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FUZZY-NEURO-GENETIC AEROFIN CONTROL

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Abstract. *In this paper fuzzy-neuro-genetic control of an electromechanical actuator (EMA) system for aerofin control (AFC), with permanent magnet brush DC motor driven by a constant current driver, is investigated. In our previous papers, nonlinear model of the EMA-AFC system and different classical and hybrid classical-computationally intelligent control systems have been designed and tested. In this paper we have proposed fuzzy and neuro-fuzzy control with genetic optimization. Proposed intelligent control systems, providing good transient response and system behaviour, have been validated by various numerical experiments and compared to previous results.*

Key words: *aerofin, electromechanical actuator, constant current driver, fuzzy control, genetic algorithms, neuro-fuzzy control*

1. INTRODUCTION

Due to the increased importance placed on maintainability, the use of electromechanical actuation is becoming increasingly popular in aerospace industry and thus electromechanical actuators (EMAs) are being used more in the actuation of flight critical control surfaces. Wide acceptance by the aerospace community and successful application for flight-critical actuation requires good understanding of the dynamic properties of these actuators, which drives forward extensive research, development and testing [1-4].

In our previous research [7-9] we considered an electromechanical actuator system for aerofin control (AFC), driven by a permanent magnet brush DC motor. For this application we developed a constant current motor driver. Control signal was pulse width modulated (PWM). Physical realization of such solution is usually simpler and cheaper than the conventional voltage driver.

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Also, in [7-9,13] we have introduced a simulation model of the EMA-AFC system, taking into account nonlinearities due to mechanical limitations of the fin deflection, limited motor torque and angular velocity, friction in gears and bearing, backlash in gears and lever mechanism, etc. We have also modelled the current motor driver, which was of the importance for understanding the behaviour of the system and the control algorithm synthesis. We have shown that the developed model matches the real EMA-AFC system dynamics, and is suitable for further investigation, thus it was also used in this study.

Initially, in [8-9] we have developed control with conventional PID position controller and nonlinear NPID controller for EMA-AFC system, which were experimentally validated in testing system. In [13], computational intelligence techniques, namely genetic algorithms and fuzzy logic, have been introduced to propose control algorithm improvements, resulting in hybrid fuzzy gain scheduling of PID controllers implemented as fuzzy supervisory control and genetic optimization of conventional controller parameters. In this paper we investigate pure computationally intelligent alternatives to previous solutions, with the aim to investigate a full range of conventional, hybrid and computationally intelligent control solution.

Therefore we propose fuzzy-neuro-genetic solutions for the aerofin control. Validation through numerical experiments is presented, results are compared to previous ones and advantages and drawbacks of intelligent approaches are commented on.

2. AFC SYSTEM, TEST BENCH AND MODEL

Aerofin control (AFC) system, considered here, is the control of the missile using four grid fins. The grid fins configuration is depicted in Fig .1.

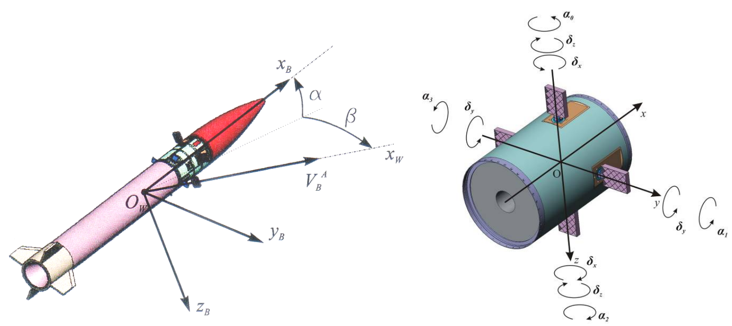

Fig. 1 Missile layout and principal actuator placement for aerofin control

By deflecting grid fins, moments are generated about the centre of mass, which in turn rotate the airframe. The resulting incidence angles generate aerodynamic forces, which accelerate vehicle in the desired direction [4]. The missile autopilot sends roll, pitch, and yaw commands (δ_x , δ_y and δ_z) to the AFC system, which are separated into individual fin commands, i.e. angles α_i, where i=0,1,2,3. Each actuator module requires independent position control of the surface deflection, usually less than 10°.

Fig. 2 schematically illustrates fin actuator assembly, while Fig. 3 presents the EMA-AFC test bench, designed to provide simulation of real load forces in the AFC system.

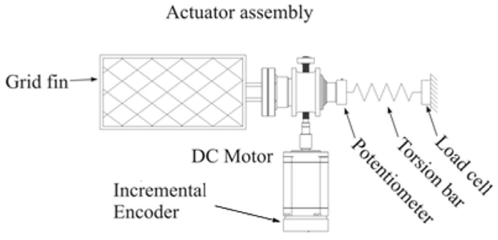

Fig. 2 Fin actuator assembly

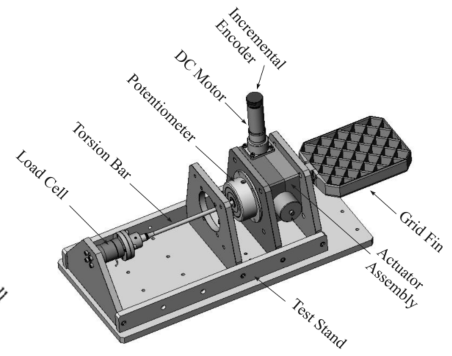

Fig. 3 EMA-AFC test bench.

The control computer is actually an onboard computer (OBC) providing control signal which is pulse width modulated, and 2 flags are forwarded to the motor driver [7,8]. To simulate inertial load, the grid fin has been mounted on the actuator assembly.

Nonlinear simulation model of the EMA-AFC system has been presented in our papers [7-9], along with the effective approximation of the motor driver. According to mechanical design parameters and vendor motor specifications, model coefficients have been fully defined.

3. Controller Design

As stated before, control systems presented here are extensions to our previous results published in [7-9,13]. There we have considered PID position controller [6], its nonlinear modification NPID [5] as well as fuzzy supervisory control as a form of PID gain scheduling [11]. Moreover, we have applied genetic algorithms for optimization of all proposed controllers [12] in that way exploring efficiently hybrid conventional-computationally intelligent [14,15] solutions. Contrary to that, we have explored here pure soft computing alternatives to our previous results.

3.1. GA optimized Fuzzy PD controller

The most-used classical direct fuzzy PD controller has been designed, as fuzzy alternative to our previous classical solutions indicating that proportional and derivative terms could stabilize the system and provide good performance.

Universes of discourse of the input and output variables have been selected on the basis of previous extensive experience with the system. For example, fin deflection that is allowed is ±10° (although maximal error that could be expected is in the interval [-20°, 20°] since from one extreme fin position the opposite one could be commanded), while control output is limited to the range [-2.5V, 2.5V]. To provide for efficient performance optimization, input values of the error and its derivative and output value are multiplied with corresponding gains K_P, K_D and K_U.

Fuzzy partitioning of the input and output controller variables has been performed by choosing 5 primary fuzzy sets for each variable which are marked with corresponding linguistic terms that occur in fuzzy control rules, and are shown in Figure 4.

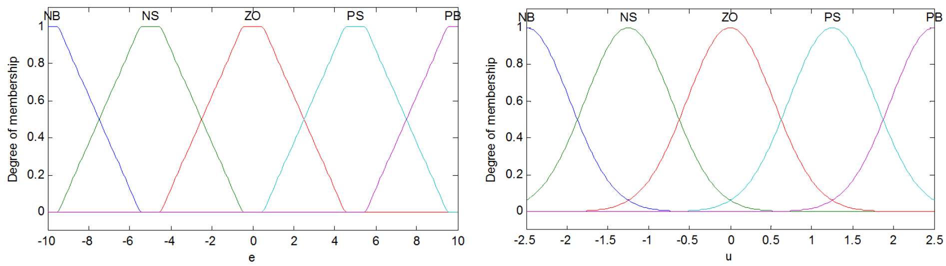

Fig. 4 Choice of the primary fuzzy sets and membership functions defined on the appropriate universes of discourse for one of two input variables and controller output

Rule base applied is complete and conservative, i.e. it has 25 rules and resembles common solution for fuzzy PD controller. The rule base and corresponding controller surface are presented in Figure 5.

1. If (e is NB) and (de/dt is NB) then (u is NB)
2. If (e is NB) and (de/dt is NS) then (u is NB)
3. If (e is NB) and (de/dt is ZO) then (u is NS)
4. If (e is NB) and (de/dt is PS) then (u is NS)
5. If (e is NB) and (de/dt is PB) then (u is ZO)
6. If (e is NS) and (de/dt is NB) then (u is NB)
7. If (e is NS) and (de/dt is NS) then (u is NS)
8. If (e is NS) and (de/dt is ZO) then (u is NS)
9. If (e is NS) and (de/dt is PS) then (u is ZO)
10. If (e is NS) and (de/dt is PB) then (u is PS)
11. If (e is ZO) and (de/dt is NB) then (u is NS)
12. If (e is ZO) and (de/dt is NS) then (u is NS)
13. If (e is ZO) and (de/dt is ZO) then (u is ZO)
14. If (e is ZO) and (de/dt is PS) then (u is PS)
15. If (e is ZO) and (de/dt is PB) then (u is PS)
16. If (e is PS) and (de/dt is NB) then (u is NS)
17. If (e is PS) and (de/dt is NS) then (u is ZO)
18. If (e is PS) and (de/dt is ZO) then (u is PS)
19. If (e is PS) and (de/dt is PS) then (u is PS)
20. If (e is PS) and (de/dt is PB) then (u is PB)
21. If (e is PB) and (de/dt is NB) then (u is ZO)
22. If (e is PB) and (de/dt is NS) then (u is PS)
23. If (e is PB) and (de/dt is ZO) then (u is PS)
24. If (e is PB) and (de/dt is PS) then (u is PB)
25. If (e is PB) and (de/dt is PB) then (u is PB)

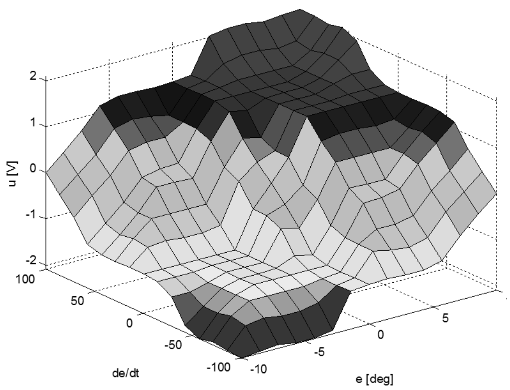

Fig. 5 Rule base and controller surface for conservative Fuzzy PD controller

Applying Mamdani's minimum operation as fuzzy implication function, the firing strength and i-th rule control decision are given by the expressions:

$$\alpha_i = \mu_{\tilde{A}_i}(E_0) \wedge \mu_{\tilde{B}_i}(\dot{E}_0), \quad \mu_{\tilde{C}_i'}(w) = \alpha_i \wedge \mu_{\tilde{C}_i}(w), \tag{01}$$

while the overall controller fuzzy control decision, conclusion $\tilde{C}$, is defined with:

$$\mu_{\tilde{C}}(w) = \mu_{\tilde{C}_1'}(w) \vee \mu_{\tilde{C}_2'}(w) \vee \ldots \vee \mu_{\tilde{C}_{25}'}(w) = [\alpha_1 \wedge \mu_{\tilde{C}_1}] \vee \ldots \vee [\alpha_{25} \wedge \mu_{\tilde{C}_{25}}]. \tag{02}$$

Since it was not possible to linearize the current motor driver due to two-level current output, extensive simulation was necessary. Input/output gains of the controller were expected to be around unity since domains of the controller variables were chosen realistically on the basis of previous experience. Experimental fine tuning provided $K_P = 1$, $K_D = 0.9$ and $K_U = 1$. To provide for less obvious but possibly optimal value set of controller gains, genetic optimization technique has been used to fine tune K_P and K_D, providing simple and robust alternative to experimental parameter adjustment. Since control output is limited to the range [-2.5V, 2.5V] which corresponds to domain of the output fuzzy variable, value $K_U = 1$ was fixed.

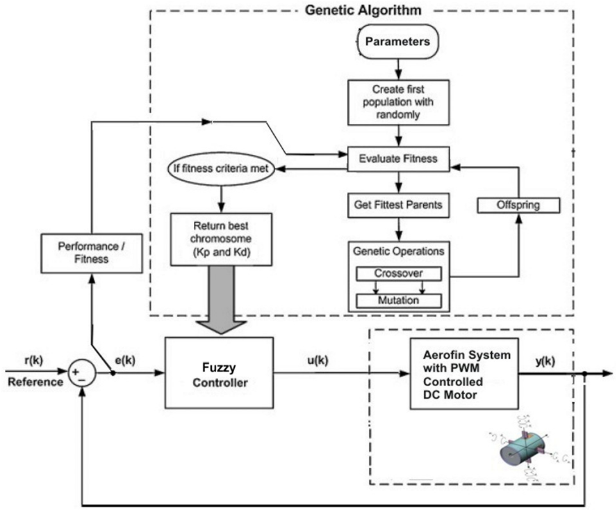

Fig. 6 Offline fuzzy controller input gains optimization

Genetic algorithms are one of the evolutionary computational intelligence techniques [10], inspired by Darwin's theory of biological evolution and pioneered by Holland. GAs provide solutions using randomly generated bit strings (chromosomes) for different types of problems, searching the most suitable among chromosomes that make the population in the potential solutions space. It is an alternative to the traditional optimal search approaches in which it is hard to find the global optimum for nonlinear and multimodal optimization problems. Thus, GAs have been successful in solving combinatorial problems [10] as well as in many control applications such as parameter identification and control structure design [12].

Here we have implemented GA for controller gains tuning in offline approach, as it is presented in Figure 6. Therefore, we defined the cost function to minimize tracking error. Designed cost function was defined as:

$$J = \sum_{i=1}^{N} |e_i| = \sum_{i=1}^{N} |r_i - y_i|, \tag{03}$$

where r is reference variable, y is controlled output, e is control error and N is number of patterns. GAs performance depends on its parameters values, so GA parameters were selected by making numerous experiments.

Finally, the obtained GA optimized Fuzzy PD controller gains were $K_P = 0.689$ and $K_D = 0.5$, while the best obtained fitness value was J = 284308.

3.2. GA optimized modified Nfuzzy PD controller

With the aim to further improve the controller performance, we have proposed modifications of the conventional Fuzzy PD controller. Actually, the EMA AFC system performed well with GA optimized Fuzzy PD when the error signal was large, i.e. the transient response is fast, but when the error approaches zero, the system becomes too slow. This is quite reasonable, because for large values of the reference input angles α_r, the load torque from aerodynamic force is maximal. In addition, there are effects of friction and gear backlash.

Modifications to input/output membership functions and rule base, as well as resulting improved controller surface are presented in Figs 7 and 8.

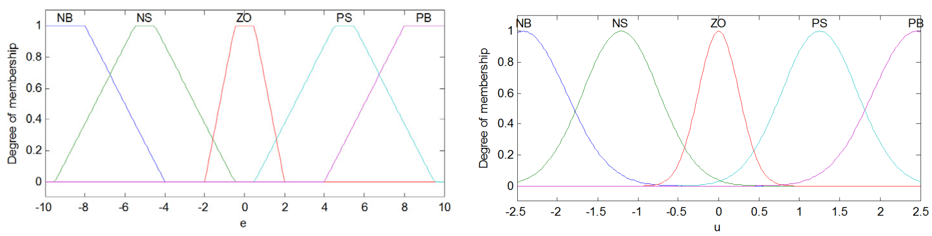

Fig. 7 Modified membership functions of NFuzzy PD controller

Input gains of the modified Nfuzzy PD controller were determined by the same offline optimization with GAs as with conventional Fuzzy PD. Parameters have been adopted as $K_P = 0.69$ and $K_D = 0.57$, while resulting performance index was J = 277690.

3.3. Neuro-fuzzy PD controller

To further improve performance of the designed fuzzy PD control systems, a powerful tuning strategy has been used. Namely, by converting output fuzzy membership functions to singletons, Mamdani fuzzy PD controller has been made theoretically equal to Takagi-Sugeno-Kang controller with constants in the consequent rule parts. Further, obtained TSK fuzzy system has been trained using powerful and well-known neuro-fuzzy ANFIS strategy [16].

1. If (e is NB) and (de/dt is NB) then (u is NB)
2. If (e is NB) and (de/dt is NS) then (u is NB)
3. If (e is NB) and (de/dt is ZO) then (u is NS)
4. If (e is NB) and (de/dt is PS) then (u is NS)
5. If (e is NB) and (de/dt is PB) then (u is ZO)
6. If (e is NS) and (de/dt is NB) then (u is NB)
7. If (e is NS) and (de/dt is NS) then (u is NS)
8. If (e is NS) and (de/dt is ZO) then (u is NS)
9. If (e is NS) and (de/dt is PS) then (u is ZO)
10. If (e is NS) and (de/dt is PB) then (u is PS)
11. If (e is ZO) and (de/dt is NB) then (u is NS)
12. If (e is ZO) and (de/dt is NS) then (u is NS)
13. If (e is ZO) and (de/dt is ZO) then (u is ZO)
14. If (e is ZO) and (de/dt is PS) then (u is PS)
15. If (e is ZO) and (de/dt is PB) then (u is PS)
16. If (e is PS) and (de/dt is NB) then (u is NS)
17. If (e is PS) and (de/dt is NS) then (u is ZO)
18. If (e is PS) and (de/dt is ZO) then (u is PS)
19. If (e is PS) and (de/dt is PS) then (u is PS)
20. If (e is PS) and (de/dt is PB) then (u is PB)
21. If (e is PB) and (de/dt is NB) then (u is ZO)
22. If (e is PB) and (de/dt is NS) then (u is PS)
23. If (e is PB) and (de/dt is ZO) then (u is PS)
24. If (e is PB) and (de/dt is PS) then (u is PB)
25. If (e is PB) and (de/dt is PB) then (u is PB)

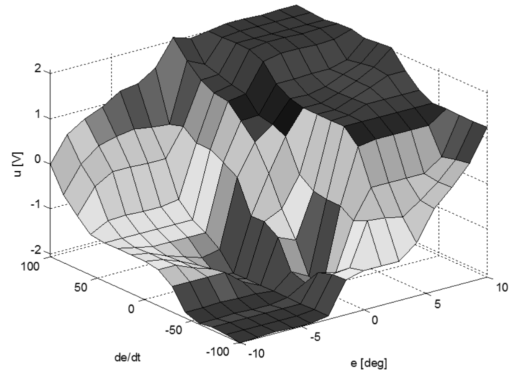

Fig. 8. Rule base and controller surface of the modified NFuzzy PD controller

ANFIS structure. Consider a first-order Takagi-Sugeno-Kang (TSK) fuzzy inference system [16] that consists of two rules:

$$\text{Rule 1: If X is } A_1 \text{ and Y is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1$$
$$\text{Rule 2: If X is } A_2 \text{ and Y is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2 \qquad (04)$$

Fig. 9 illustrates the fuzzy reasoning mechanism and the corresponding ANFIS architecture, respectively.

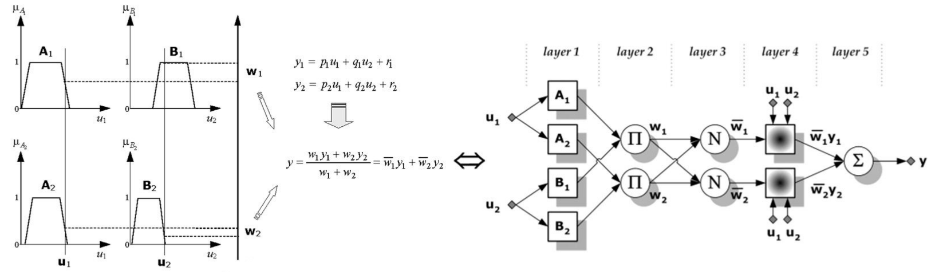

Fig. 9 First-order TSK fuzzy model using trapezoidal membership functions and corresponding ANFIS architecture

Node functions in the same layer of ANFIS are of the same function family, as described below where O_i^j denotes the output of the i^{th} node in layer j.

Layer 1: Each node in this layer generates membership grades of a linguistic label. For instance, the node function of i^{th} node might be

$$O_i^1 = m_{A_i}(u_1) = \max\left[\min\left(\frac{u_1 - a}{b - a}, 1, \frac{d - u_1}{d - c}\right), 0\right] \tag{05}$$

where u_1 is the input to node I, A_i is the linguistic label (small, large, etc.) associated with this node, and $\{a, b, c, d\}$ is the parameter set that changes the shape of the trapezoidal membership function. Parameters in this layer are referred to as the premise parameters.

Layer 2: Each node in this layer calculates the firing strength of each rule via multiplication

$$O_i^2 = w_i = \mu_{A_i}(u_1) \times \mu_{B_i}(u_2), \qquad i = 1,2 \tag{06}$$

Layer 3: The i^{th} node of this layer calculates the ratio of the i^{th} rule's firing strength to the sum of all rules firing strength

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{07}$$

Layer 4: Node i in this layer has the following node function:

$$O_i^4 = \overline{w}_i y_i = \overline{w}_i (p_i u_1 + q_i u_2 + r_i) \tag{08}$$

Where $\overline{w}_i$ is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer are referred to as the consequent parameters.

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals, producing the classification result:

$$O_i^5 = overall\ output = \sum_i \overline{w}_i y_i = \frac{\sum w_i y_i}{\sum w_i} \tag{09}$$

The hybrid learning algorithm. The hybrid learning algorithm of ANFIS consists of two alternating parts:

- Back propagation/gradient descent (BP/GD) which calculates error signals (defined as the derivative of the squared error with respect to each node output) recursively from the output layer backward to the input nodes, and
- the recursive least squares estimation (RLSE) method, which finds a feasible set of consequent parameters. Given fixed values of premise parameters, the overall output can be expressed as a linear combination of the consequent parameters

$$y = \overline{w}_1 y_1 + \overline{w}_2 y_2 = (\overline{w}_1 u_1) p_1 + (\overline{w}_1 u_2) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 u_1) p_2 + (\overline{w}_2 u_2) q_2 + (\overline{w}_2) r_2 \tag{10}$$

Here, as it was explained, ANFIS version with constant consequent parts instead of linear combinations of inputs was used, making it equivalent to Mamdani Fuzzy PD controller with singleton consequent output variable fuzzy sets.

Using ANFIS hybrid learning algorithm, starting Fuzzy PD controller has been fine tuned to replicate behaviour of the GA optimized nonlinear PID controller we have proposed in our previous paper [13], being referent in the sense that it provides superior closed loop performance. To facilitate for that, NPID controller has been reduced to NPD controller, GA optimized and used as a role model for neuro-fuzzy controller fine tuning. Such a controller uses modified error signal as input:

$$e_c(t) = \mathrm{sign}(e(t)) \cdot \sqrt{|e(t)|} \,. \tag{11}$$

The error function (11) has a large gradient around zero, i.e. it behaves as scheduled parameters of the PD. Now, the modified PD controller becomes

$$u(t) = K_p e_c(t) + K_D \dot{e}_c(t) \,, \tag{12}$$

where GA optimized values $K_P = 1.765$ and $K_D = 0.142$ were used.

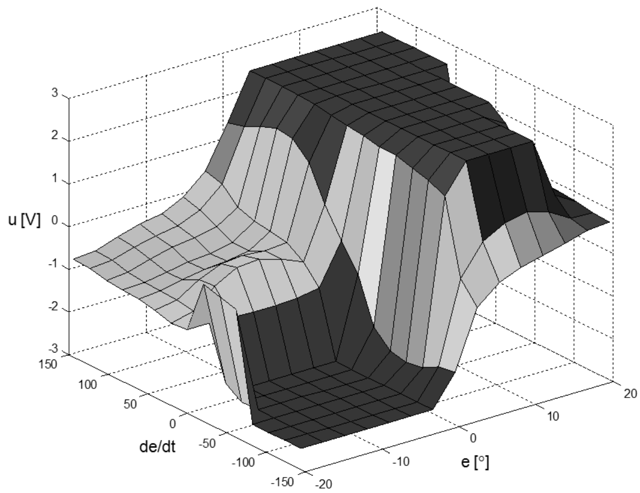

Fig. 10 Control surface of the neuro-fuzzy trained PD controller

Apart from ANFIS tuning, numerous elements of the neuro-fuzzy controller could be hand-tuned to correct some negative training consequences at the bordering areas of controller surface. Finally, the obtained resulting control surface which provided best performance is presented in Fig. 10.

3.4. Comparison of proposed controllers performance

In Table I the performances of all proposed controllers, namely classical Fuzzy PD controller, modified NFuzzy PD controller and Neuro-fuzzy trained PD controller, have been summarized.

Table I Comparison of controller performances

Controller	Fitness function J
Fuzzy PD experimentally suboptimally tuned (Kp=1, Kd=0.9)	527000
Fuzzy PD GA optimally tuned (Kp=0.689, Kd=0.5)	284308
Modified NFuzzy PD suboptimally tuned (Kp=1, Kd=0.9)	522801
Modified NFuzzy PD GA optimally tuned (Kp=0.69, Kd=0.57)	277690
Neuro-fuzzy trained PD	249090

Table I overviews fitness function values, i.e. overall error indices according to Eq. (03) for various controllers, for square reference of magnitude ±10°, lasting 4s with frequency of 1Hz. Smaller fitness function values indicate better performance, i.e. smaller overall output error.

Conducted simulation validations of the proposed GA optimized Fuzzy PD, GA optimized modified NFuzzy PD, and neuro-fuzzy tuned PD controller in the EMA-AFC testing system are presented in Fig. 11, using our simulation model. As during the genetic optimization, square wave reference input with the maximum allowed magnitude $|\alpha_{rmax}|$ =10° was used for testing.

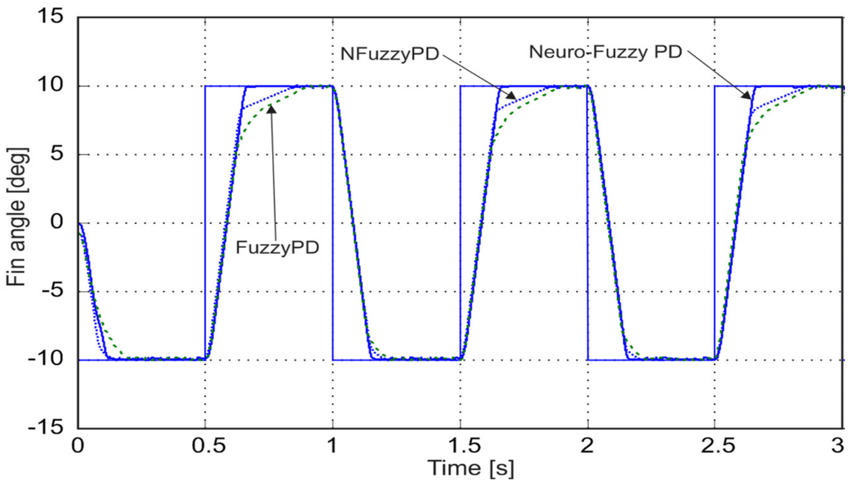

Fig. 11. Comparison of the square wave responses for different controllers

Since our simulation model has been experimentally validated in our previous publications, we concluded that the presented simulation results verified our strategy of improving starting computationally intelligent control in order to enhance performance.

4. CONCLUSION

A nonlinear model of the electromechanical actuator system for aerofin control, presented in our previous papers [7-9], has been used as a starting point for results presented here. Also, our previous results regarding aerofin include both conventional PID position controller and nonlinear modification of PID controller as well as hybrid conventional computationally intelligent approaches for the system. Namely, GA optimization of both PID controller and nonlinear modification of the PID controller as well as a form of fuzzy gain scheduling of PID controller combined with offline genetic optimization strategy have all previously been introduced [7-9,13].

Being motivated by those results, here we have explored pure computationally intelligent control options for the EMA-AFC testing system, based on our experience from extensive experimentation with the system. Namely, we have developed conventional Fuzzy PD control and modified NFuzzy PD control with emphasized nonlinearity, and also applied GA optimization of crucial controller parameters. Finally, we have proposed neuro-fuzzy PD controller and improved previous result by training it to mimic referent GA optimized nonlinear PD controller, which was developed on the basis of our previous results.

The validity of the proposed approaches has been demonstrated in the EMA-AFC previously verified model, simulating real operating conditions. The obtained results show increased performances of the transient response and justify validity of the applied approaches. Results are comparable to conventional and hybrid control solutions we have proposed previously. Some of the previously developed top performing solutions for the system remain unchallenged in terms of performance, but on the other hand some other possibilities are opened by the controllers proposed here. Namely, fuzzy-genetic-neuro control solutions developed remain with understandable structure and with large number of modifiable parameters providing for endless tuning possibilities should such a demand occur. Also, some safety rules that could handle critical or otherwise special situations that might occur in the system could easily be handled by adding fuzzy rules designed to handle them.

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FAZI-NEURO-GENETSKO UPRAVLJANJE AEROKRILA

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U ovom radu razmatrano je fazi-genetsko-neuro upravljanje elektromehaničkog aktuatora aerokrila za kontrolu leta projektila, pokretanim motorom jednosmerne struje sa četkicama i permanentnim magnetom koji je pogonjen drajverom sa konstantnom strujom. U našim prethodnim radovima, na osnovu razvijenog nelinearnog modela sistema, razvijena su i testirana različta konvencionalna i hibridna konvencionalno-inteligentna upravljanja. U ovom radu predloženo je fazi i neuro-fazi upravljanje sa genetskom optimizacijom. Predloženi inteligentni upravljački sistemi, koji obezbeđuju dobro ponašanje sistema, su verifikovani numeričkim simulacijima i upoređeni sa prethodnim rezultatima.

Ključne reči: *upravljačko krilo, elektromehanički aktuator, drajver sa konstantnom strujom, fazi upravljanje, genetski algoritmi, neuro-fazi upravljanje*