RULES EVALUATION OF A KNOWLEDGE BASE

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Abstract

The single evaluation of the rules of a knowledge base has a special significance in Fuzzy-Genetic Systems, as these systems use such evaluation in selection processes. This paper describes a methodology to evaluate rules of a knowledge base. The single evaluation of each rule will be carried out from the global evaluation of the knowledge base to which it belongs. Finally, this paper includes those aspects that can improve the behaviour of the above methodology and proposes a rules classification depending on their single evaluation. This classification will allow to add new uses to the single evaluations of rules.

Keywords: Fuzzy Logic Controllers, genetic algorithms, machine learning, rules based systems.

1 INTRODUCTION

Fuzzy Logic Controllers (FLC) [1] are expert systems that include human knowledge in their knowledge bases by means of Fuzzy Control Rules [2] The structure of a Fuzzy Controller is showed in the following figure [2,3]:

We can notice that there isn't any module in the structure of the Fuzzy Controller which is in charge of the knowledge acquisition. With this aim, we can add to such structure a system based on Genetic Algorithms [4] which is responsible for the learning.

There are two approaches for the learning in Fuzzy-Genetic systems [2]:

- **Pittsburgh** approach: in which population are knowledge bases.
- **Michigan** approach: in which population are rules.

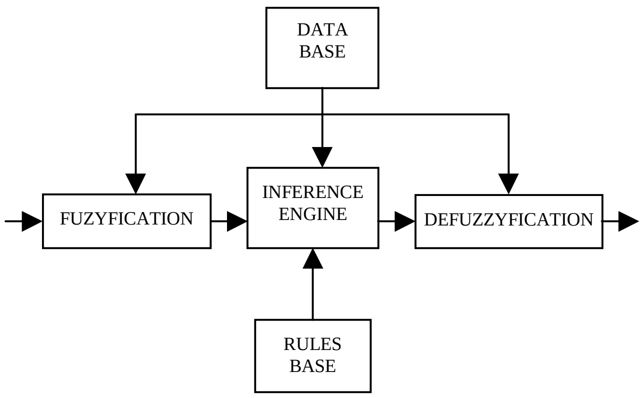

Figure 1: Structure of a Fuzzy Controller.

Under these conditions, selection processes are necessary to be used by the Genetic Algorithms [2,3,5], being advisable to have evaluated the knowledge bases in the case of Pittsburgh and the rules in an individual way in both cases, the Pittsburgh [6] and the Michigan one.

In this paper, a methodology to evaluate the rules of a knowledge base are presented. Once these rules have been evaluated, these will be classified in three types depending on their evaluation: good, bad and null rules.

As a consequence of the application of the methodology proposed, different actions with the three types of rules will be suggested, attending to the previous classification.

2 METHODOLOGY

The methodology which is presented for the rules evaluation of a knowledge base, will be carried out from the evaluation of the knowledge base to which it belongs.

Obviously, this evaluation must be carried out from different starting points (p_1, p_2,..., p_{n-1}, p_n) so that these are a representative group of the space. See Fig.2.

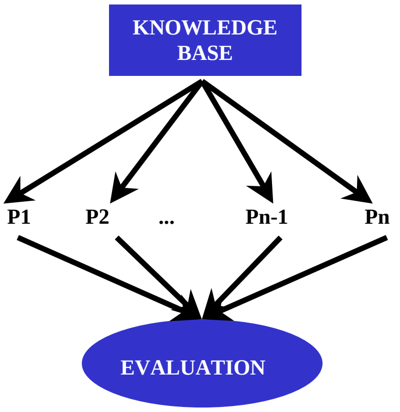

Figure2: Evaluation of a knowledge base.

The diagram used for the evaluation of a knowledge base corresponds to the one showed in Fig.3.

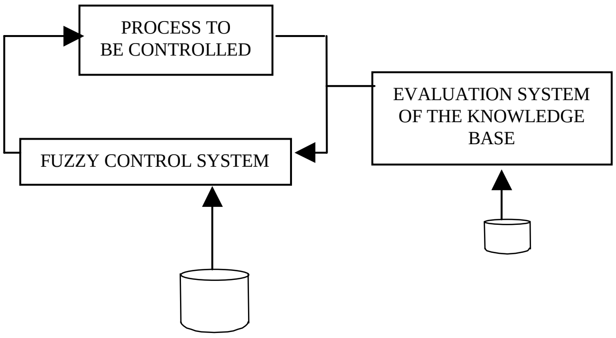

Figure 3: Structure of the evaluation system of knowledge bases.

Two knowledge bases are used in this diagram: one for the control system and another one for the evaluation system. So, the evaluation which is carried out is an expert one.

2.1 PREVIOUS EVALUATION OF THE KNOWLEDGE BASE.

To evaluate the control system knowledge base, it is used a fuzzy system [7] The inputs of this system are the system states to be controlled and the output is the instantaneous evaluation (E_{in}) of the system state to be controlled. These instantaneous evaluations are stored in a historic file of instantaneous evaluations. This historic file allows to obtain a partial evaluation (E_p) of the control system knowledge base, as the system to be controlled has been studied from a single starting point of view. To evaluate the knowledge base properly, it is necessary different starting points to obtain a weighting of the partial evaluations afterwards.

2.2 SINGLE EVALUATION OF RULES

Once the knowledge base is evaluated (E_r), the methodology consists in withdrawing temporally the rule to be evaluated (R_i) and carrying out a new evaluation of the resulting knowledge base (E_{Ri}) From the evaluation of the original knowledge base (E_r), and the one of the resulting knowledge base (E_{Ri}), we will obtain a value which will be the evaluation of the rule that has been withdrawn.

$$C_{Ri} = E_T - E_{Ri} + 0.5 \qquad (1)$$

The evaluation obtained for each rule, using the expression (1) is not normalised in the interval [0,1] To obtain this normalisation, the evaluations are cut off to higher and lower limits at the beginning. That is, to 0 if the resulting evaluation is lower than 0, and to 1 if the resulting evaluation is higher than 1.

In the following figure an example of a rule evaluation is presented.

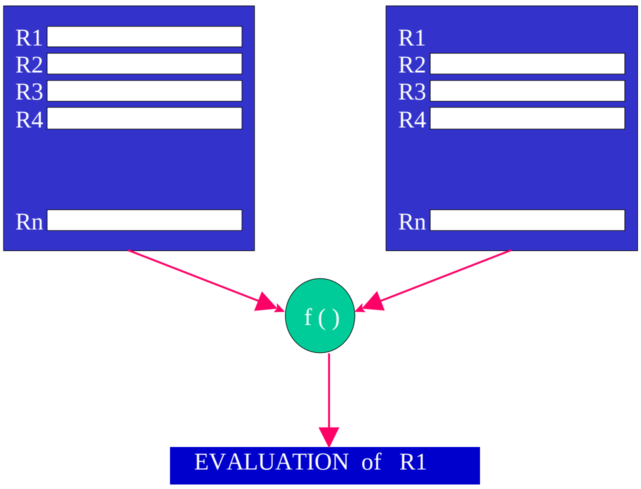

Figure 4: Evaluation Methodology of rule R1.

Depending on the value of C_{Ri}, we will make the following rules classification:

Table 1: Rules classification.

Classification	C_{Ri}
Good Rule	$C_{Ri} > 0.5$
Bad Rule	$C_{Ri} < 0.5$
Null Rule	$C_{Ri} = 0.5$

The rules classification of the knowledge base is carried out because after the methodology used, different actions are suggested to be taken in the different types of rules. These actions are mainly aimed towards the optimisation of the learning processes that have been used (genetic algorithms).

If this methodology is used to all the rules that form a knowledge base, we would have a working diagram as follows:

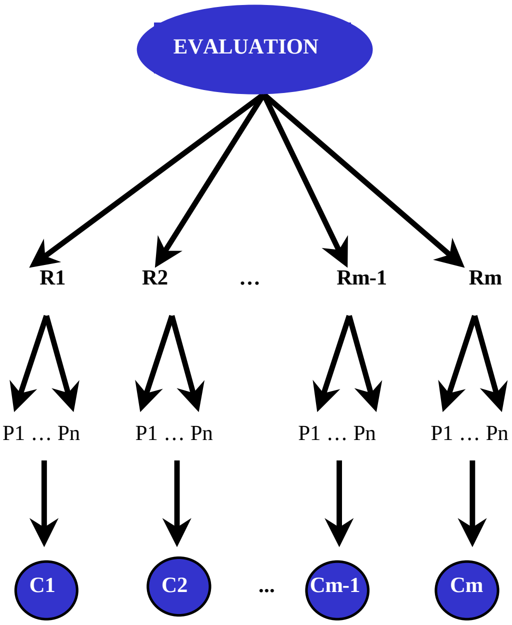

Figure 5: Global working of the presented methodology.

3 RESULTS

The methodology offered has been applied to a control system. The system that was controlled was the inverted pendulum. Now, some obtained results are showed:

3.1 KNOWLEDGE BASES WITH RULES TO BE EVALUATED

The following knowledge base is the one used by the control system. In this case the variables are normalised to 1.

R1: IF (ANG = 3) and (VEL. ANG = 2) THEN (POWER = 8)
R2: IF (ANG = 1) and (VEL. ANG = 1) THEN (POWER = 1)
R3: IF (ANG = 1) and (VEL. ANG = 2) THEN (POWER = 2)
R4: IF (ANG = 1) and (VEL. ANG = 3) THEN (POWER = 3)
R5: IF (ANG = 3) and (VEL. ANG = 1) THEN (POWER = 7)
R6: IF (ANG = 3) and (VEL. ANG = 3) THEN (POWER = 9)
R7: IF (POSITION = 1) THEN (POWER = 1)
R8: IF (POSITION = 2) THEN (POWER = 5)
R9: IF (POSITION = 3) THEN (POWER = 9)
R10: IF (POSITION =11) THEN (POWER =5)

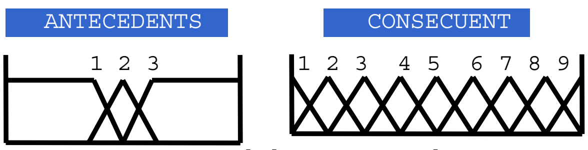

Figure 6: Knowledge Base to evaluate.

3.2 PREVIOUS EVALUATIONS OF THE KNOWLEDGE BASE

In Figure 7 the previous knowledge base evaluation is presented. Each line on the graph is a historic file of the instantaneous evaluations for each starting point. From this information, the knowledge base evaluation is made. This evaluation is showed with a numeric value in figure 7.

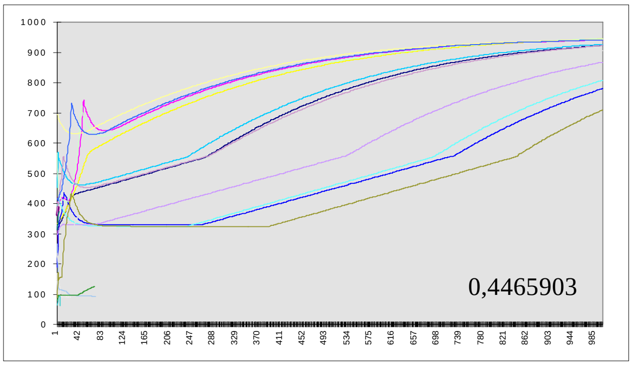

Figure 7: Knowledge base Evaluation.

A line disappears when the inverted pendulum has fallen.

3.3 SINGLE RULE EVALUATION

In the next figure, the evaluation of the first rule of the control system is presented, withdrawing it from the knowledge base and evaluating the knowledge base again.

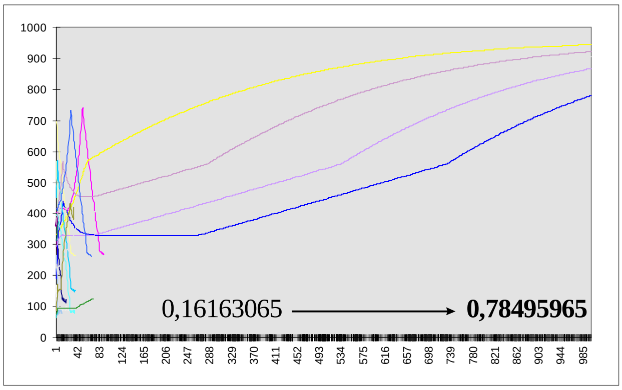

Figure 8: Rule R1 Evaluation. “Good Rule”.

We can notice that after withdrawing this rule, the behaviour of the knowledge base degenerates and so, the value will be superior to 0.5 (0.78495965), being classified this rule as "good rule".

Figure 9 shows the evaluation of a "Bad rule", in this case R7. When R7 is deleted, the knowledge base behaviour is better, so this rule is considered a "Bad rule".

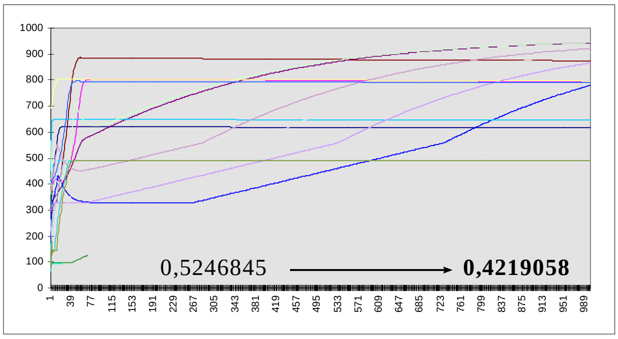

Figure 9: Rule R7 Evaluation. "Bad Rule".

Finally, table 2 shows the evaluation obtained for each rule of a knowledge base.

Table 2: Evaluation Results.

BASES EVALUATION		RULES EVALUATIÓN
BASE	0,4465903	
R1	0,16163065	0,78495965
R2	0,37145335	0,57513695
R3	0,19956905	0,74702125
R4	0,19949125	0,74709905
R5	0,2360168	0,7105735
R6	0,41121095	0,53537935
R7	0,5246845	0,4219058
R8	0,45002615	0,49656415
R9	0,47955105	0,46703925
R10	0,44514	0,5014503

4 CONCLUSIONS

The conclusions obtained from the methodology presented above are as follows:

- The results obtained allow to assert that the methodology presented is an useful tool to evaluate rules. However, this methodology implies a high computational cost. In a fuzzy-genetic learning system, the time of rules evaluation can be, sometimes, reduced if there is a list with all the "Bad Rules" that have been found. When a rule appears, it is checked whether it belongs to a list of "Bad Rules", and if so, it is not included in the knowledge base.

- Interaction between rules. There are some rules that work properly in a group way but not in an individual one.

- This methodology, when applied in an inverted way, can be used for knowledge acquisition. Instead of deleting rules to evaluate them, rules are added and the behaviour of the new knowledge base is checked; if it improves, we can say that knowledge has been acquired.

- Formation of a rules list with an unwilling behaviour, "bad rules". These rules will represent a "Negative Knowledge". Some studies are being developed in which some actions with these rules are suggested.

- Knowledge compression with gains in knowledge. It is possible to withdraw the "bad rules" from a knowledge base, improving the behaviour of the control system.

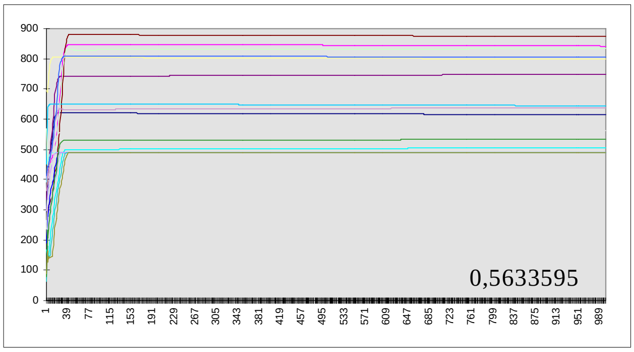

Figure 10: Evaluation of Knowledge Base without "Bad Rules".

- We are working on the Fuzzyfication of the rules classification so that we can propose another type of use to this classification.

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