules) being sufficient to establish their center of gravity C_i. Let there have N linguistic rules like: *IF De is Dei, then* $u=C_i$. The controller output is obtained calculating the center of gravity:

$$u(De)\frac{\sum_{i=1}^{N} C_i \mu_{i(De_i)}}{\sum_{i=1}^{N} \mu_{i(De_i)}} \tag{2}$$

The membership function should be defined in such a way that the resulting control surface corresponds to the characteristics of the controlled process. This membership function can be interpreted as a (fuzzy) utility function in decision making, as a gradual rule in the sense of Dubois in fuzzy logic, or as a nonlinear gain factor in control engineering. It describes a goal to satisfy such as small error or a gradual relation between the controller input and the output (Kaymak et al., 1996).

The design of the FLC involves shaping the control surface by identifying a correct fuzzy relation, selecting suitable aggregation, implication and deffuzzification operators, and tuning the membership functions for the particular control problem. The tuning of various elements requires the determination of a large number of parameters such as the place of the membership function cores and the overlap between the membership functions.

The response of the FLC is characterized by a nonlinear control surface in the product space of input and output variables.

4. Architecture of a fuzzy logic control

We speak of fuzzy control when part of automation is carried out in fuzzy logic. Its mission is the same as that of a classic controller, namely: to manage the command and control data of the process. The structure of the fuzzy logic can therefore be reduced to a controlled system, see Figure 2 (Passino & Yurkovich, 1998).

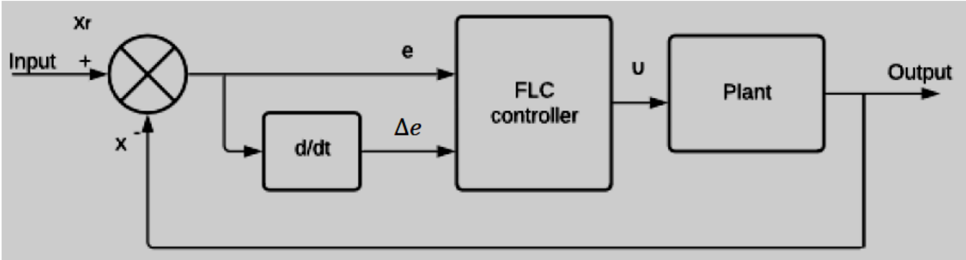


Figure 2. Architecture of a fuzzy logic controller

From the value of the output variable, the fuzzy controller is used to determine the appropriate command to the process. This is generally calculated for automatic systems thanks to the two inputs **e** and **Δe** and the inference of fuzzy rules.

In general, "**e**" represents the difference between the output signal of the process and the setpoint:

$$e(t) = X_r(t) - X(t) \tag{3}$$

Δe is the variation of the error between the process output signal and the setpoint.

$$\Delta e(t) = \frac{de}{dt} \tag{4}$$

The FLC is made up of rules of the form as a small algorithm (5):

Begin

if **e** is A_i and

Δe is B_j then (5)

U is C_k

End

Where A_i, B_j and C_k are the linguistic variables, $i=1 \ldots n_1$; $j=1 \ldots n_2$ *and* $k=1,\ldots m$.

The control surface of a two-input, single-output system is shown in Figure 3, where **e** and **de** represent the inputs and **u** represents the controller output. For a PD fuzzy controller type, **e** represents error and **de** represents error change.

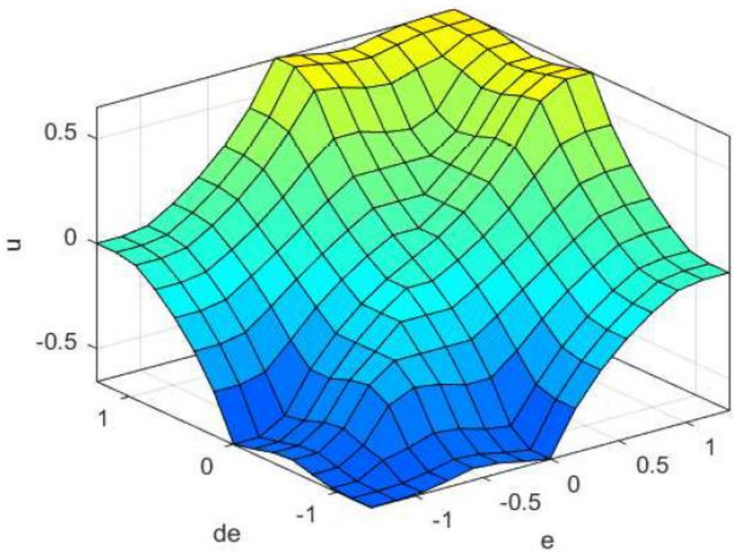


Figure 3. Fuzzy decision surface

This form of three dimensional nonlinearity, implemented by the fuzzy controller, is sometimes called "the Control Surface" and it is affected by all of the main parameters of the fuzzy controller (Passino & Yurkovich, 1998; Coleman, 2006).

5. General modeling of the autonomous underwater vehicle

Modeling of autonomous underwater vehicle (AUV) requires the step of defining the reference frames from which the evolution of the device will be described, as shown in Figure 4. First, an absolute reference is defined:

$$R_0 = (0, x_0, y_0, z_0) \tag{6}$$

where:

- x_0 : the longitudinal axis coincides with the geographic north;
- y_0 : the transverse axis is directed towards the east;
- z_0 : the normal axis is directed downwards (seabed).

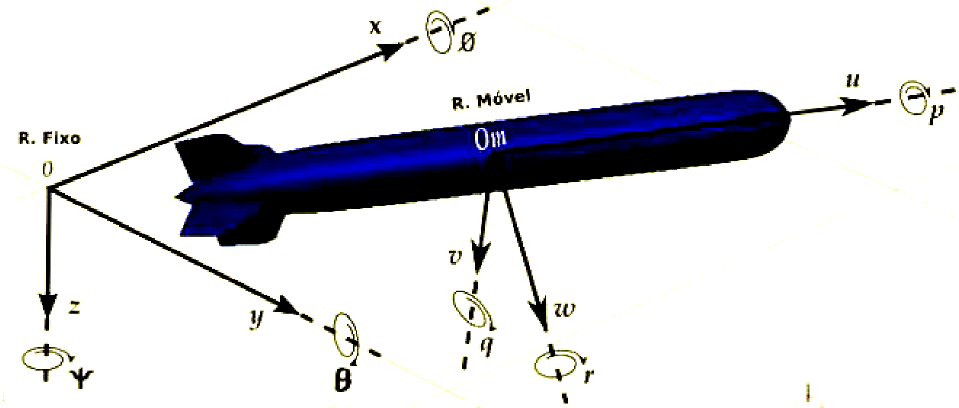


Figure 4. Fixed and inertial landmarks

The main characteristic of this tire is that it is stable with respect to the ground, which gives it the characteristics of a Galilean or inertial tire. The effect of the earth's rotation is minimal on and around the machine. A second reference $R_v = (C, x_v, y_v, z_v)$ associated with the vehicle makes it possible to express the speeds of the machine.

The main axes of the palaces of the vehicle correspond to the axes of the chassis:

- X_v : a longitudinal axis directed from the rear of the vehicle to the front;
- Y_v : transverse axis oriented to starboard;
- Z_v : normal axis directed from top to bottom.

The choice of the point of origin C for this frame is strategic.

The SNAME [Society of Naval Architects and Marine Engineers] offers a method for selecting its location based on the technical characteristics of a vehicle.

The velocity vector is represented by equation (7) as following (Ishaque et al., 2011):

$$v = [u \text{ v } w \; p \; q \; r]^T \tag{7}$$

u: forward speed; v: sliding speed; w: descent speed; $p = \dot{\phi}$: roll speed; $q = \dot{\theta}$: pitch speed; $r = \dot{\psi}$: yaw rate.

Using Euler angles, the position and orientation of the vehicle can be described as a vector η with respect to the global reference frame:

$\eta = [x\ y\ z\ \phi\ \Theta\ \Psi]^T$

x, y et z : three position components

ϕ: The roll angle

Θ : The pitch angle

Ψ : The yaw angle

The correspondence between the two coordinate systems is given by the Euler angle transformation:

$$\dot{\eta} = J(\eta)v \tag{8}$$

where J is the Euler angle transformation matrix which can be described by three rotations in a fixed order. The nonlinear vehicle dynamics can be expressed in a compact form as follows:

$$M\dot{v} + C(v)v + D(v)v + g(\eta) = B(v)u \tag{9}$$

Where:

M is the 6×6 inertial matrix including the hydrodynamic added mass.

$C(v)$ is the matrix of Coriolis and centripetal forces.

$D(v)$ is the hydrodynamic damping matrix.

$g(\eta)$ is the Vector of restoring forces and moments.

$B(v)$ is the 6×3 control matrix.

Simplified rigid body motion equations in heave and pitch can be written according to the following criteria assuming that the origin coincides with the center of gravity and that sway (v) and yaw (r) are zero:

Some simplifications are cited in (Ishaque et al., 2011) which give the following linear model of AUV:

$$\begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{\theta} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} -0.6529 & -2.4522 & 0.0855 & 0 \\ 3.2219 & -3.1309 & -44.6794 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & -4.11 & 0 \end{bmatrix} \begin{bmatrix} w \\ q \\ \theta \\ z \end{bmatrix} + \begin{bmatrix} 0.4147 \\ -3.6757 \\ 0 \\ 0 \end{bmatrix} \cdot u \tag{10}$$

where u is the control signal.

6. Simulation results and discussion

In this application, we will apply the FLC controller on the model of an AUV in order to control its angular position around a given reference. Two cases are detailed in this simulation according to the number of membership functions (MFs), number of inputs to the FLC and the absence or presence of the disturbances. The objective of this application focuses on the influence of the number of membership functions (or fuzzy rules) on the performances of the regulated system. In order to check the influence of the number of RF on the performance of the time output of the system to be controlled (AUV), we will add an additional input to the FLC regulator which is the variation of the error (de) then; we will change this last entry with that of the possible disturbances (d) as an entry of the FLC.

6.1. Simulation without disturbances with two inputs (error and its variation)

In this 1st case, the variation of the error is used as a second input to the FLC regulator and also, five cases of number of fuzzy membership functions are applied: 3, 5, 7, 9 and 11MFs or the fuzzy rule functions: 7RF, 13 RF, 29 RF, 51 RF and 91 RF. The fuzzy rules located in the gray boxes in the tables are saturated rules and are not necessarily used for this controlled system.

The abbreviations of the membership functions are:

VPL: very positive large.
PL: positive large;
PM: positive medium
PS: positive small
VPS: very positive small
Z: zero;
VNS:very negative small
NS: negative small
NM: negative medium
NL: negative large;
VNL: very negative large.

The membership functions used in this point are indicated according to the Tables 1 to 5:

Table 1. Case of 03 membership functions

de \ e	PL	Z	NL
NL	Z	NL	NL
Z	PL	Z	NL
PL	PL	PL	Z

Table 2. Case of 05 membership functions

de \ e	PL	PS	Z	NS	NL
NL	Z	NS	NL	NL	NL
NS	PS	Z	NS	NL	NL
Z	PL	PS	Z	NS	NL
PS	PL	PL	PS	Z	NS
PL	PL	PL	PL	PS	Z

Table 3. Case of 07 membership functions

de \ e	PL	PM	PS	Z	NS	NM	NL
NL	Z	NS	NM	NL	NL	NL	NL
NM	PS	Z	NS	NM	NL	NL	NL
NS	PM	PS	Z	NS	NM	NL	NL
Z	PL	PM	PS	Z	NS	NM	NL
PS	PL	PL	PM	PS	Z	NS	NM
PM	PL	PL	PL	PM	PS	Z	NS
PL	PL	PL	PL	PL	PM	PS	Z

Table 4. Case of 09 membership functions

de \ e	VPL	PL	PM	PS	Z	NS	NM	NL	VNL
VNL	Z	NS	NM	NL	VNL	VNL	VNL	VNL	VNL
NL	PS	Z	NS	NM	NL	VNL	VNL	VNL	VNL
NM	PM	PS	Z	NS	NM	NL	VNL	VNL	VNL
NS	PL	PM	PS	Z	NS	NM	NL	VNL	VNL
Z	VPL	PL	PM	PS	Z	NS	NM	NL	VNL
PS	VPL	VPL	PL	PM	PS	Z	NS	NM	NL
PM	VPL	VPL	VPL	PL	PM	PS	Z	NS	NM
PL	VPL	VPL	VPL	VPL	PL	PM	PS	Z	NS
VPL	VPL	VPL	VPL	VPL	VPL	PL	PM	PS	Z

Table 5. Case of 11 membership functions

de \ e	VPL	PL	PM	PS	VPS	Z	VNS	NS	NM	NL	VNL
VNL	Z	VNS	VNS	NS	NS	NM	NL	NL	VNL	VNL	VNL
NL	VPS	Z	VNS	VNS	NS	NS	NM	NL	NL	VNL	VNL
NM	VPS	VPS	Z	VNS	VNS	NS	NS	NM	NL	NL	VNL
NS	PS	VPS	VPS	Z	VNS	VNS	NS	NS	NM	NL	NL
VNS	PS	PS	VPS	VPS	Z	VNS	VNS	NS	NS	NM	NL
Z	PM	PS	PS	VPS	VPS	Z	VNS	VNS	NS	NS	NM
VPS	PL	PM	PS	PS	VPS	VPS	Z	VNS	VNS	NS	NS
PS	PL	PL	PM	PS	PS	VPS	VPS	Z	VNS	VNS	NS
PM	VPL	PL	PL	PM	PS	PS	VPS	VPS	Z	VNS	VNS
PL	VPL	VPL	PL	PL	PM	PS	PS	VPS	VPS	Z	VNS
VPL	VPL	VPL	VPL	PL	PL	PM	PS	PS	VPS	VPS	Z

The simulation results in this 1st case are illustrated in the Figures 5, 6. Figure 7 illustrate the decision surface of the FLC in the case of 3, 5, 7, 9 and 11MFs.

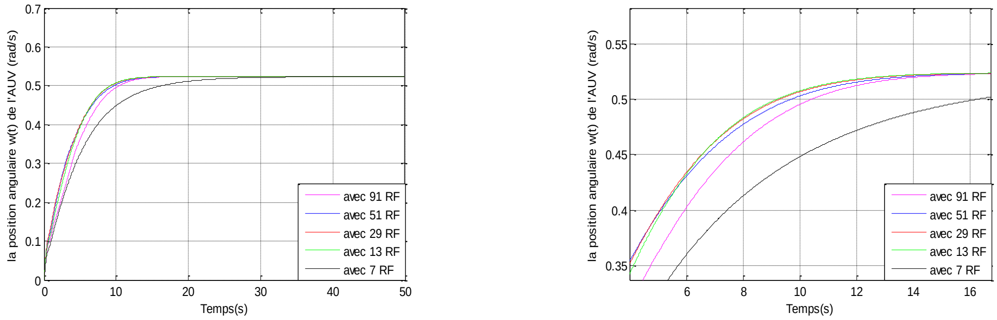


Figure 5. The angular position w(t) of the 1st case (and their 'zoom')

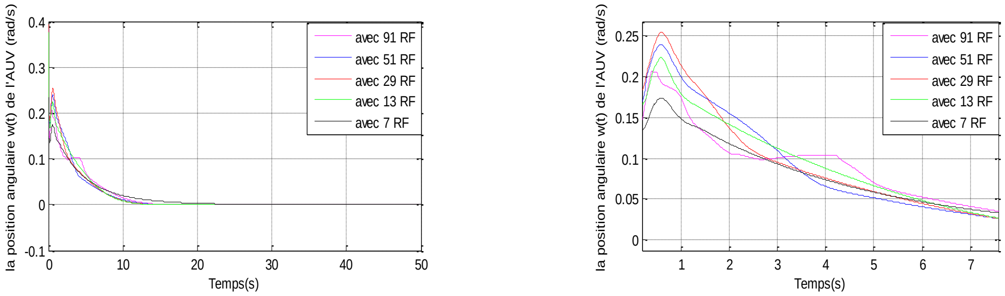


Figure 6. The control signal of the 1st case (and their ,'zoom')

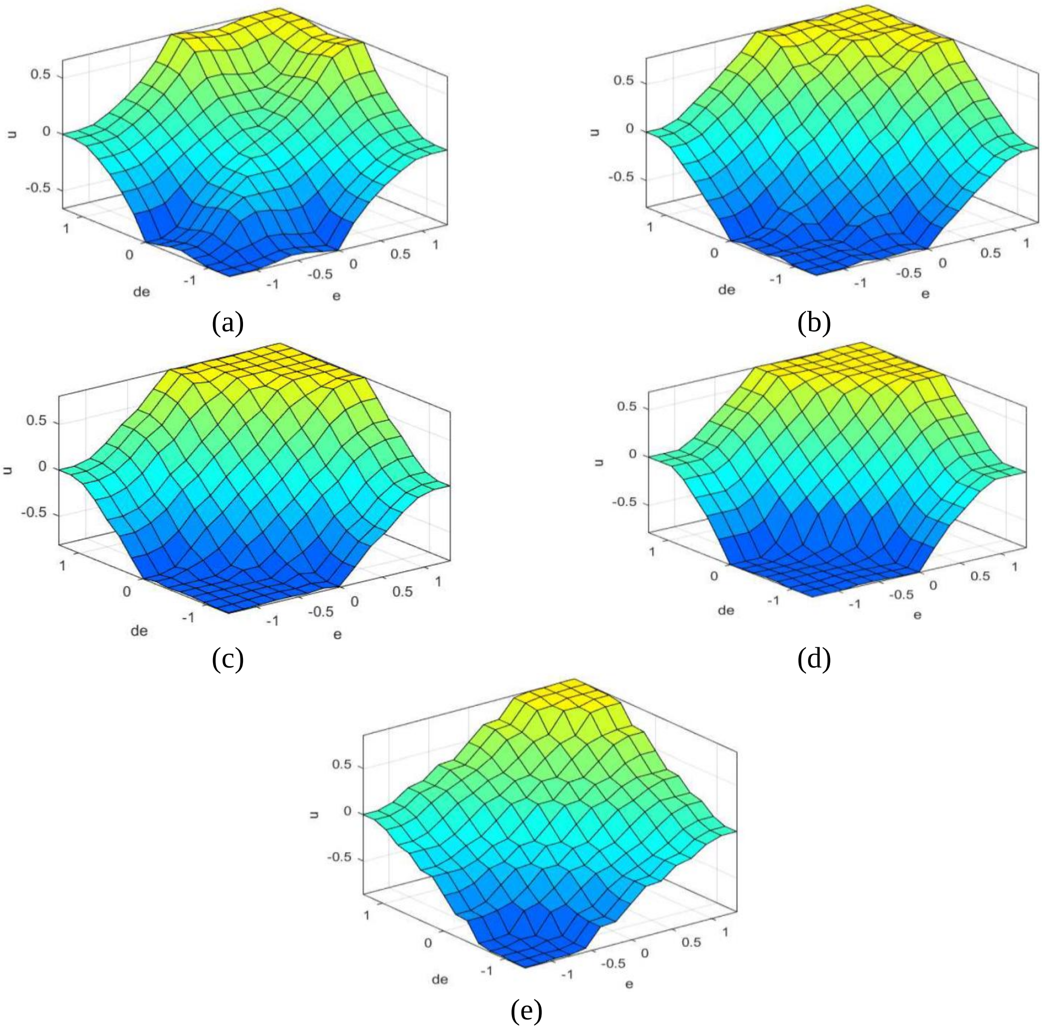


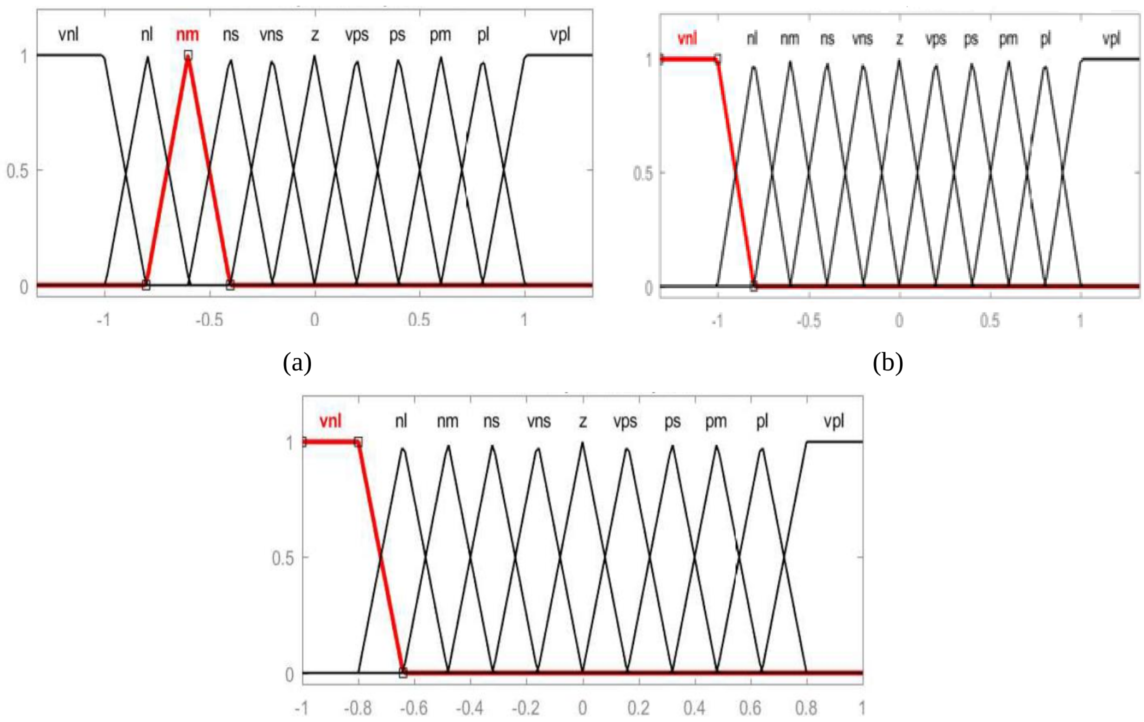
Figure 7. Decision surface of the fuzzy inference engine for
(a): 3 MFs, **(b):** 5MFs, **(c):** 7 MFs, **(d):** 9 MFs and **(e):** 11 MFs.

The temporal performances of this 1st case are given in the Table 6.

Table 6. Temporal performances obtained in the 1st case

	tm	tr	D%	Vinf	e
Case of (11 MF or 91 RF)	4.0881	10.1939	0.00%	0.5236	0.0000
Case of (09 MF or 51 RF)	3.7100	9.4495	0.00%	0.5236	0.0000
Case of (07 MF or 29 RF)	3.2992	9.0667	0.00%	0.5236	0.0000
Case of (05 MF or 13 RF)	3.5081	8.9779	0.00%	0.5236	0.0000
Case of (03 MF or 7 RF)	4.7444	15.7048	0.00%	0.5235	0.0001

From above results, it can be seen that the temporal response of this system takes the same form with certain changes in the response and rise time values according to the variation in the number of fuzzy rules (or membership functions) and also the increase of this number leads us to declare that the best value of this number is 5 MFs in terms of performance and whatever the change in this number of fuzzy rules might be, the performance remains unchangeable to the best, i.e., that the number 05 MFs is the optimum in this case. This result can be interpreted by the decision control surface which is shaped by the rule base and the linguistic values of the linguistic variables.



(c)

Figure 8. Membership functions plots of variable
(a): 1st variable input “e”, **(b):** 2nd variable input “de” and **(c):** output variable “u”.

The membership functions plots of error “e”, error variation “de” and control signal “u” for 1st case are shown in Figure 8.

6.2. Simulation with disturbances (error and disturbances)

In this 2nd case, the 2nd entry "the variation of the error" will be replaced by the value of possible disturbances and that it will be the 2nd entry of the FLC regulator and also, five cases of number of fuzzy rules are used (3MF, 5MF, 7MF, 9MF,) or (9RF, 25RF, 49RF, 81RF and 11MF). The random disturbances d(t) are shouted which varies from -0.01 to 0.01 in the time interval [30s, 40s].

General model of the simulation of this 2nd case on Simulink is illustrated in the Figure 9.

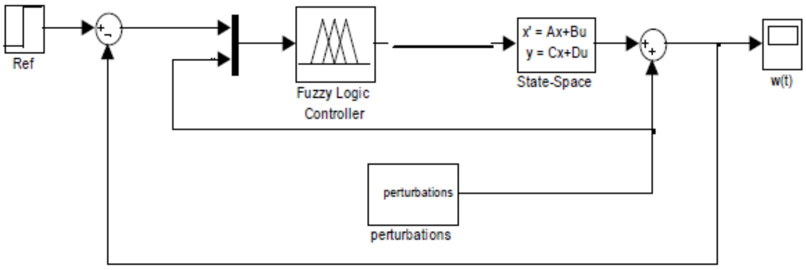


Figure 9. Simulation model of the 2nd case (two inputs) with disturbances

The membership functions used in this point are indicated according to the tables (7 to 11):

Table 7. Case of 03 membership functions

d \ e	PL	Z	NL
NL	PL	PL	Z
Z	PL	Z	NL
PL	Z	NL	NL

Table 8. case of 05 membership functions

d \ e	PL	PS	Z	NS	NL
NL	PL	PL	PL	PS	Z
NS	PL	PL	PS	Z	NS
Z	PL	PS	Z	NS	NL
PS	PS	Z	NS	NL	NL
PL	Z	NS	NL	NL	NL

Table 9. case of 7 membership functions

d \ e	PL	PM	PS	Z	NS	NM	NL
NL	PL	PL	PL	PL	PM	PS	Z
NM	PL	PL	PL	PM	PS	Z	NS
NS	PL	PL	PM	PS	Z	NS	NM
Z	PL	PM	PS	Z	NS	NM	NL
PS	PM	PS	Z	NS	NM	NL	NL
PM	PS	Z	NS	NM	NL	NL	NL
PL	Z	NS	NM	NL	NL	NL	NL

Table 10. Case of 09 membership functions

d \ e	VPL	PL	PM	PS	Z	NS	NM	NL	VNL
VNL	VPL	VPL	VPL	VPL	VPL	PL	PM	PS	Z
NL	VPL	VPL	VPL	VPL	PL	PM	PS	Z	NS
NM	VPL	VPL	VPL	PL	PM	PS	Z	NS	NM
NS	VPL	VPL	PL	PM	PS	Z	NS	NM	NL
Z	VPL	PL	PM	PS	Z	NS	NM	NL	VNL
PS	PL	PM	PS	Z	NS	NM	NL	VNL	VNL
PM	PM	PS	Z	NS	NM	NL	VNL	VNL	VNL
PL	PS	Z	NS	NM	NL	VNL	VNL	VNL	VNL
VPL	Z	NS	NM	NL	VNL	VNL	VNL	VNL	VNL

Table 11. Case of 11 membership functions

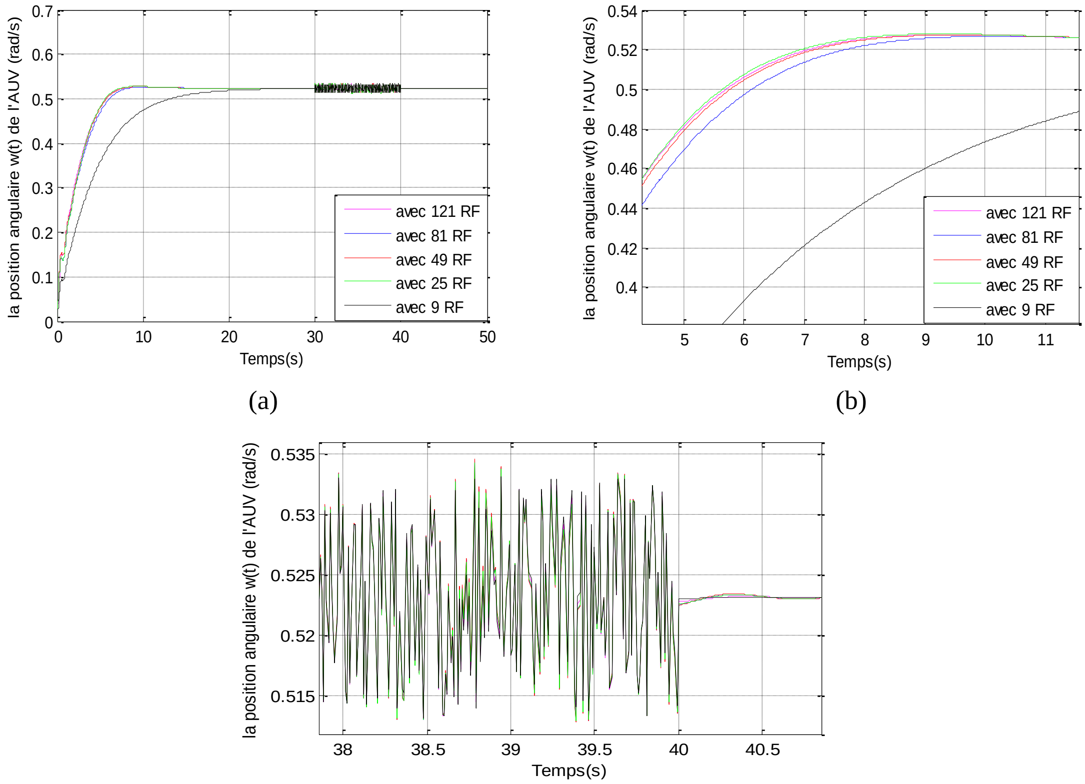
d \ e	VPL	PL	PM	PS	VPS	Z	VNS	NS	NM	NL	VNL
VNL	VPL	VPL	VPL	PL	PL	PM	PS	PS	VPS	VPS	Z
NL	VPL	VPL	PL	PL	PM	PS	PS	VPS	VPS	Z	VNS
NM	VPL	PL	PL	PM	PS	PS	VPS	VPS	Z	VNS	VNS
NS	PL	PL	PM	PS	PS	VPS	VPS	Z	VNS	VNS	NS
VNS	PL	PM	PS	PS	VPS	VPS	Z	VNS	VNS	NS	NS
Z	PM	PS	PS	VPS	VPS	Z	VNS	VNS	NS	NS	NM
VPS	PS	PS	VPS	VPS	Z	VNS	VNS	NS	NS	NM	NL
PS	PS	VPS	VPS	Z	VNS	VNS	NS	NS	NM	NL	NL
PM	VPS	VPS	Z	VNS	VNS	NS	NS	NM	NL	NL	VNL
PL	VPS	Z	VNS	VNS	NS	NS	NM	NL	NL	VNL	VNL
VPL	Z	VNS	VNS	NS	NS	NM	NL	NL	VNL	VNL	VNL

The temporal performances of this 2nd case are given in the Table 12.

Table 12. Temporal performances obtained in the 2nd case

	tm	tr	D%	Vinf	e
Case of (11 MF or 121 RF)	2.1188	5.5883	0.74%	0.5236	0.0000
Case of (09 MF or 81 RF)	2.2875	6.0044	0.61%	0.5236	0.0000
Case of (07 MF or 49 RF)	2.2278	5.6582	0.76%	0.5236	0.0000
Case of (05 MF or 25 RF)	2.2638	5.5296	0.84%	0.5236	0.0000
Case of (03 MF or 09 RF)	3.9975	12.7445	0.00%	0.5235	0.0001

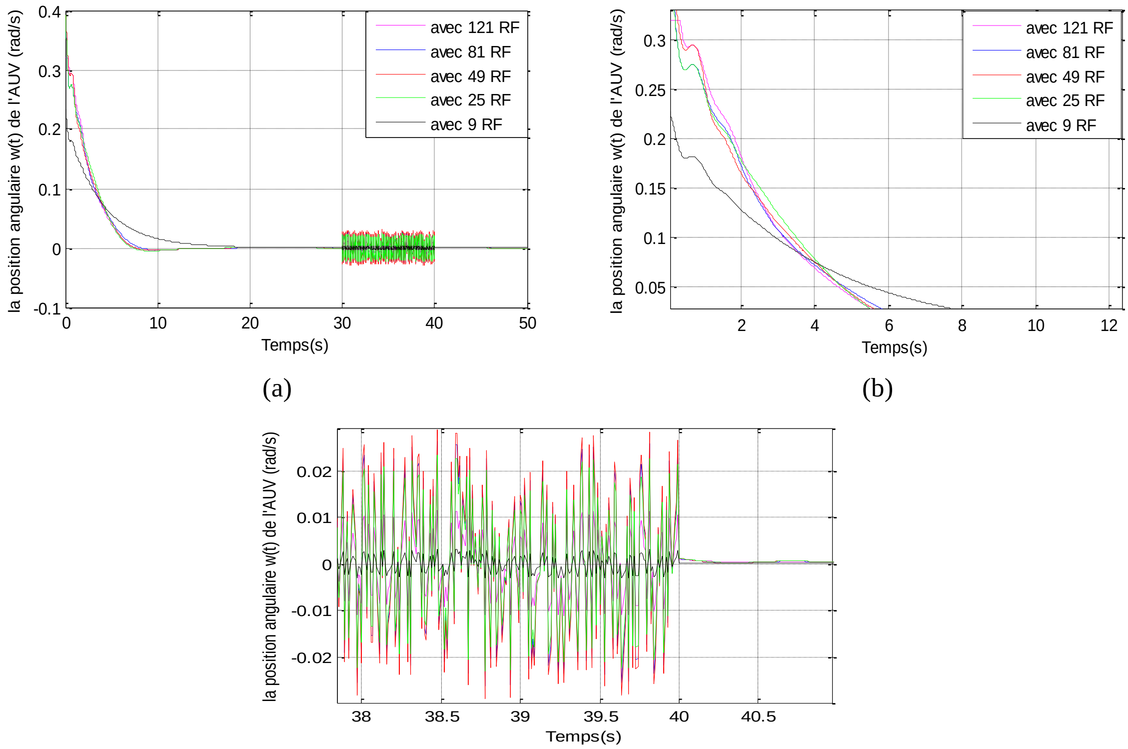
The simulation results in this 2nd case are illustrated in the Figures 10 and 11.



(a) (b)

(c)

Figure 10. (a) angular position w(t) in 2nd case, **(b)** and **(c)** their "zooms”



(a) (b)

(c)

Figure 11. (a) control signal w(t) in 2nd case, **(b)** and **(c)** their “zooms”

The results of simulation in the presence of disturbance (2^{nd} case) show the effectiveness of introducing these disturbances as input variables to the FLC and also, the best optimal value of the number of MF is 5 and the performances remain almost the same if this number exceeds 5 MFs.

6.3. Results interpretation

In order to obtain the best temporal performances, the change of the number of fuzzy rules (or number of membership functions) must remain fixed at 5MFs and this is interpreted by the limit decision surface of an FLC as indicated in section (4). Concerning the disturbances which are added as an additional input to the FLC, the control takes into consideration these disturbance values to deliver an adequate control signal to the system after a few undesirable oscillations and to make it always stable in steady state.

7. Conclusion

In this paper, the impact of the number of membership functions on the performance of the Fuzzy Logic Controller regulator has been analyzed. After the choice of inputs (either the error and its variations or the error and the disturbance signal) of the FLC, it was applied to a linear model of an AUV. The results obtained showed that it is sufficient to limit the number of fuzzy membership functions to 5 because the increase of this number does not lead to obtaining better results than those obtained by the FLC regulator with a number of RF greater than 5. This result can be interpreted by the decision limit surface of the FLC controller. Also, the introduction of disturbances as an input of the FLC regulator makes it possible by to take into consider its value and to permanently stabilize the disturbed system.

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