Neuro-fuzzy Control of Integrating Processes

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Fuzzy technology is adaptive and easily applicable in different areas.Fuzzy logic provides powerful tools to capture the perception of natural phenomena. The paper deals with tuning of neuro-fuzzy controllers for integrating plant and for integrating plants with time delay. The designed approach is verified on three examples by simulations and compared plants with classical PID control. Designed fuzzy controllers lead to better closed-loop control responses then classical PID controllers.

Keywords: *fuzzy logic, integrating processes, time delay, PID control, fuzzy control*

Introduction

Fuzzy logic is a simple and powerful tool to modelling systems because it enables a mathematical formalization of ill defined problems, see e.g Tanaka and Sano (1991). A useful introduction to fuzzy logic are for example Kosko (1994) and Fang (1997). Fuzzy set theory provides a mathematical framework that is appropriate for handling the complexity of systems, see e. g. Klir and Yuan (1997). There are a lot of examples of geological objects that do not fit well into traditional classifications: Demicco and Klir (2004), Fang and Chen (1990), Kosko (1994), Mujumdar and Sasikumar (2002), Aroba et al. (2007). Ratitsch and Schulz purpose applications in the areas of geochemistry and hydrology - Ratitsch (2000), Schulz et al. (1999). The utility of fuzzy mathematics in analyzing and understanding the compositional heterogeneity of clay minerals was shown in Varadachari et al. (2003).The examples of applications of fuzzy logic to stratigraphy and porosity are mentioned in Fang (1997). Fuzzy sets were successfully incorporated in the geographic information systems (GIS) supporting geographic problem solving, see e. g. Petry et al. (2005). This book includes examples of the use of fuzzy sets in issues such as terrain features, landscape morphology, spatial extents and approaches for spatial interpolation. A variety of applications using fuzzy sets are covered including data mining, spatial decision making, ecological simulation, and reliability in GIS. The fuzzy logic technique in GIS provides a flexible tool to test a conceptual exploration model when there is good data coverage within the area of interest, see e. g. Sawatzky et al. (2009) . Spatial modelling using GIS techniques for indentifying areas of mineral prospectivity have become increasingly popular because of their data driven approach and transparency, see e. g. Bonham-Carter et al. (1989), Agterberg et al. (1993), Harris et al. (2001). The genesis of mineral deposits is a good example for situations where the high complexity of physical and chemical processes can lead to an incomplete understanding of the deposit information. Application of the fuzzy technology in mineral processing processes can be found in Cierpisz and Heyduk (2002) and Karr and Weck (1996). PID controllers are the most widely used controllers in industry. Popularity of them can be attributed partly to their robust performance in a wide range of operating conditions and partly to their functional simplicity. PID controllers provide robust and reliable performance for most systems if the PID parameters are tuned properly. Various tuning methods are described for example in Johnson et al. (2005), Ogunnaike and Ray (1994). Integrating models appear while modelling mass or energy accumulation, rotation of machineries, etc. They contain undesirable pole which needs to be shifted by suitable design of a feedback loop. Time delay in controlled systems has negative and unpleasant features with regard to feedback control and its quality, too. However, delay terms are inherent parts of many processes, plants and objects. The combination of integrating behaviour of the system and time delay makes controller design more difficult, and it requires utilization of some advanced procedures. Nowadays, PID tuning methods are proposed to deal with various integrating processes, see e.g. Åström and Hägglund (2006), Vítečková and Víteček (2008), Vítečková and Víteček (2009), Zhang et al. (2004). Chien and Fruehauf proposed an internal model control (IMC) method to find the settings for a PI controller used for control of a process consisting of an integrator and a time delay - Chien and Fruehauf (1990). Tyreus and Luyben proposed an alternative approach based on classical frequency response methods for PI controller settings in Tyreus and Luyben (1992). Wang and Cluett also discussed mentioned control problem and proposed a PID controller design method based on specification in terms of demanded control on signal trajectory which is scaled with respect to the magnitude of the coefficient in the second term of the Taylor's series expansion in Wang and Cluett (1997). In recent years, increasing attention has been paid to the problems of stability analysis and controller design for time delay systems, see e. g. Lee et al. (2000), Zhang et al. (1999). Visioli proposed a tuning method for integrating systems

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in Visioli (2001). Chidambaram and Sree introduced a simple method for the PI, PD and PID controller settings for integrating processes based on matching the coefficients of corresponding powers of s in the numerator and those in the denominator of the closed-loop transfer function for a servo problem, see e.g. Chidambaram and Sree (2003). PID control is widely used to control stable processes; however, its application to integrating processes is less common. In this paper, we propose fuzzy PID controllers for integrating processes with time delay. Three numerical examples are presented to confirm the effectiveness of the proposed neuro-fuzzy control. Using of fuzzy control can lead in these cases to more successful control than using of classical controllers.

Methods

Analytical dominant multiple pole method

The analytical dominant multiple pole method (Vítečková (2001), Vítečková and Víteček (2008), Vítečková and Víteček (2009)) is based on the assumption that the dominant pole of the control system is multiple and real, which ensures the stable non-oscillatory control process closed to the marginal process. Simultaneously, it is supposed that the influence of the non-dominant zeros and poles can be neglected. Let us have a control system depicted in Fig.1. Here, $e(s)$, $w(s)$, $u(s)$ and $y(s)$ are the Laplace transforms of the control error, the reference value, the control input and the controlled output; $G_C(s)$ is the controller transfer function; $G_P(s)$ is the plant transfer function. The transfer function of the standard PID controller is following

$$G_C(s) = K_C(1 + \frac{1}{T_I s} + T_D s) \tag{1}$$

where K_C is the proportional term weight (the controller gain), T_I is the integral time, T_D is the derivative time. The multiple dominant pole of the control system is obtained by the solution of the equation system

$$\frac{d^i N(s)}{ds^i} = 0, \ i = 0, 1, \ldots, m \tag{2}$$

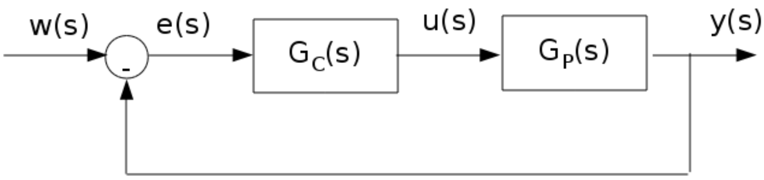

Fig. 1: Control system with standard controller.

where $N(s)$ is the characteristic polynomial of the control system, and m is the number of the controller adjustable parameters. The characteristic polynomial $N(s)$ of the control system Fig. 1 can be determined on the basis of the open-loop transfer function $G_0(s)$ (3) in the form (4).

$$G_0(s) = G_C(s)G_P(s) = \frac{M_0(s)}{N_0(s)} \tag{3}$$

$$N(s) = M_0(s) + N_0(s) \tag{4}$$

Fuzzy PID controller

The fuzzy controllers are usually based on the structure of the standard PID controllers. Fuzzy PID control has following (absolute) form:

$$u(t) = f(e(t), \frac{de(t)}{dt}, \int_0^t e(\tau)d\tau) \tag{5}$$

Takagi-Sugeno fuzzy inference system is generated using subtractive clustering in the form:

$$If \ e \ is \ A_i \ and \ \frac{de(t)}{dt} \ is \ B_i \ and \ \int e \ is \ C_i \ Then \ f_i = p_i e + q_i \frac{de(t)}{dt} + r_i \int e + s_i, \ i = 1, \ldots, n \tag{6}$$

where e is the control error, p_i, q_i, r_i, s_i are consequent parameters, and n is number of rules. Various types of functions can be used for fuzzification, and the symmetric Gaussian function (*gaussmf* in MATLAB) μ is chosen for fuzzification of inputs in this approach. The symmetric Gaussian function depends on two parameters σ and c as it is seen in (7), where x represents $e, \frac{de}{dt}, \int e$.

$$\mu(x;\sigma,c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{7}$$

For obtaining of all needed parameters, it is necessary to have the data sets of $e, \frac{de}{dt}, \int e$ and u at first. These data can be obtained by simulations of control of processes using classical PID controllers. Stability of the system can be studied. In this paper, an Adaptive Neuro Fuzzy Inference System (ANFIS) based PID controller is applied, see e. g. Jang (1993). The ANFIS structure with first order Sugeno model, Gaussian membership functions with product inference rule are used at the fuzzification level. Hybrid learning algorithm that combines least square method with gradient descent method is used to adjust the parameter of membership function.

Results and Discussion

In the paper, the controlled processes with transfer functions (8)-(10) were considered

$$\frac{k}{s(Ts+1)} \tag{8}$$

$$\frac{k}{s}e^{-T_d s} \tag{9}$$

$$\frac{k}{s(Ts+1)}e^{-T_d s} \tag{10}$$

where k is the process gain, T is the process time constant, T_d is the process time delay, s is the complex variable in the Laplace transform.

Example 1

Let us have the first order and integrating plant without time delay described by the transfer function (11)

$$\frac{1}{s(1.5s+1)} \tag{11}$$

The feedback PID controller (1) was tuned using above described dominant multiple pole method by Vítečková and Víteček (2009). The found controller parameters were $K_C = 3.556$, $T_I = 3.375$, $T_D = 0.8438$ and the controller was used for control of the process (11). Simulations of control were used for obtaining the data sets of $e, \frac{de}{dt}, \int e$ and u that were needed for the fuzzy controller design with the Takagi-Sugeno-type fuzzy inference system (6). The parameters σ and c obtained for the Gaussian symmetric function (7) are listed in Table 1. The consequent parameters in the control rule are listed in Table 2 . Fig. 2 demonstrates the graphical representation of the Takagi-Sugeno fuzzy inference system, and Fig. 3 shows the structure of Anfis.

Tab. 1: Parameters of the Gaussian Membership Functions

e		de		$\int e$	
σ	c	σ	c	σ	c
0.041	-0.0011	0.16	2.8x10^{-4}	0.022	0.0043

Tab. 2: Consequent Parameters

p_i	q_i	r_i	s_i
8.9	3.9	1.9	0.0

Neuro-fuzzy and PID controllers were compared in the task of set-point tracking and in the task of disturbance rejection. Fig. 4 presents the comparison of the simulation results obtained by designed neuro-fuzzy controller and PID controller tuned using dominant multiple pole method when step changes of the reference w are from 1 to 1.2 at

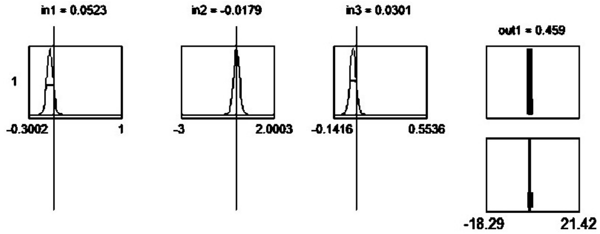

Fig. 2: Fuzzy inference system for the system (11).

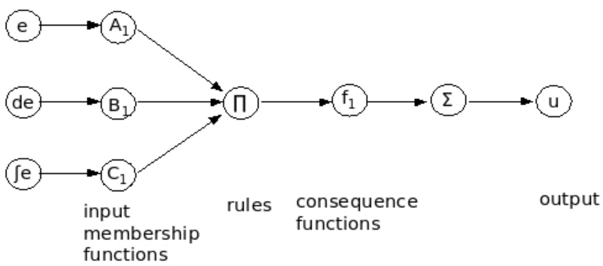

Fig. 3: Structure of Anfis for the system (11).

time t=20 and from 1.2 to 0.9 at time t=40. Fig. 5 presents the simulation results of the neuro-fuzzy and PID control in the case when disturbances affect the controlled process. Disturbances are represented by their step changes from 1 to 1.5 at time t=20 and from 1.5 to 0.5 at time t=40. The comparison of the neuro-fuzzy controller and PID controller was made using *IAE* and *ISE* integral performance indexes described as follows:

$$IAE = \int_0^\infty |e|\, dt \tag{12}$$

$$ISE = \int_0^\infty e^2 dt \tag{13}$$

The *IAE* and *ISE* values are given in Table 3.

Tab. 3: Comparison of the Simulation Results by IAE and ISE

Controller	Set-point Tracking		Disturbance rejection	
	IAE	*ISE*	*IAE*	*ISE*
Neuro-fuzzy	1.57	0.48	2.54	0.56
PID	2.56	0.90	4.52	1.42

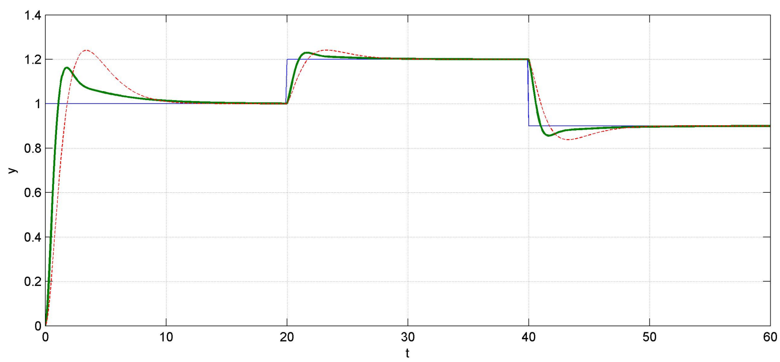

Fig. 4: Closed-loop control responses in the task of set-point tracking: reference (blue line), PID controller (red line), fuzzy controller (green line).

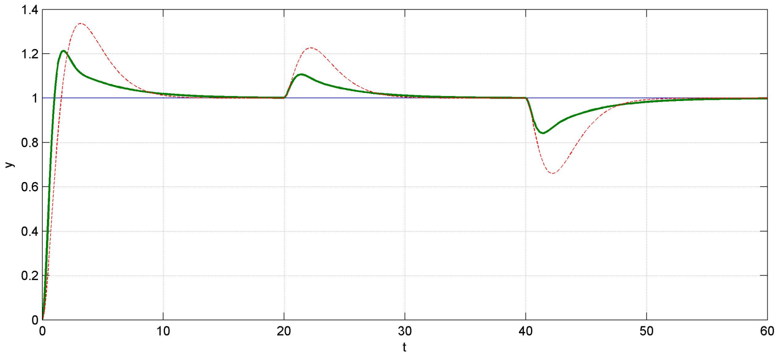

Fig. 5: Closed-loop control responses in the task of disturbance rejection: reference (blue line), PID controller (red line), fuzzy controller (green line).

Example 2

Suppose further the integrating plant with time delay:

$$\frac{0.05}{s}e^{-5s} \tag{14}$$

The parameters of the feedback PID controller (1) tuned using the dominant multiple pole method by Vítečková and Víteček (2009) are: K_C=3.556, T_I=3.375, T_D=0.8438. The parameters σ and c obtained for the Gaussian symmetric function (7) are listed in Table 4. The consequent parameters are listed in Table 5. Fig. 6 demonstrates the Takagi-Sugeno fuzzy inference system and Fig. 7 shows the structure of Anfis for the system (14).

Tab. 4: Parameters of the Gaussian Membership Functions

e		de		$\int e$	
σ_i	c_i	σ_i	c_i	σ_i	c_i
0.063	-5.5×10^{-4}	0.102	-1.0×10^{-3}	0.338	0.026
0.063	-8.3×10^{-4}	0.102	-8.7×10^{-5}	0.338	-3.75
0.063	-5.7×10^{-5}	0.102	5.9×10^{-3}	0.338	-1.33

Tab. 5: Consequent Parameters

p_i	q_i	r_i	s_i
4.9	11.46	0.39	-0.006
5.0	10.97	0.4	0.013
4.9	11.52	0.43	0.049

Neuro-fuzzy and PID controllers were again compared in the task of set-point tracking and in the task of disturbance rejection. Fig. 8 presents the comparison of the simulation results obtained by designed neuro-fuzzy controller and PID controller tuned using dominant multiple pole method when step changes of the reference w are from 1 to 1.2 at time t=100 and from 1.2 to 0.9 at time t=200. Fig. 9 presents the simulation results of the neuro-fuzzy and PID control in the case when disturbance changes from 1 to 1.5 at time t=70 and from 1.5 to 0.5 at time t=140. Anfis performs static non-linear mapping from input to output space, but it cannot be used without modification to represent dynamic system. In order to identifity dynamic systems, a combination of Anfis with some time delay units and feedback is required. Hence, nonlinear dynamic systems or varying time dealy can be modelled by Anfis combined with some time delay units. Anfis is not available for all of the fuzzy inference system options. Specifically, Anfis only supports Sugeno-type systems. All output membership functions must be the same type and either be linear or constant. Different rule cannot share the same output membership function, namely the number of output membership functions must be equal to the number of rules. The comparison of the neuro-fuzzy controller and the PID controller was made also using IAE and ISE integral performance indexes and their calculated values are given in Table 6.

Tab. 6: Comparison of the Simulation Results by IAE and ISE

Controller	Set-point Tracking		Disturbance rejection	
	IAE	*ISE*	*IAE*	*ISE*
Neuro-fuzzy	16.95	8.17	22.10	13.03
PID	23.46	10.96	32.95	16.23

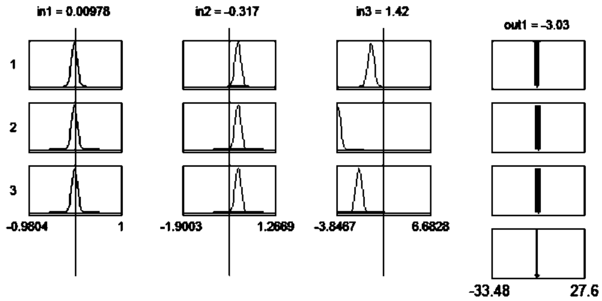

Fig. 6: Fuzzy inference system for the system (14).

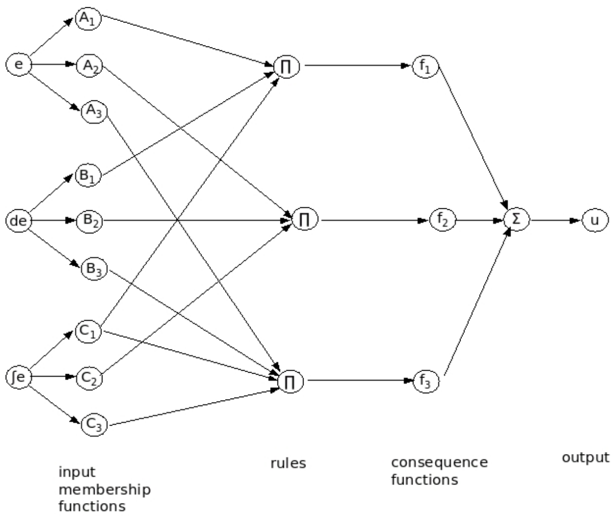

Fig. 7: Structure of Anfis for the system (14).

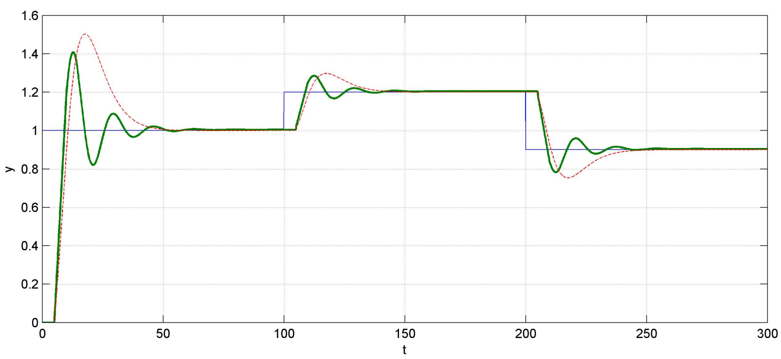

Fig. 8: Closed-loop control responses in the task of set-point tracking: reference (blue line), PID controller (red line), fuzzy controller (green line).

Example 3

In the 3^{rd} example, let us have the first order integrating plant with time delay:

$$\frac{0.05}{1.5s+1}e^{-5s} \tag{15}$$

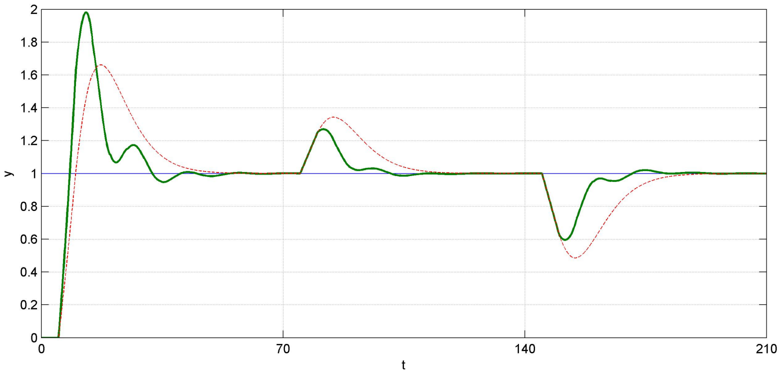

Fig. 9: Closed-loop control responses in the task of disturbance rejection: reference (blue line), PID controller (red line), fuzzy controller (green line).

The parameters of the feedback PID controller (1) tuned using the dominant multiple pole method by Vítečková and Víteček (2009) are: K_C=3.556, T_I=3.375, T_D=0.8438. The parameters σ and c obtained for the Gaussian symmetric function (7) are listed in the Table 7. The consequent parameters are listed in Table 8. Fig. 10 presents the comparison of the simulation results obtained by neuro-fuzzy controller and PID controllers tuned using dominant multiple pole method. Fig. 11 presents the simulation results of the neuro-fuzzy and PID control in the case when disturbances affect the controlled process. Disturbances were represented by step changes from 1 to 1.5 at t=50 and from 1.5 to 0.5 at t=100.

Tab. 7: Parameters of the Gaussian Membership Functions

e		de		$\int e$	
σ_i	c_i	σ_i	c_i	σ_i	c_i
0.046	-2.5×10^{-4}	0.176	$-3.29\text{x}10^{-4}$	0.109	1.7×10^{-3}
0.046	1.1×10^{-4}	0.176	-1.09×10^{-4}	0.109	-1.49
0.046	2.2×10^{-4}	0.176	-2.10×10^{-4}	0.109	-0.49

Tab. 8: Consequent Parameters

p_i	q_i	r_i	s_i
2.33	2.84	0.30	-0.001
1.99	4.00	1.0	0.007
2.03	3.83	1.14	0.079

Comparison of the neuro-fuzzy controller and the PID controller done using *IAE* and *ISE* criteria is given in Table 9.

Tab. 9: Comparison of the Simulation Results by IAE and ISE

Controller	Set-point Tracking		Disturbance rejection	
	IAE	*ISE*	*IAE*	*ISE*
Neuro-fuzzy	3.93	1.45	7.33	2.59
PID	5.47	1.98	26.93	16.78

Conclusion

In this paper, simple neuro-fuzzy PID controllers are proposed for integrating process, one of them without and two other with dead-time. Designed fuzzy controllers lead to better control performance in both tasks, the set-point tracking and disturbance rejection. Comparison of designed fuzzy controllers with classical PID controller tuned by

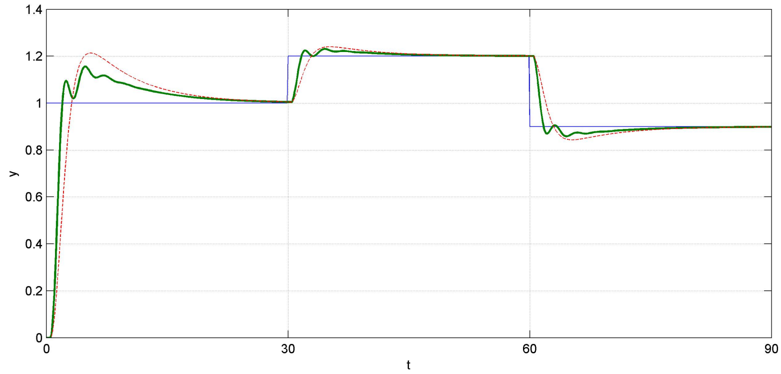

Fig. 10: Closed-loop control responses in the task of set-point tracking: reference (blue line), PID controller (red line), fuzzy controller (green line).

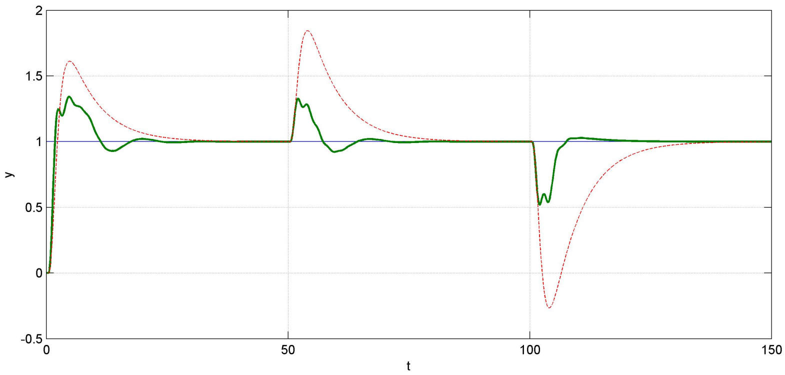

Fig. 11: Closed-loop control responses in the task of disturbance rejection: reference (blue line), PID controller (red line), fuzzy controller (green line).

the dominant multiple pole method is based on simulation experiments. Presented simulation results demonstrate the superiority of the proposed fuzzy approach.

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