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A Mixed Binary-Real NSGA II Algorithm Ensuring Both Accuracy and Interpretability of a Neuro-Fuzzy Controller

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ABSTRACT

In this work, a Neuro-Fuzzy Controller network, called NFC that implements a Mamdani fuzzy inference system is proposed. This network includes neurons able to perform fundamental fuzzy operations. Connections between neurons are weighted through binary and real weights. Then a mixed binary-real Non dominated Sorting Genetic Algorithm II (NSGA II) is used to perform both accuracy and interpretability of the NFC by minimizing two objective functions; one objective relates to the number of rules, for compactness, while the second is the mean square error, for accuracy. In order to preserve interpretability of fuzzy rules during the optimization process, some constraints are imposed. The approach is tested on two control examples: a single input single output (SISO) system and a multivariable (MIMO) system.

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1. INTRODUCTION

The ubiquitous trade-off between system accuracy and complexity is particularly important in fuzzy systems [1]-[3]. Complexity, related to the interpretability of the fuzzy system, is determined by the compactness, considered through the number of rules in the rule base, the number of input variables involved in each rule and distinguishability of the fuzzy sets [1]. Numerous approaches have been suggested for dealing with this problem and to increase the interpretability of fuzzy systems. These approaches are mainly based on a suitable structure of the fuzzy system (e.g. a hybrid structure) [4]-[10] or on the use of specific training algorithm (e.g. methods in the field of multiobjective optimization or evolutionary optimization) [11]-[17].

In this work, a Neuro-Fuzzy controller (NFC) is adopted for implementing a Mamdani fuzzy inference system (FIS), the aim of our method is not only to achieve appropriate accuracy of the controller, but also to ensure the possibility of interpretability of the knowledge within it. So, in order to guaranty completeness of fuzzy partitions, a special partitioning using triangular membership functions is adopted. Then, an improved multiobjective Pareto based genetic algorithm called Mixed Binary-Real Non dominated Sorting Genetic Algorithm II (NSGA II) is used for both parameter and structure optimization of the NFC. Two objectives are involved in the optimization process: extract a reduced number of rules in the rule base and reduce the mean square error. This paper is organized as follows. In section II, a NFC structure is introduced. The multiobjective algorithm solution procedure is presented in section III. Section IV presents the application to two examples: The control of the pole and cart system and control of a helicopter simulator model. Finally, section V gives the conclusion of this paper.

2. STRUCTURE OF THE NEURO FUZZY CONTROLLER

This section presents a Neuro-Fuzzy Controller network, called NFC that implements a Mamdani FIS. A schematic diagram of the proposed NFC structure is shown in Figure 1. For the simplicity of presentation, NFC with any number of inputs but only one output is developed. The NFC system consists of five layers: an input layer, a membership (fuzzification) layer, AND layer, OR layer and a deffuzification layer. Next we shall indicate the signal propagation and operation functions of the nodes in each layer.

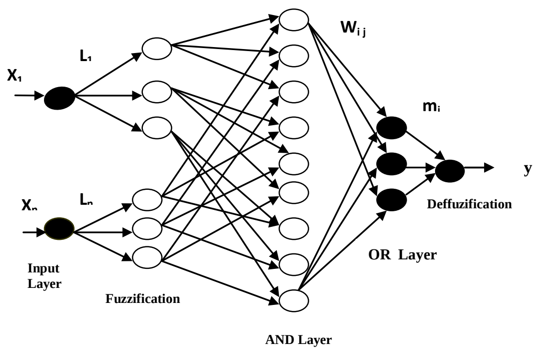


Figure 1. Structure of the proposed NFC

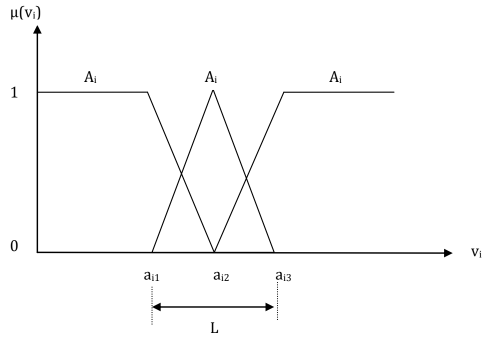


Figure 2. Triangular symmetric partitioning of universe of discourse with three fuzzy subsets

Layer1 (input layer): The nodes in this layer are input nodes with crisp input $x_i, i = 1 \dots n,$ they are transmission nodes, they only transmit input values to the next layer.

$$v_i = x_i \tag{1}$$

Layer2 (fuzzification layer): Nodes at this layer compute the value of the membership function of inputs v_i. All nodes connected to the same input node have the same weight L_i corresponding to the central part of the universe of discourse of input variables. In order to guaranty completeness and distinguishability of fuzzy partitions, a triangular symmetric partitioning is used as shown in Figure 2. The output of node (i,j) is given by:

$$\mu_{A_{ij}}(v_i) = \begin{cases} v_i(N_i - 1/L_i) + (N_i - 1/2) - j + 2\,, \\ \quad \text{if } a_{ij-1} < v_i < a_{ij} \\ -v_i(N_i - 1/L_i) - (N_i - 1/2) + j, \\ \quad \text{if } a_{ij} < v_i < a_{ij+1} \\ 1 \;, \quad v_i < a_{i1} \text{ ou } \; v_i > a_{iNi} \end{cases} \tag{2}$$

With fuzzy subsets $A_{ij}\,, i = 1,\dots,n\,;\ j = 1,\dots,N_i$, the number of fuzzy sets associated with variable i, and the summits of the fuzzy sets are given by:

$$a_{ij} = (-(1/2) + ((j-1)/(N_i - 1)))L_i \;, \;\; with \;\; i = 1, \dots, n \; et \; j = 1, \dots, N_i \tag{3}$$

Layer3 (AND layer): Each node of this layer represents a fuzzy rule. The following AND operation is applied to each rule node:

$$y_k^{And} = \mu_{A_{1j1}}(v_1).\mu_{A_{2j2}}(v_2) \dots \mu_{A_{njn}}(v_n), j_i = 1 \dots N_i, i = 1 \dots n, k = 1 \;\dots \prod_{i=1}^{n} N_i \tag{4}$$

Layer4 (OR layer): In this layer, rules with the same consequence are integrated through the fuzzy OR operation which is implemented by:

$$y_l^{OR} = 1 - \prod_{k=1}^{Na}(1 - y_k^{AND} W_{kl}), \;\; l = 1, \dots, N_o \tag{5}$$

Where W_{kl} are the binary weights associated with node k of the AND layer and node l of the OR layer, N_a number of nodes in the AND layer and N_o the number of fuzzy sets associated with the output variable. Since one rule has only one consequence, W_{kl} must be binary:

$$W_{kl} \in \{0,1\} \; \forall \; k, l \quad (6)$$

Layer5 (deffuzifacation layer): node at this layer realizes the deffuzification operation using the center of gravity rule

$$u = \sum_{i=1}^{No} m_i y_i^{OR} / \sum_{i=1}^{No} y_i^{OR} \quad (7)$$

Where m_i are real weights corresponding to the centers of the triangular fuzzy sets of the output variable and can be expressed by:

$$m_i = \left(-\frac{1}{2} + \frac{i-1}{Ni-1}\right) Lo, \quad i = 1, \dots, No \quad (8)$$

Where Lo is the central part width of the output variable universe of discourse.

3. SOLUTION USING MULTIOBJECTIVE ALGORITHM

3.1. Problem definition

The previous section describes a structure of a NFC that implements a Mamdani fuzzy inference system. A multi input one output Mamdani system is composed of rules with fuzzy consequences. $A_{1j_1}, A_{2j_2}, \dots, A_{nj_n}$ and B_k are respectively fuzzy sets associated with the fuzzy input variables and the fuzzy output variable. $W_{ik} \in \{0,1\}$ are binary weights that model the consequence of a rule such that $W_{ik} = 1$ if rule i has consequence B_k and 0 otherwise.

Moreover if the granularity of the output fuzzy variable is M then if $W_{ik} = 0$ for $k = 1 \dots M$, rule i have no consequence and is not included in the rule base. The maximum possible number of rules is given by all combinations of antecedent variables fuzzy sets and is:

$$NR = N_1 \times N_2 \times \dots \times N_q \times \dots N_n \quad (9)$$

With $N_q, q = 1 \dots n$, the number of fuzzy sets associated with input variable x_q. Since rule *i* have at most one consequence, we have the constraints:

$$\sum_{k=1}^{M} W_{ik} \leq 1 \quad (10)$$

The total number of rules is thus:

$$J = \sum_{i=1}^{NR} \sum_{k=1}^{M} w_{ik} \quad (11)$$

The degrees of freedom of such a system are the number of fuzzy sets for each fuzzy variable N_q, the binary variables W_{ik} defining the rules and the real parameters Li and Lo of the triangular membership function of input and output variables respectively.

The most general modelling problem can be expressed as finding all these parameters in order to achieve a certain degree of accuracy and a compact rule base. This is formulated as two objective optimization problems:

Find $N_q, q = 1 \dots n,\; M,\; Li,\; Lo$ and W_{ik} so that

$$Min\left(\left(J_1 = \frac{1}{T}\sum_{t=1}^{T}\big(e(t)\big)^2\right), \left(J_2 = \sum_{i=1}^{NR}\sum_{k=1}^{M} W_{ik}\right)\right) \quad (12)$$

With $e(t)$ is the error at t, and T is the time horizon.

Clearly it is possible to solve this monolithic problem as a whole. However this solution procedure may lack flexibility and may not be desirable at least for two reasons. First, it leads to a quite complicated solution procedure in terms of dimensionality and data structure. Second and more importantly, it leaves no design alternatives for the decision maker. The problem is thus recast as finding the real parameters Li, Lo and the binary weights W_{ij}.

3.2. A mixed binary-real NSGAII multiobjective algorithm

Multiobjective algorithms are based on the concepts of Pareto optimality which is defined in terms of dominance. Given a minimization problem with vector-valued objective function:

$$Min\ f(x) = (f_1(x), f_2(x), \dots, f_m(x)) \tag{13}$$

$x1$ is said to dominate $x2$ iff:

$$\begin{cases} f_i(x1) \leq f_i(x2), \ \ \forall\, i \in 1, \dots, m \\ \exists j \in 1, \dots, m\, , f_j(x1) < f_j(x2) \end{cases} \tag{14}$$

The multiobjective problem is stated as a multiobjective optimization statement, in which, the optimization implies to find a set of non-dominated solutions to approximate the Pareto front, where all the solutions are Pareto-optimal.

In this study, the NSGA-II algorithm with certain modifications is applied to settle the multiobjective problem set in the previous section. NSGA-II [18] algorithm is an improved version of no dominated sorting genetic algorithm (NSGA) which uses a fast non-dominated sorting procedure and an elitist preserving approach and has no niching operator parameters.

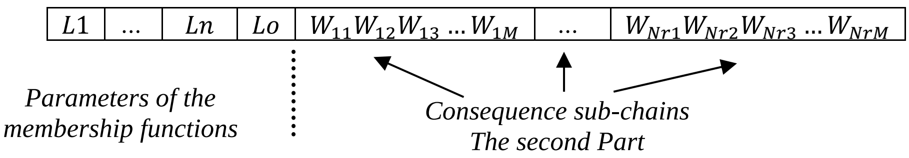
At first, the population is initialized as usual, and then it is sorted based on a fast non-dominated sorting to rank the population fronts. In this procedure, two entities are calculated for each individual (p); the domination count (np) which indicates the number of individuals that dominate the individual (p) and the set of individuals (Sp) that the individual (p) dominates.

Once the non-dominated sort is complete, a parameter called crowding distance is calculated for each individual, and then tournament selection with crowed comparison operator is made between two individuals randomly selected from parent population. The individual with lower front number is selected if the two individuals come from different fronts. The individual with higher crowding distance is selected if the two individuals are from the same front.

Then, a new offspring population is generated using the modified genetic operators: mixed binary-real crossover and mutation. Finally, the combined population formed by the offspring population and the parent population is sorted according to non-domination .Here, elitism is ensured because all previous and current individuals are included in the new population and only the best individuals are selected as the new parent population.

3.2.1. The population individual

Each individual in the population is composed of two parts: the first contains the real parameters of the membership function associated with the input and output fuzzy variables; the second contains the binary weights W_{ik} that model the rule consequence:



Where the sub-chain: $/\ W_{i1}W_{i2}W_{i3} \dots W_{iM}\ /, W_{ik} \ \in \{0, 1\}$ defines the consequence of rule i and will be called a consequence sub-chain in the sequel. As mentioned above, constraint (10), only one binary weight in a given consequence sub-chain can be equal to one and if all binary weights are zero then the associated rule has no consequence and is not included in the rule base. The length of consequence sub-chain is equal to M, the granularity of the output variable and the total number of binary weights is given by $N_r \times M,\ N_r$ the number of possible rules defined above. Moreover, when using binary representation of the rules, there is no need to alter the basic definitions of the genetic operators. In this work, the membership functions are isosceles triangles uniformly distributed in the universe of discourse as shown in Figure 2. Thus, for each fuzzy variable we need only to determine the central part of the universe of discourse to deduce the uniform distribution of all fuzzy sets in the universe of discourse. This modelling will reduce considerably the length of the individual.

3.2.2. Mixed binary-real crossover

A two point crossover is used: the first point falls within the first part of the individual (real crossover) and the second point within the second part (binary crossover).

1. Real crossover*:* parameters of the first part of the individual are really coded and an extended intermediate crossover [19] is used, thus two offspring ($O1$ *and* $O2$) are built from two parents P_1 and P_2 as the following:

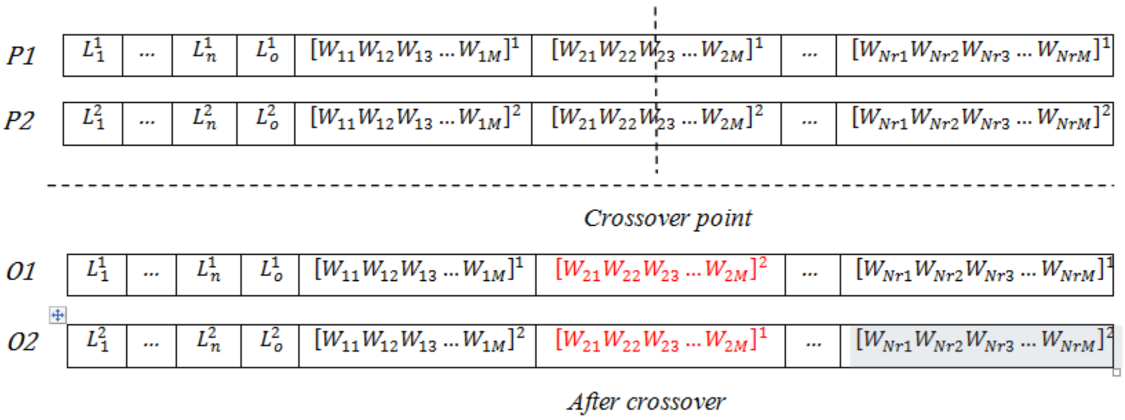
$$O_1 = P_1 + \alpha_1(P_2 - P_1) \tag{15}$$

$$O_2 = P_2 + \alpha_2(P_1 - P_2) \tag{16}$$

Where α_i is a randomly chosen value in the interval $[-0.25, 1.25]$.

This crossover is performed for each parameter of the first part of the individual.

2. Binary crossover*:* In order to handle constraints (10), crossover in the second part of the individual is altered as follows:



Thus, an exchange of consequence sub-chains corresponding to the crossover point is performed.

3.2.3. Mixed binary-real mutation

A non-uniform mutation operator [19] is applied on the first part of the individual. If mutation falls in the second part, as usual, a one is mutated to a zero and a zero is mutated to one. However in this latter case, constraint (10) may be violated and we may have two one's in the same consequence sub-chain, the associated rule will have two consequences. In order to keep (10) satisfied, if there are two one's in the same consequence sub-chain, the bit that was one before mutation is set to zero.

4. SIMULATION RESULTS

Two application examples are presented: a controller design for the pole and cart system and a multivariable decentralized controller for a helicopter simulator model.

4.1. The control of the pole and cart system

The control objective is to balance the pole by applying a force on the basis of the cart. Although simple in nature, it presents some nice features for controller benchmarking: it is highly nonlinear when far from the vertical equilibrium and is sensitive to parameters variation as initial conditions, pole length and mass. The dynamical nonlinear model is given by:

$$\ddot{\theta} = \frac{gsin\theta + cos\theta\left(\frac{-F - ml\dot{\theta}^2 sin\theta}{m_c + m}\right)}{l\left(\frac{4}{3} - \frac{mcos^2\theta}{m_c + m}\right)} \quad (17)$$

The NFC has two inputs, the pole angle $\theta(t)$ and its variation $\Delta\theta(t)$ and the output is the force F to be applied to the cart. Three symmetric triangular fuzzy membership functions (NEGATIVE (N), ZERO (Z) and POSITIVE (P)) are used for both inputs and output. So initially, there are six nodes in the fuzzification layer, nine nodes in the AND layer and three nodes in the OR layer (Figure 1). The goal of the mixed binary-real NSGA II is to find optimal values of $Li\ (L1, L2), Lo$ and W_{ij} such that:

$$Min\left(\left(J_1 = \sum_{k=1}^{500} |\theta(k)| + 10^{-2}|F(k-1)| + |\Delta\theta(k)|\right), \quad \left(J_2 = \sum_{i=1}^{9}\sum_{j=1}^{3} W_{ij}\right)\right) \quad (18)$$

This problem is recast as a maximization problem:

$$Max\left(f_1 = \frac{10^5}{1 + 20J_1}, \quad f_2 = \frac{10}{1 + J_2}\right) \quad (19)$$

The cost J_1 is obtained from a closed loop simulation with a nominal model having a pole with mass $m = 0.1\,Kg$ and a length $l = 1m$ and a cart with mass $m_c = 1\,Kg$. The initial conditions are: $\theta(0) = 20^o\ and\ \dot{\theta}(0) = 0^o/s$. There are 30 parameters evolved in the optimization problem which uses the following values: maximum generation=100, population size=100, crossover probability=0.8 and mutation probability=0.03.

Figure 4 shows the whole set of solutions obtained at the last generation. The extracted solutions on the Pareto front correspond to the best individual having the fitness values: $f_1 = 1{,}783\ and\ f_2 = 1{,}667$.The optimal values of the real parameters are: $L1 = 23{,}0666\,, L2 = 74{,}9882\,, Lo = 606{,}9333$.

And the optimal binary weights $W =$ [000 100 000 100 010 000 010 001 000] Corresponding to a NFC with a reduced structure containing five nodes in the fuzzification layer, five nodes in the AND layer and three nodes in the OR layer as illustrated in Figure 3.

Table 1. Fuzzy rules interpreted by the Neuro-fuzzy controller

θ(t) / Δθ (t)	N	Z	P
N		**N**	**Z**
Z	**N**	**Z**	**P**

The knowledge accumulated within the structure of the obtained NFC is interpreted as Mamdani FIS with the five reduced fuzzy rules given in table 1.The Neuro-fuzzy controller was tested for robustness in situations different from the nominal one. The results are shown in Figures 5 and 6, the controller was particularly sensitive to the pole length with success for $0.25m \le L \le 1.5m$ (Figures 9 and 10), to the pole mass with success for $0.05Kg \le m \le 0.7Kg$ (Figures 11and 12) and to the initial conditions with success for $10° < \theta(0) < 60°$ (Figures 7 and 8).

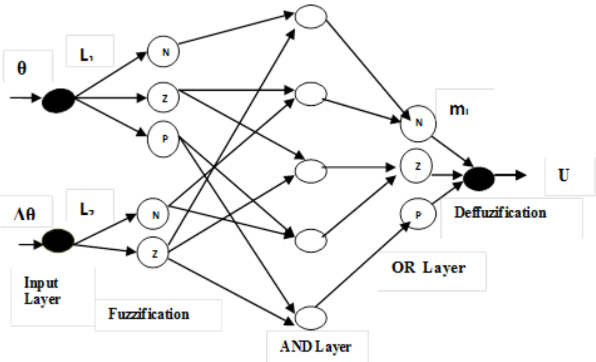


Figure 3. Structure of the optimized NFC

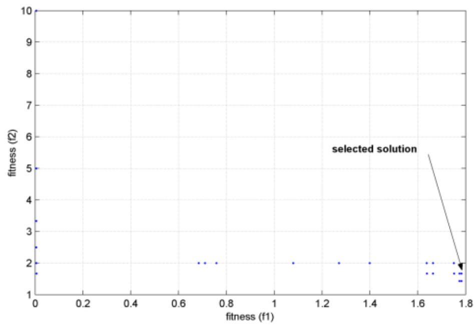


Figure 4. Distribution of the population of the last generation

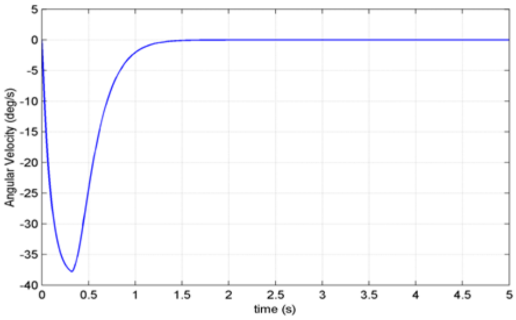


Figure 5. Variation of the pole angle from The initial condition (200, 00/s)

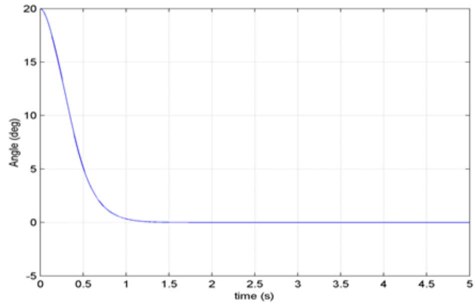


Figure 6. Variation of the angular velocity from the initial condition (200, 00/s)

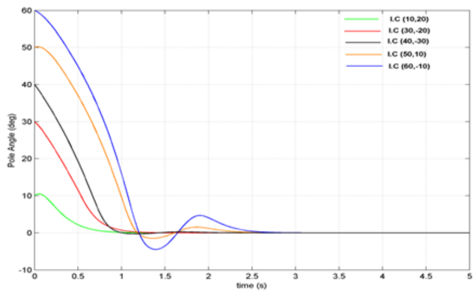


Figure 7. Variation of the pole angle for different initial conditions

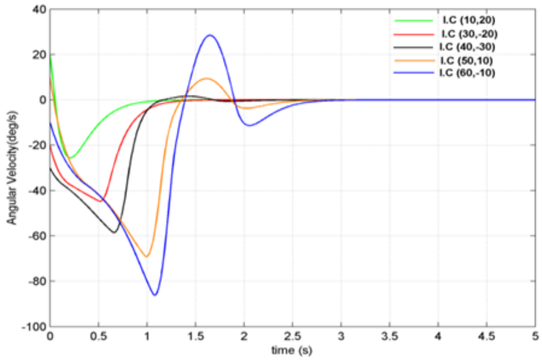


Figure 8. Variation of the angular velocity for different initial conditions

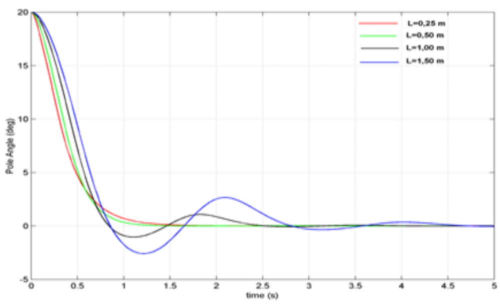


Figure 9. Variation of the pole angle for different pole lengths

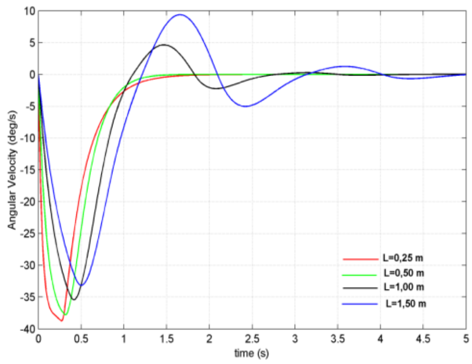


Figure 10. Variation of the angular velocity for different pole lengths

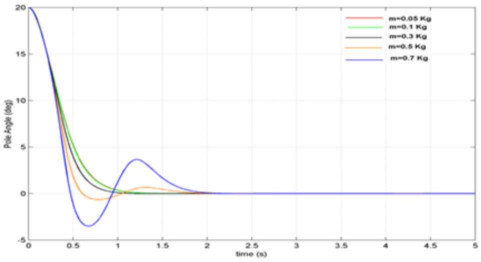


Figure 11. Variation of the pole angle for different pole mass

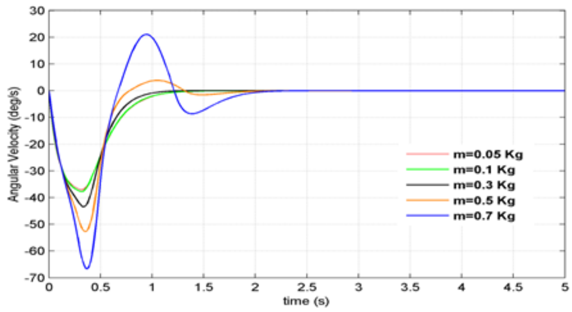


Figure 12. Variation of the angular velocity for different pole mass

4.2. Control of a helicopter simulator model

The helicopter simulator to be controlled is the CE 150 laboratory helicopter made by Humusoft Ltd [20]. The laboratory helicopter set-up comprises a body carrying two DC motors which drive the propellers. The helicopter body has two degrees of freedom; the elevation angle φ, i.e. the angle between the vertical axis and the longitudinal axis of the helicopter body and the azimuth angle ψ, i.e. the angle in the horizontal plane between the longitudinal axis of the helicopter body and its zero position.

The voltage driving the main motor u_1 and the voltage driving the tail motor u_2 affect both the elevation angle and the azimuth; therefore we can say that the mentioned interactions make the system multivariable. The helicopter model can be represented as a non-linear multi-variable (MIMO) system with inputs u_1 and u_2 and two outputs φ and ψ.

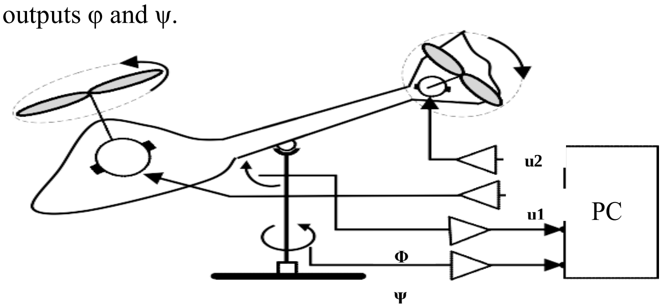


Figure 13. Helicopter configuration

The mathematical model of the helicopter simulator is given by the following differential equations:

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = -8{,}764 x_2 sin x_1 - 3{,}4325 x_4 u_1 cos x_1 - 0{,}4211 x_2 + 0{,}0035 {x_5}^2 + 46{,}35 {x_6}^2 + 0{,}8076 x_5 x_6 + 0{,}0259 x_5 + 2{,}9749 x_6$$

$$\dot{x}_3 = x_4$$

$$\dot{x}_4 = -2{,}1401 x_4 + 31{,}8841 {x_8}^2 + 14{,}2029 x_8 + 21{,}7150 x_9 - 1{,}4010 u_1$$

$$\dot{x}_5 = -6{,}6667 x_5 - 2{,}7778 x_6 + 2u_1$$

$$\dot{x}_6 = 4x_5$$

$$\dot{x}_7 = -8x_7 - 4x_8 + 2u_2$$

$$\dot{x}_8 = 4x_7$$

$$\dot{x}_9 = -1{,}3333 x_9 + 0{,}0625 u_1$$

Where $x_1 = \psi, x_2 = \dot{\psi}, x_3 = \varphi, x_4 = \dot{\varphi}$

The control objective is to stabilize the helicopter body around a set point reference(φ_r, ψ_r). For this, a decentralized control technique is adopted by using two Neuro-fuzzy controllers; one for the elevation angle and the other for the azimuth.

Each Neuro-fuzzy controller has two inputs error $e(k)$ and change in error $\Delta e(k)$ and one output $u(k)$. Three symmetric triangular fuzzy membership functions (Negative (N), Zero (Z) and Positive (P)) are used for both inputs and outputs. The goal of the mixed binary-real NSGA II is to find optimal values of the real widths of the central part of the universe of discourse of the input variables and output variables for both controllers: $L_{e1}, L_{\Delta e1}, L_{u1}, L_{e2}, L_{\Delta e2}, L_{u2}$ and to extract an optimal structure corresponding to a reduced set of fuzzy rules for both controllers described by the binary weights $w_{ij}{}^1 and\, w_{ij}{}^2$ respectively, so 60 parameters are evolved in the optimization problem which uses the following values:

Population size=100, maximum generations=100, crossover Probability=0.8, mutation probability=0.01.

The minimization problem is given by:

$$\mathrm{Min}\left(J_1 = \sum_{k=1}^{N} |e_1(k)| + |e_2(k)|, \quad J_2 = \sum_{i=1}^{9}\sum_{j=1}^{3} W_{ij}{}^1 + \sum_{i=1}^{9}\sum_{j=1}^{3} W_{ij}{}^2 \right) \tag{20}$$

Where:

$(k) = \psi_r(k) - \psi(k)$ and $e_2(k) = \varphi_r(k) - \varphi(k)$

This problem is recast as a maximization problem:

$$\mathrm{Max}\left(f_1 = \frac{10^6}{1 + 20J_1}, \; f_2 = \frac{10}{1 + J_2} \right) \tag{21}$$

Test simulations were carried for the set point references $\psi_r = 1$ *and* $\varphi_r = 1$ with 30 seconds as time simulation. The population of the last generation is plotted in Figure 14 which shows clearly the obtained front after 100 generations. The extracted solutions in the front are as follows:

The optimal real parameters are:

$$L_{e1} = 9.0989, L_{\Delta e1} = 2.1647, L_{u1} = 5.9648, L_{e2} = 7.4927, L_{\Delta e2} = 1.1852, L_{u2} = 3.3399$$

And the optimal binary weights are:

$$W^1 = [001\ 100\ 001\ 010\ 010\ 010\ 001\ 100\ 010]$$
$$and\ W^2 = [000\ 000\ 010\ 100\ 010\ 000\ 100\ 001\ 001]$$

The knowledge accumulated within the structure of the two obtained NFC is interpreted as Mamdani FIS with the following fuzzy rules (table 2 and 3):

Table 2. Fuzzy rules interpreted by the first Neuro-fuzzy controller

$\Delta e_1(t)$ \ $e_1(t)$	NE	ZE	PO
NE	**PO**	**ZE**	**PO**
ZE	**NE**	**ZE**	**NE**
PO	**PO**	**ZE**	**ZE**

Table 3. Fuzzy rules interpreted by the second Neuro-fuzzy controller

$\Delta e_2(t)$ \ $e_2(t)$	NE	ZE	PO
NE		**NE**	**NE**
ZE		**ZE**	**PO**
PO	**ZE**		**PO**

Figure 15 and Figure 16 show respectively the azimuth angle and the elevation angle, we notice that both outputs reach the references ($\psi_r = 1$ and $\varphi_r = 1$) very smoothly and in less than 5 seconds while the elevation angle presents an overshoot of about 10%. Control signal outputs of the two NFC are illustrated in Figure 17 and Figure 18. These obtained NFCs were tested for a change in azimuth and elevation angle set point references. On the one hand, figures 19, 20, 21 and 22 show the simulation results when $\psi_r = 1$ and $\varphi_r = 0$, it can be see that the variation of the azimuth is very smooth and the disturbance in the elevation angle is quickly eliminated. On the other hand, figures. 23, 24, 25 and 26 show the simulation results when $\psi_r = 0$ and $\varphi_r = 1$, we observe that the variation of the elevation angle does not disturb the azimuth angle.

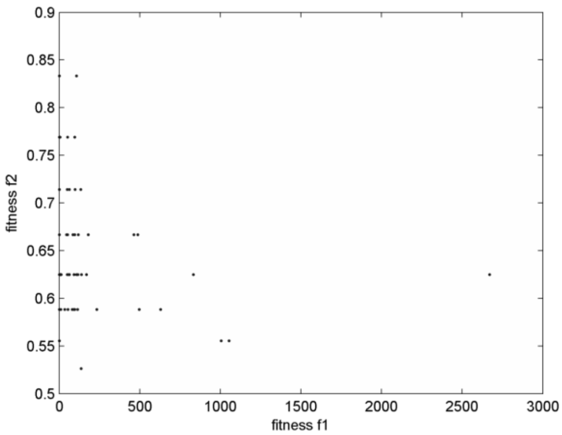


Figure 14. Distribution of the population of the last generation

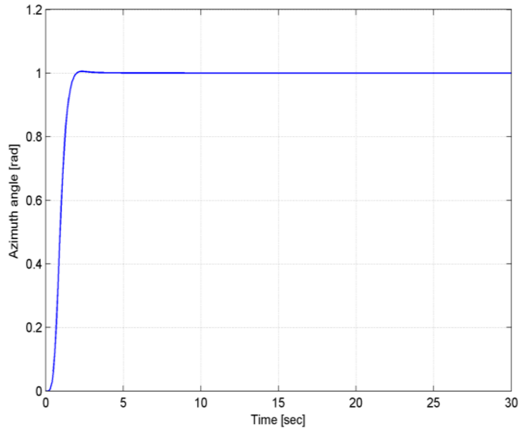


Figure 15. Azimuth angle (set point references: $\psi_r = 1$ and $\varphi_r = 1$)

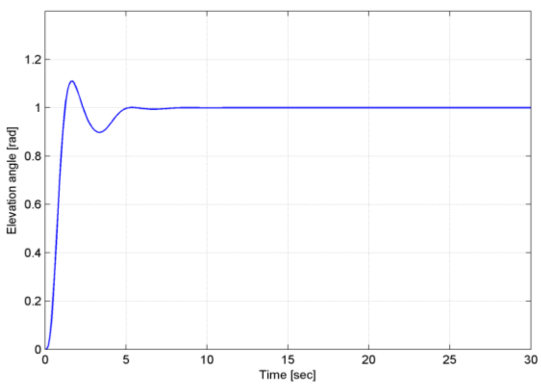


Figure 16. Elevation angle ($\psi_r = 1$ and $\varphi_r = 1$)

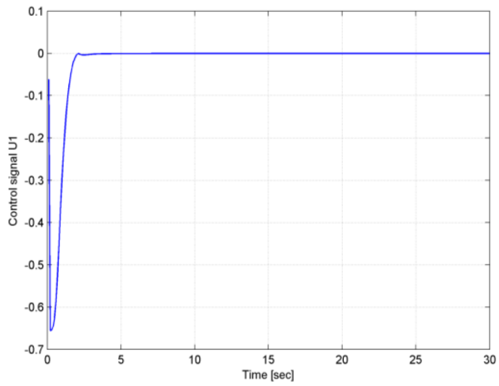


Figure 17. Control signal U_1($\psi_r = 1$ and $\varphi_r = 1$)

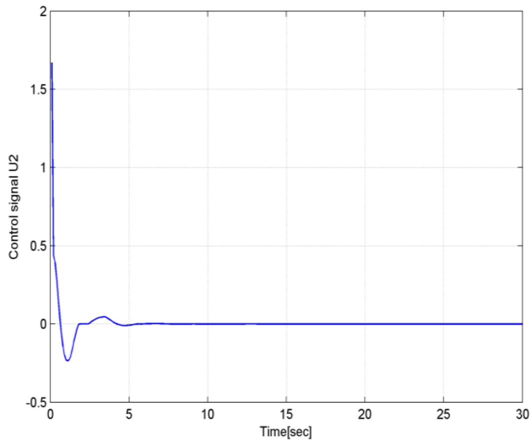


Figure 18. Control signal U2($\psi_r = 1 \ and \ \varphi_r = 1$)

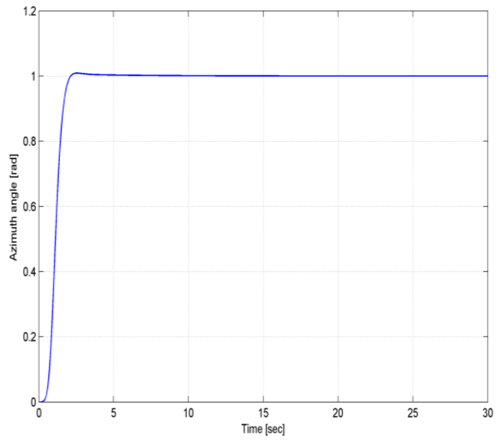


Figure 19. Azimuth angle ($\psi_r = 1 \ and \ \varphi_r = 0$)

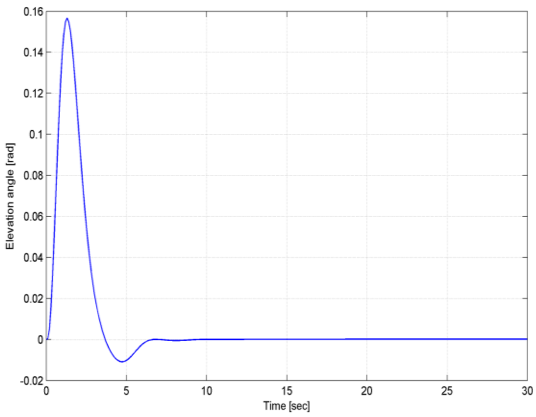


Figure 20. Elevation angle ($\psi_r = 1 \ and \ \varphi_r = 0$)

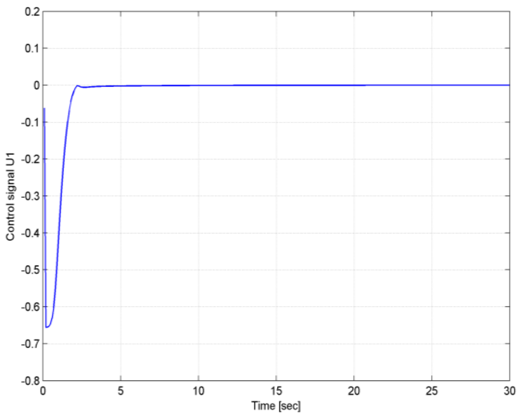


Figure 21. Control signal U1 ($\psi_r = 1 \ and \ \varphi_r = 0$)

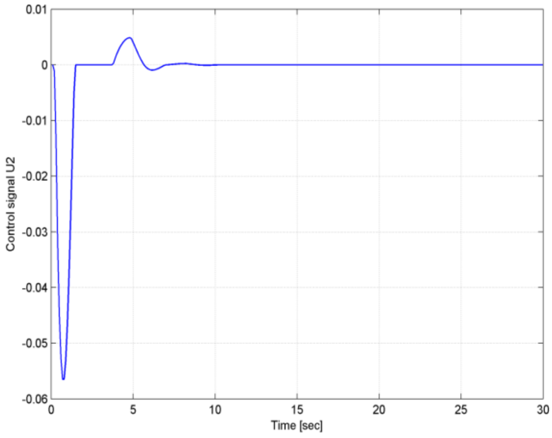


Figure 22. Control signal U2 ($\psi_r = 1 \ and \ \varphi_r = 0$)

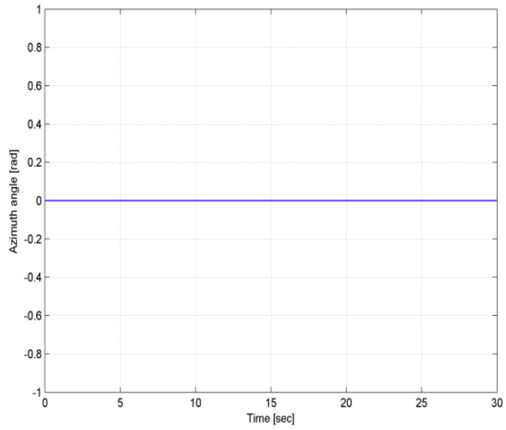


Figure 23. Azimuth angle ($\psi_r = 0 \ and \ \varphi_r = 1$)

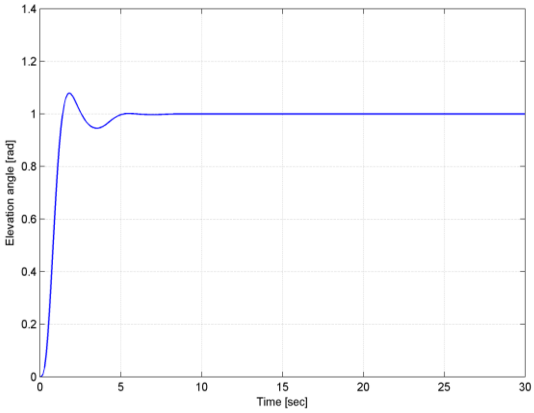


Figure 24. Elevation angle ($\psi_r = 0$ and $\varphi_r = 1$)

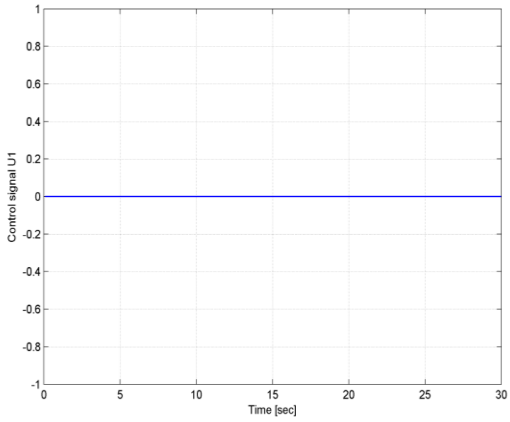


Figure 25. Control signal U_1 ($\psi_r = 0$ and $\varphi_r = 1$)

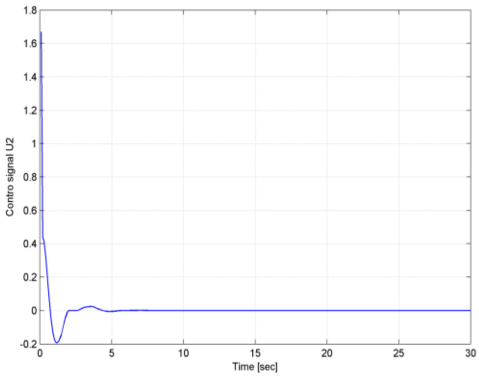


Figure 26. Control signal U_2 ($\psi_r = 0$ and $\varphi_r = 1$)

5. CONCLUSION

In this work, we proposed a new method for designing Neuro-fuzzy controllers to obtain controllers working not only with good accuracy, but also ensuring high interpretability of the knowledge accumulated within it. This trade-off between interpretability and accuracy in fuzzy inference system design is cast as two objective optimization problems. To cope with this problem, a new multiobjective Pareto based genetic algorithm called mixed Binary-Real Non dominated Sorting Genetic Algorithm II is used to design optimally both membership functions of the input/output variables and fuzzy rule base modeled by the binary weights of the network on which constraints are imposed in order to preserve interpretability of fuzzy rules during the optimization process. Due to the complexity of this optimization problem the genetic operators are improved. The method provides a set of solutions from which interesting solutions, belonging to the Pareto front, are extracted. The performance of this approach is verified with two examples: a controller design for the pole and cart system and a multivariable decentralized controller design for a helicopter simulator model. For both problems, the optimization process produced compact Neuro-fuzzy controllers with high accuracy and robustness and very good interpretability. Hence, our simulation results allow to assume that our aims were achieved.

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