Memorias del Congreso Nacional de Control Automático
ISSN: 2594-2492

Design of a PID controller based on Adaptive Fuzzy Spiking Neurons

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Abstract: The design of the control law for a PID controller is developed with base on the innovative learning algorithm of the Adaptive Fuzzy Spiking Neurons (AFSNs), for tuning of the proportional, integral and derivative gains, and the filter coefficient of a PID controller in parallel form. The PID controller for a gas turbine model is presented as an illustrative example. The simulation of the results of the application of the AFSNs for the tuning of the gains of the PID controller are performed in Matlab^{TM} environment.

Keywords: Learning algorithm, fuzzy neuron, Adaptive Fuzzy Spiking Neuron, PID tuning, control law.

1. INTRODUCTION

The artificial neurons models [Gupta (1992), Gupta (1993), Hilera-González and Martínez-Hernando (2000), Sánchez-Camperos and Alanís-García (2006)] had been applied in areas like control, industrial processes and signal processing. For the control of processes, the tuning of the parameters of the PID controllers, have been performed by different methods, for example [Sánchez-Parra (2010), Sánchez-Parra et al. (2011), Yu and Rosen (2013), Jun Young Lee Maolin Jin and Pyung Hun Chang (2014)].

The purveyance of electricity has been a determining factor at present, which is why more efficient and ecological electricity generating plants are required. For a gas turbine of a Combined Cycle generation plant [Sánchez-Parra (2010), Sánchez-Parra et al. (2011)], the control system with PIDs for the nominal plant model and a fault condition plant model is proposed. The control system self-tune the PID gains for the first seconds of the process, then the PID parameters or gains are switched to the fixed values tuned by the learning algorithm of the Adaptive Fuzzy Spiking Neurons (AFSNs), for the models of the plant [Sánchez-Parra (2010), Sánchez-Parra et al. (2011)]. The adaptation of the gains or weights are performed with the novel method of the AFSNs [Ramírez and Pérez (2002), Ramírez-Mendoza et al. (2011), Ramírez-Mendoza (2014), Ramírez-Mendoza et al. (2018), Ramírez-Mendoza (2018), Ramírez-Mendoza et al. (unpublished), Ramírez-Mendoza (unpublished)], until achieving the stability of the model of the gas turbine, for the nominal plant and for the plant subject to fault that could be produced by the friction in the rotor of the turbo generator [Sánchez-Parra (2010), Sánchez-Parra et al. (2011)]. It is based on the time-invariant linear models of the nominal plant and the plant with fault, which would be switched according to the faults agree with [Sánchez-Parra (2010), Sánchez-Parra et al. (2011)].

Here is proposed the design of the law of control for tuning the parameters of a PID controller in parallel form with base on the innovative method, the adaptive learning algorithm of AFSNs developed in [Ramírez and Pérez (2002), Ramírez-Mendoza et al. (2011), Ramírez-Mendoza (2014), Ramírez-Mendoza et al. (2018), Ramírez-Mendoza (2018), Ramírez-Mendoza et al. (unpublished), Ramírez-Mendoza (unpublished)]. The application of the method of the AFSNs to tune the parameters of the PID controller of the model of a gas turbine [Sánchez-Parra (2010), Sánchez-Parra et al. (2011)], is presented as an illustrative example for the search of solutions of great importance such as the production of electrical energy.

The main contribution of this article is the tuning of the parameters of a PID controller obtained with a novel method, the AFSNs [Ramírez and Pérez (2002), Ramírez-Mendoza et al. (2011), Ramírez-Mendoza (2014), Ramírez-Mendoza (2018), Ramírez-Mendoza (unpublished)]. The desired output or reference of the plant, is given.

For the control system developed here, the plant model is required to tune the gains of the PID controller. The results of the simulation are presented in Matlab^{TM} environment.

1.1 Adaptive Fuzzy Spiking Neuron

The block diagram of the Adaptive Fuzzy Spiking Neuron with its neural features is shown in (Fig. 1). The dendritic inputs are $z_{inj}(k) = 0, \dots, 1$ for unipolar signals, and $z_{inj}(k) = -1, \dots, 1$ for bipolar signals.

Synaptic and somatic operations such as the aggregation operation and the non-linear activation function are based on fuzzy logic and fuzzy neurons [Zadeh (1977), Gupta (1992), Gupta (1993)]. The activation function could be step or sigmoidal type. The learning algorithm of the AFSNs developed in recent years, has the advantage of presenting less complexity than other learning algorithms for neural networks [Hilera-González and Martínez-Hernando (2000), Sánchez-Camperos and Alanís-García (2006)].

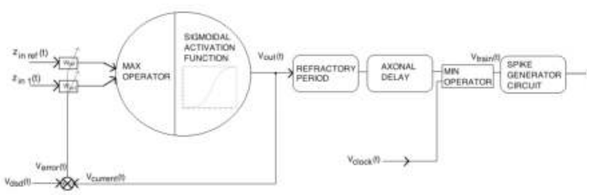

Fig. 1. Block diagram of the Adaptive Fuzzy Spiking Neuron with its neural features.

2. DESIGN OF THE CONTROL LAW OF A PID CONTROLLER BASED ON AFSNs.

2.1 Tuning of the parameters of the PID with the method of the AFSNs.

The adaptive learning algorithm proposed in [Ramírez-Mendoza (2014), Ramírez-Mendoza (2018), Ramírez-Mendoza (unpublished)] for the AFSNs is applied to design the control law for tuning the proportional (P), integral (I) and derivative (D) gains, and the filter coefficient ($N = 1/T_f$) of a PID controller in parallel form. The inputs of the AFSNs are no fuzzy, there is no refractory period or axonic delay, or they have a value of zero, also the Spike Generator Circuit (SGC) is not used.

The transfer functions of plants H(s) for the examples 1 and 2, and agree with [Sánchez-Parra (2010), Sánchez-Parra et al. (2011)] are:

$$\mathrm{H_1(s)} = \frac{c_1 s^4 + c_2 s^3 + c_3 s^2 + c_4 s + c_5}{d_1 s^7 + d_2 s^6 + d_3 s^5 + d_4 s^4 + d_5 s^3 + d_6 s^2 + d_7 s + d_8} \quad (1)$$

$$\mathrm{H_2(s)} = \frac{c_1 s^4 + c_2 s^3 + c_3 s^2 + c_4 s + c_5}{d_1 s^7 + d_2 s^6 + d_3 s^5 + d_4 s^4 + d_5 s^3 + d_6 s^2 + d_7 s + d_8} \quad (2)$$

Where the values of coefficients are described in Tab. 1.

Table 1. Coefficients of $\mathbf{H_1(s)}$ and $\mathbf{H_2(s)}$.

Coefficients	$\mathrm{H_1(s)}$	$\mathrm{H_2(s)}$
c_1	5.168×10^5	3.668×10^5
c_2	7.537×10^5	5.56×10^5
c_3	4.293×10^5	3.328×10^5
c_4	1.266×10^5	1.038×10^5
c_5	0.1052×10^5	0.1088×10^5
d_1	1	1
d_2	8.331	6.84
d_3	21.05	16.31
d_4	25.06	19.17
d_5	15.95	12.38
d_6	5.516	4.455
d_7	0.9408	0.8243
d_8	0.05764	0.05956

The block diagram for the examples 1 and 2, with the transfer functions of the plants $\mathrm{H_1(s)}$ and $\mathrm{H_2(s)}$, and the design of the control law for the PID controller based on the learning algorithm of the AFSNs are shown in Figs. 2 and 3.

For the examples 1 and 2, with (1) and (2), the control system is based on the block diagram of Figs. 2 and 3, respectively. Fig. 2 shows the configuration of the AFSNs, six independent fuzzy neurons to tune the PID parameters (self-tuning), for the first stage in the first seconds of the process. Fig. 3 shows the configuration of the AFSNs, four independent fuzzy neurons to tune the PID parameters (fixed or static values), for the second stage of the process.

The method consists of two stages:

- The first stage tune the parameters of PID controller with the learning algorithm of the AFSNs and agree with (3) and Fig. 2. For the example 1, (1), the first stage is for $0 \le t < 6$ seconds. For the example 2, (2), the first stage is for $0 \le t < 5$ seconds.

$$\mathrm{PID(s)} = \mathrm{pid}(w_{1P} \cdot w_{2P}, w_{1I} \cdot w_{2I}, w_{1D}, w_{1T_f}) \quad (3)$$

- The second stage tune the parameters of the PID controller also with the learning algorithm of the AFSNs and agree with (4) and Fig. 3. For the example 1, (1), the second stage is for $6 \leq t \leq 60$ seconds. For the example 2, (2), the second stage is for $5 \leq t \leq 60$ seconds.

$$\mathrm{PID}(s) = \mathrm{pid}(w_{1P}, w_{1I}, w_{1D}, w_{1T_f}) \tag{4}$$

- The values of the learning weights in the time $k = 60$ [seconds] (601 samples), are the parameters of PID controller according to (4), for the plant $H_1(s)$ for $t \geq 6$ seconds, the value of the parameters are:

$$w_{1P} = 0.0021 \qquad w_{1D} = 0.0021$$
$$w_{1I} = 0.0021 \qquad w_{1T_f} = 0.0021$$

For the plant $H_2(s)$ for $t \geq 5$ seconds, the value of the parameters are:

$$w_{1P} = 0.0015 \qquad w_{1D} = 0.0015$$
$$w_{1I} = 0.0015 \qquad w_{1T_f} = 0.0015$$

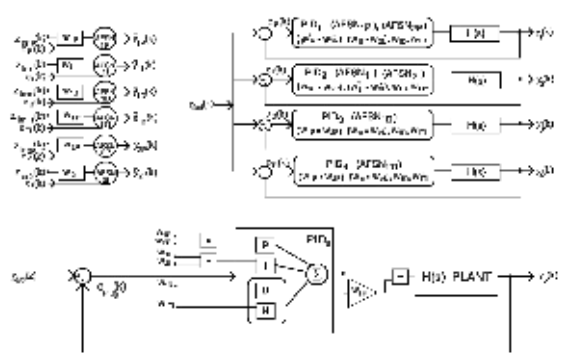

Fig. 2. Block diagram of the Plant and PID controller law for first stage.

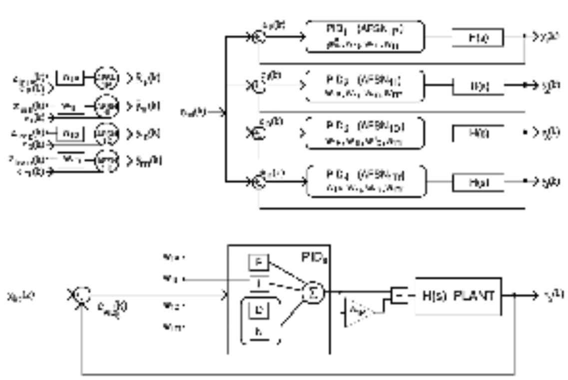

Fig. 3. Block diagram of the Plant and PID controller law for second stage.

3. SIMULATION RESULTS

For examples 1 and 2, (1) and (2), the initial conditions are:

- The values of the weights are $w_{refAFSNiP}(k) = w_{inAFSNiP}(k) = w_{refAFSNiI}(k) = w_{inAFSNiI}(k) = w_{refAFSNiD}(k) = w_{inAFSNiD}(k) = w_{refAFSNiT_f}(k) = w_{inAFSNiT_f}(k) = 1$.
- The inputs $z_{refAFSNi}(k) = 1, z_{inAFSNi}(k) = 1$ and the desired output $\widetilde{y_{dsd}}(k)$ is a unit step.
- The ideal values of the weights are unknown.
- The sampling frequency is 10 samples/sec.
- The values for the parameters *a* and *b* [Ramírez-Mendoza (2014), Ramírez-Mendoza (2018), Ramírez-Mendoza (unpublished)], are *a* = 11 and *b* = 6.
- The threshold values for all the AFSNs are $V_{threshold1\mathrm{AFSNi}}(k) = 0$.
- The initial values of the learning factors are $\gamma_{AFSNiP} = \gamma_{AFSNiI} = \gamma_{AFSNiD} = \gamma_{AFSNiT_f} = 1$.
- Specifically, for the examples $H_1(s)$ and $H_2(s)$ (Figs. 2-3), it is proposed to limit the value of the learning factors in the interval
  $n \leq \gamma_{AFSNiP}, \gamma_{AFSNiI}, \gamma_{AFSNiD}, \gamma_{AFSNiT_f} \leq 1$
  where $n = 0.00001$

Optimization of the tuning of the parameters of the PID controller with the AFSNs method, is dynamic. The simulation results for example 1 $H_1(s)$, (1) are shown in Figs. 4-5.

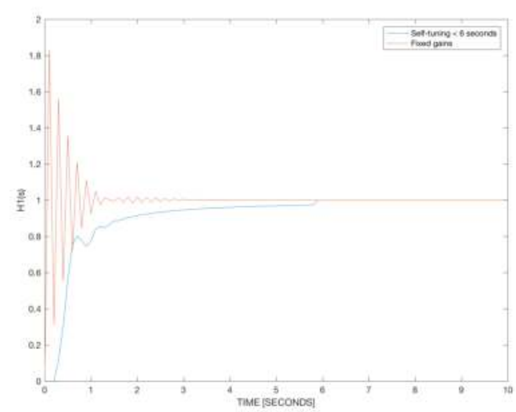

Fig. 4. Response of $H_1(s)$ with a PID controller to unit step.

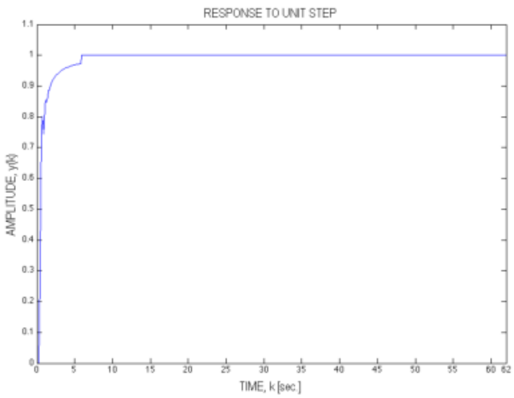

Fig. 5. Response of $H_1(s)$ with a PID controller to unit step.

The simulation results for example 2 $H_2(s)$, (2) are shown in Fig. 6.

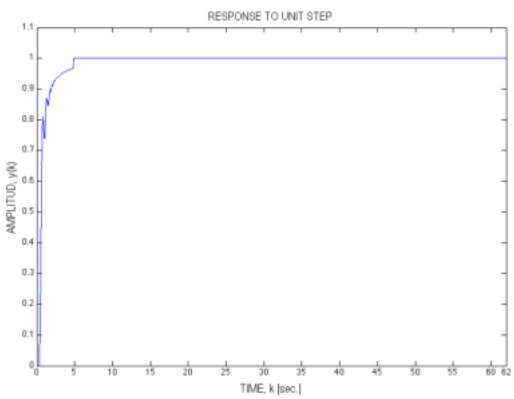

Fig. 6. Response of $\mathrm{H}_2(\mathrm{s})$ with a PID controller to unit step.

The results of the simulations are performed in Matlab™ environment. The overshoot in the unit step response, for the transfer functions of (1) and (2) is less than 1%, and is reached in 10 seconds.

5. CONCLUSIONS

The design of the PID controller law for the parameter estimation of PID controller, with the innovative learning algorithm of the AFSNs is very efficient because the overshoot of the response to unit step is less than 1% and is obtained in less than 10 seconds. Applications of the AFSNs method would be for example in automatic control, parameter identification, industrial processes and trajectory tracking for Unmanned Aerial Vehicles [Ramírez-Mendoza, A. et al. (2018), Ramírez-Mendoza, A. M. E. et al. (unpublished)].

As future work for the application of the AFSNs method is proposed to estimate the parameters of a single fault tolerant PID controller and compare the results with those obtained in this work [Ramírez-Mendoza, A. M. E. (unpublished)].

Another application for the AFSNs method would be for low-scale unmanned aerial vehicles (UAVs) in the navigation and trajectory tracking system for experimental aerodynamic tests [Ramírez-Mendoza, A. M. E. (2016)].

ACKNOWLEDGEMENT

This work was supported by UNAM and CONACYT Research Fellows – UANL, FIME, CIIIA, program. I also appreciate the valuable comments of Cristina Verde for the completion of this article.

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