

# Tuning Fuzzy PD controller using Tabu Search

Talbi .N<sup>1,2</sup>, Belarbi .K<sup>2</sup>

<sup>1</sup>Electronic Department. Faculty of science and technology, University of Jijel, Jijel, Algeria

<sup>2</sup>Electronic Department. Faculty of Engineering, Mentoury University, Constantine, Algeria

Email [t\\_nesrine2003@yahoo.fr](mailto:t_nesrine2003@yahoo.fr), [Kbelarbi@yahoo.fr](mailto:Kbelarbi@yahoo.fr)

**Abstract---** Fuzzy controllers are represented by if-then rules and thus can provide a user friendly and understandable knowledge representation. Metaheuristic algorithms have been widely used for optimal design of fuzzy controllers. In this paper, we propose new auto-tuning fuzzy PD controllers using Tabu Search (TS) for generating knowledge bases for fuzzy logic systems. The algorithm dynamically adjusts the membership functions and fuzzy rules according to different environments. it was tested on the control of angle of inverted pendulum.

**Keys word-** Fuzzy PD controller, Tuning Fuzzy PD controller, Tabu Search, Inverted pendulum.

## I. INTRODUCTION

Fuzzy systems are being used successfully in an increasing number of application areas; they use linguistic rules to describe systems. These rule-based systems are more suitable for complex system problems where it is very difficult, if not impossible, to describe the system mathematically.

One of the most important considerations in designing any fuzzy system is the generation of the fuzzy rules as well as the membership functions for each fuzzy set. In most existing applications, the fuzzy rules are generated by experts in the area, especially for control problems with only a few inputs. With an increasing number of variables, the possible number of rules for the system increases exponentially, which makes it difficult for experts to define a complete rule set for good system performance. An automated way to design fuzzy systems might be preferable.

Several researches are busy exploring the integration of evolutionary algorithms with the automatic design or optimization of fuzzy logic controllers either by learning the fuzzy *if-then* rules [1] [2]. The first method results in a self tuning controller in which a GA adapts the fuzzy membership functions [3].

Global optimization is the task of finding the absolutely best set of admissible conditions to achieve the objective, formulated in mathematical terms. The use of Tabu Search (TS) which is metaheuristic algorithm seems to be the most promising approach to

such problems because of their efficiency and simplicity of implementation. The biggest difference of the TS algorithm is the use of memory during the search process [4,5,6]. TS employs an explicit memory to store historical information on the course of the search trajectory. Thus, memory is used to guide the selection of the next solutions. This property of the TS algorithm is a significant superiority over other optimization algorithms mentioned above.

In this paper, our aim is to design an optimal adaptive evolving fuzzy PD control system wherein the fuzzy membership functions and the rule bases are optimized using TS procedure.

The paper is organized as follows: in Section 2, The fuzzy logic controller is described. In Section 3, we summarize the Tabu Search technique. Section 4 is composed of three parts: it let's show the mathematical model of the inverse pendulum, then initial fuzzy PD controller type Mamdani with 3 rules are being built, then we do the optimization of fuzzy PD controller by Tabu Search, we tested the robustness of controller for different initial conditions . Finally, we end with a conclusion.

## II. FUZZY PD CONTROLLER

### A. Inference with Fuzzy Systems

Two different types of FSs are usually distinguished in the literature according to the form of the rules and the type of inputs and outputs used [7].

- Mamdani Systems: Proposed by Mamdani [8], who was able to translate Zadeh's preliminary assumptions about fuzzy logic [9] to a real control problem. Systems of this sort, which are the most extensively used, consist of four main components: a *knowledge base*, an *IE* and the *fuzzification* and *defuzzification* interfaces. The rules used in these systems have the following form:

IF  $X_1$  is  $A_1$  AND ... AND  $X_n$  is  $A_n$  THEN  $Y$  is  $B$   
(1)

Traditionally, the input to the system is a real crisp value  $x$ , and so is the output  $y$ . Although Mamdani proposed the min–max operators to carry out the fuzzy implications, more operators have been proposed, [10], [11].

- Takagi–Sugeno–Kang Systems: Takagi, Sugeno, and Kang [12], [13] proposed a new model based on rules where the antecedent was composed of linguistic variables and the consequent was represented by a function of the input variables. In this paper, however, we will not concentrate on this type of systems.

### B. Structure of a fuzzy logic controller

A basic FLC can be decomposed into four basic components [14]. These are fuzzification unit, knowledge base (rule base and data base), decision making unit (inference unit), and defuzzification unit (Fig. 1). Fuzzification unit transforms the measurement data into fuzzy sets. Knowledge base consists of a rule base and data base. This unit has knowledge about the physical system to be controlled. Decision making unit defines how the system should make inferences through the fuzzy rules contained in the rule base. Defuzzification unit aggregates the outputs of all the rules that have fired for the particular input fuzzy sets to produce a crisp output.

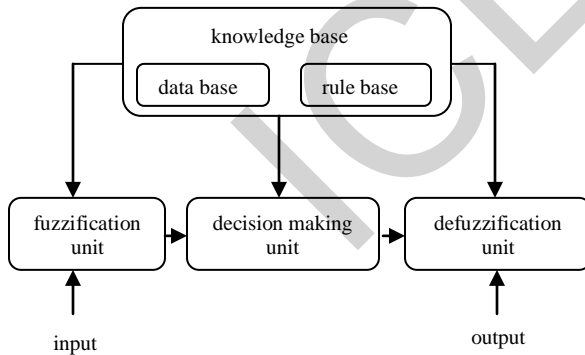


Fig. 1. Configuration of a basic fuzzy logic controller.

Typically, the inputs to the fuzzy controllers are the error and the change of error. This choice is physically related to classical PID controllers. We consider the classical PD control law:

$$U_{PD}(k) = k_p e(k) + k_D \Delta e(k) \quad (2)$$

$K_p$  is the proportional gain,  $K_D$  the derivative gain and  $k$  is the contraction of  $kT$  where:  $k$  is a positive integer and  $T$  is the sampling time.

The error and the change of error are defined as:

$$e(k) = y_r(k) - y(k) \quad (3)$$

$$\Delta e(k) = e(k) - e(k-1) \quad (4)$$

where  $y_r$  is the reference signal and  $y$  is the control output.

### III. THE TABU SEARCH TECHNIQUE

The tabu search (TS) is a metaheuristic that can be used to solve combinatorial optimization problems. It is different from the well-known hill-climbing local search techniques in the sense that it does not become trapped in local optimal solutions, i.e. the tabu search allows moves out of a current solution that makes the objective function worse in the hope that it eventually will achieve a better solution [6,7]. The flowchart of TS algorithm procedure is shown in Fig. 2 [6].

The tabu search requires the following basic elements to be defined [15,16,17]:

- *Configuration* is a solution or an assignment of values to variables.
- A *move* characterizes the process of generating a feasible solution to the combinatorial problem that is related to the current solution (i.e. a move is a procedure by which a new (trial) solution is generated from the current one).
- *Set of candidate moves* is the set of all possible moves out of a current configuration. If this set is too large, one could operate with a subset of this set.
- *Tabu restrictions*: These are certain conditions imposed on moves which make some of them forbidden. These forbidden moves are known as *tabu*. It is done by forming a list of a certain size that records these forbidden moves. This is called *tabu list*.
- *Aspiration criteria*: These are rules that override tabu restrictions, i.e. if a certain move is forbidden by tabu restriction, then the aspiration criterion, when satisfied, can make this move allowable.

Given the above basic elements, the tabu search scheme can be described as follows: start with a certain (current) configuration, evaluate the criterion function for that configuration. Then, follow a certain set of candidate moves. If the best of these moves is not tabu or if the best is tabu, but satisfies the aspiration criterion, then pick that move and consider it to be the new current configuration; otherwise, pick the best

move that is not tabu and consider it to be the new current configuration. Repeat the procedure for a certain number of iterations. On termination, the best solution obtained so far is the solution obtained by the algorithm.

Note that the move that is picked at a certain iteration is put in the tabu list so that it is not allowed to be reversed in the next iterations. The tabu list has a certain size, and when the length of the tabu reaches that size and a new move enters that list, then the first move on the tabu list is freed from being tabu and the process continues (i.e. the tabu list is circular). The aspiration criterion could reflect the value of the criterion (objective) function, i.e. if the tabu move results in a value of the criterion function that is better than the best known so far, then the aspiration criterion is satisfied and the tabu restriction is overridden by this.

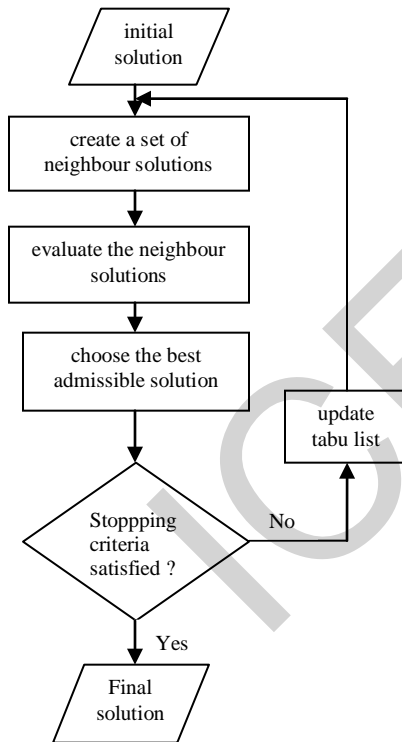


Fig. 2. Flowchart of a standard TS algorithm

In the above paragraph, we have outlined the basic steps of the tabu search procedure for solving combinatorial optimization problems. In the next section, we develop a new algorithm for evolving fuzzy logic controller by the tabu search technique.

## IV. SIMULATION & INTERPRETATIONS

### IV.1 Inverted Pendulum

the controlled system considered here is the inverted pendulum on a cart and shown in fig. 1. The dynamics of the system is expressed by four state variables: 1)  $\theta$  is the angle of the pendulum with respect to the perpendicular axis; 2)  $\dot{\theta}$  is the angular velocity of the pendulum; 3)  $z$  is the position of the car; 4)  $\dot{z}$  is the velocity of the cart. These four state variables are described by the following two second order differential equations:

$$\ddot{\theta} = \frac{g \sin \theta + \cos \theta \left( \frac{-f - m_p l \dot{\theta}^2 \sin \theta}{a} \right)}{l \left( \frac{4}{3} - \frac{m_p \cos^2 \theta}{a} \right)} \quad (5)$$

$$\ddot{z} = \frac{f + m_p l (\dot{\theta} \sin \theta - \ddot{\theta} \cos \theta)}{a} \quad (6)$$

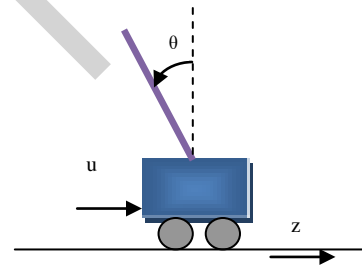


Fig. 3. An inverted pendulum system

Where  $g = 9.8 \text{ m/s}^2$  is the gravity constant,  $m_c$  (mass of the cart) 1 kg,  $m_p$  (mass of the pendulum) 0.1 kg,  $a = 1/(m_p + m_c)$ ,  $2l$  (length of the pendulum) 1m, and  $f$  the applied force in newton. Because the pivot point of the pendulum is not fixed with respect to inertia reference, so is the rotation of the pendulum and the motion of its mass center, therefore, the operating points may vary in an unknown fashion. The objective of the control system is to maintain the broom in the upright position by means of the force  $f$  for any initial position of the broom without regard to the position and velocity of the cart, hence, only (5) applicable in our design. When the system is at the stable equilibrium point, any small perturbation of the broom position from its upright equilibrium position will cause control to return the broom to the equilibrium position.

IV.2 Initial Fuzzy PD Controller

Controller is used is a fuzzy-PD where the output controller is command itself (fig. 4), we get fuzzy regulator, which realizes the control signal:  $u(k) = F(e(k), \Delta e(k))$ .

- For flexibility in the implementation of the regulator, we must limit the universe of input and output at intervals determined by the normalization of input and output, to do this, we use gains of adaptations to have the desired dynamic.
- For the Fuzzification: we used triangular membership functions to error and its derivative, with: error is difference between angle calculated and angle desired.
- Macvicar et Whelan rule base is used as follows (Table I):

e	N	Z	P
de	N	Z	P
N	N	-	-
Z	-	Z	-
P	-	-	P

Table I. rule base

- For the mechanism of inference, we used the method "min - max".
- For the defuzzification we used the centroid method.
- Normalisation gains are chosen as follows:  $G_e=0.8$  ;  $G_{de}=0.43$  ;  $G_u=460$ .

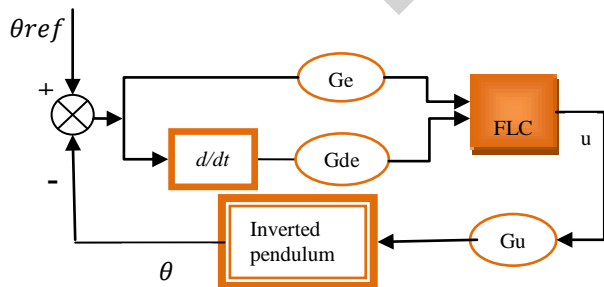


Fig. 4. The structure of FLC for angle  $\theta$

Fig. 5. respectively, shows the evolution of the angle, angular velocity and control applied to the nominal system. It is remarkable that pendulum does not reach its point of equilibrium ( $\theta = 0$ ) with FLC type Mamdani with 3 rules. So it goes in the following section the best FLC in evolving fuzzy inference by Tabu Search.

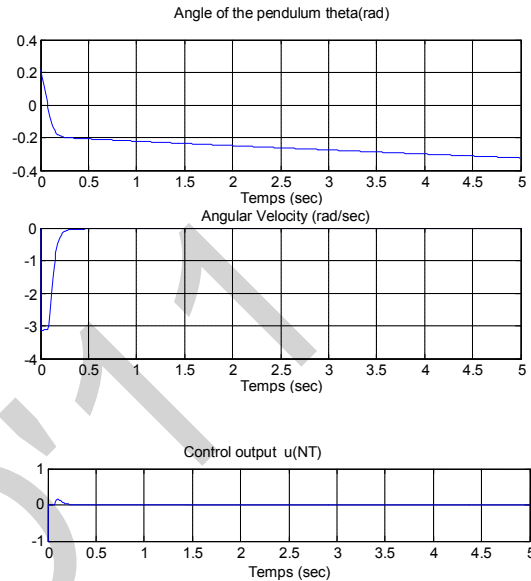


Fig. 5. Responses submitted to 3 rules for nominal parameters of the system and the initial conditions obtained Mamdani controller pendulum ( $\theta = 0.22$  ,  $\dot{\theta} = 0$  )

IV.3 The Evolution of FLC by Tabu Search

We start by presenting the incremental fuzzy algorithm by TS used for optimization of regulator type Sugeno zero order in order to control the angle of inverted pendulum.

The regulator to determine has a structure to 2 inputs (three membership functions to the error (e) et three membership functions to the variation in the error ( $\Delta e$ )) and output  $u(t)$ , with 3 rules (Table I).

Tuning fuzzy PD controller using TS is given in fig. 6 as functional block diagram. where (e) and  $\Delta e$  respectively designate the error and the variation in the error:

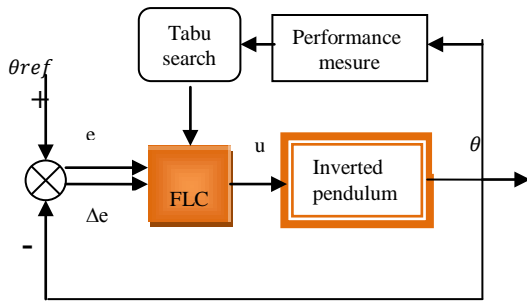


Fig. 6. evolution fuzzy control system with TS

introduced parameters in Tabu search are represented as follows:

- Modal values of triangular membership functions are respectively  $C_{11}, C_{12}, C_{13}$ , for error and  $C_{21}, C_{22}, C_{23}$ , for the variation in the error, are chooses between  $[-1 \ 1]$ , and each is encoded on a string of 4 bits, respecting the constraint :  $(C_{11} < C_{12} < C_{13})$ .
- Conclusions of rules respectively N, ZE, P, are chooses between  $[-1 \ 1]$ , and each is encoded on a string of 4 bits, respecting the constraint:  $(N < ZE < P)$ .
- the factors of scales of e and u are:  
 $G_e=0.8$   
 $G_{de}=0.43$   
 $G_u=460$
- Nbre of Neighbours :8
- Neighbours 4-bit binary encoding
- Nbre of iterations :5
- Tabu list size: 5
- function evaluation is the mean square error:  
 $MSE = \sum_1^N (\theta_{ref} - \theta)^2$

Table II provides optimal parameters obtained by the TS after five iterations:

		Modal functions membership points		
e		-0.6333 ( $C_{11}$ )	0.5000 ( $C_{12}$ )	0.8667 ( $C_{13}$ )
$\Delta e$		-0.7000 ( $C_{21}$ )	-0.1000 ( $C_{22}$ )	0.9000 ( $C_{23}$ )

(a)

The conclusions of the rules		
N	ZE	P
-1.0000	0.2333	0.6667

(b)

Table II: optimal parameters obtained by the TS. (a): for membership functions parameters, (b): for rules conclusions

Fig. 7 represents forms of input and output controller found after optimizing membership functions:

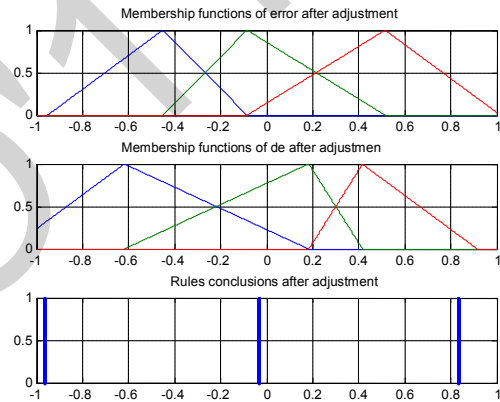


Fig. 7. Arrangement and forms of membership functions of the premises and conclusions after optimization functions

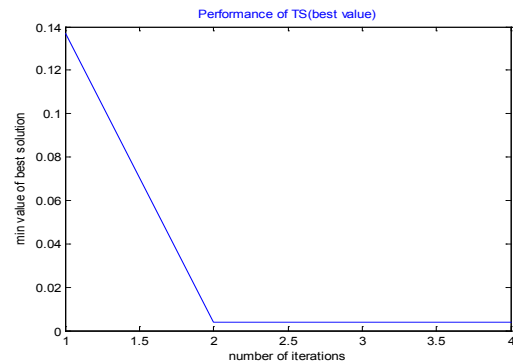


Fig. 8. Fitness function during iterations

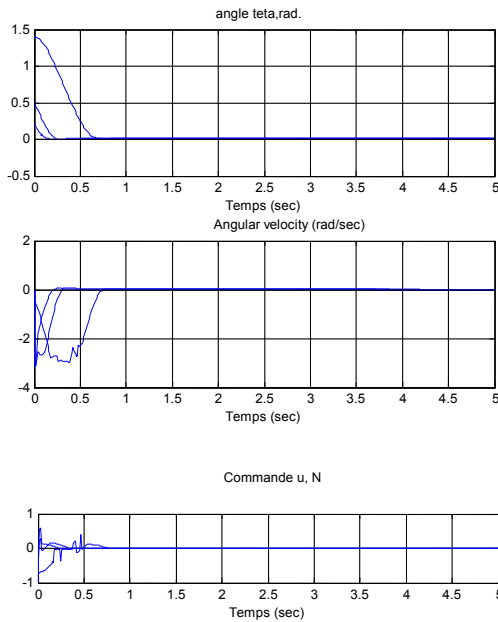


Fig. 9. the pendulum response to optimal controller for nominal parameters and different initial conditions.

The value of the function evaluation is the average quadratic error: fitness function =  $4.1151e-004$

- time calculation CPU : 1.5288 sec
- test of robustness (fig. 9) prove the fiability of the method based auto-tuning of fuuzy PD controller using Tabu Search.

Foregoing, one can conclude that use tabu search to optimize online fuzzy controller settings search gives best results taking into account time response of inverted pendulum and computation of the CPU time.

## V. CONCLUSION

The work presented in this paper concerns the command a nonlinear physical system using advanced automatic such as fuzzy logic techniques and tools such as tabu search optimization. The template of a system simple inverted pendulum is significant complexity. Indeed, it is a non-linear system instability. This characteristic qualifies it a very good example to validate commands synthesized on theoretical plane.

The given simulation example demonstrate the effectiveness of the proposed method; therefore the algorithm converges in minimum response time and minimum time calculation for the PC side.

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