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INTELLIGENT FUZZY CONTROL FOR NONLINEAR PROCESSES

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Abstract:

The paper deals with the development of a new adaptive fuzzy control method and algorithm for nonlinear dynamic systems based on the hybrid approach using fuzzy logic and genetic techniques. The new hybrid control methodology based on adaptive switching uses the principle of control parameters adaptation for all operating points of a highly nonlinear process. The control algorithm is realized by a fuzzy controller with parameter optimization for different operating points using a genetic algorithm. Proposed theoretical results are verified on a case study dealing with control design for a nonlinear model of continuously stirred tank reactor. Obtained practical results confirm the high performance and possibility of implementation of this methodology for a broad real plants in industry.

Keywords:

Adaptive control, fuzzy hybrid systems, fuzzy logic, genetic algorithms, hybrid intelligent methods, nonlinear systems.

ACM Computing Classification System:

Automated reasoning, machine learning theory, nonlinear equations, artificial intelligence.

Introduction

Automatic control methods and algorithms have developed for a long time from conventional approaches up to modern control methods featuring robustness, optimality and intelligence. In industrial practice, conventional control methods based on PID algorithms (86%), state controllers (5%), as well as new control methods and algorithms based on optimality, prediction, robustness, adaptivity and artificial intelligence approaches are the most applied currently in industry. These modern methods evolved from the latest knowledge in mathematics, informatics, communication and control theory [1]. Development of modern control methods that belong to the soft techniques has allowed further improvement of control algorithms for continuous-time processes, e.g. design and application of algorithms realized on the basis of fuzzy logic (FL), artificial neural networks (ANN), and genetic algorithms (GA). These intelligent control algorithms are designed using expert analysis or by measured input-output data, and are often easier-to-use and provide improved performance compared with control algorithms that are based on differential or difference equations [2].

Hybrid intelligent systems (HIS; neuro-fuzzy, fuzzy-genetic, neuro-genetic, etc.) are another candidate for application of computational intelligence methods which combine benefits of individual intelligent computational methods trying to eliminate their drawbacks. Application of embedded computer systems based on combined hybrid control methods can significantly improve performance, reliability, and safety of operations, systems and devices [3].

Block diagram of hybrid intelligent systems is shown in (Fig.1).

In this paper an effective hybrid intelligent control method is proposed that combines computational intelligence methods and control parameter adaptation for all operating points of a nonlinear system. The proposed approach has been tested on a case study dealing with control of continuously stirred tank reactor (CSTR).

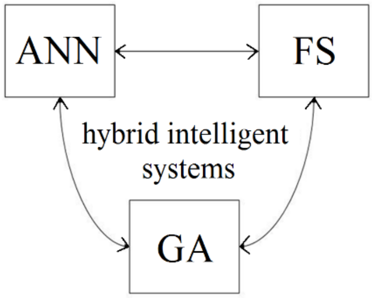

Fig.1. Block diagram of hybrid intelligent systems
(ANN – artificial neural networks, FS – fuzzy systems, GA – genetic algorithms).

1 Problem Formulation

The paper proposes a new control methodology for nonlinear systems with multiple inputs; one of them is a switching control parameter $p(t)$ used for adaptation. The fuzzy control law depends on the adaptation parameter $p(t)$ and the output variable $y(t)$. (Fig.2)

The working space (p, y) consists of a number of operating points (from 50 up to 100) either uniformly distributed or more densely concentrated around designed using genetic algorithm. Parameters of the fuzzy controller are switched during control based on the smallest Euclidean distance between the current position in the (p, y) working space, and the closest operating point.

A. Fuzzy Controller Design

In the adaptive switching hybrid control approach, well-known fuzzy controller types can be used and new types of fuzzy controller can be developed with other inputs and outputs.

Next, the incremental fuzzy PID controller with a 3-D base of rules will be considered, where the I component is realized by the control error $e(t)$, the P component is realized by the first derivative of the output variable $\mathrm{d}y(t)/\mathrm{d}t$, and the D component by the second derivative of the output variable $\mathrm{d}^2y(t)/\mathrm{d}t^2$. Output of the fuzzy controller is the derivative of control action $\mathrm{d}u(t)/\mathrm{d}t$. Inputs and outputs of the fuzzy controller are normalized to be within the range $<-1; 1>$ according to the size of the reference step change; this scaling guarantees that the whole range of the fuzzy controller for any size of the reference step is utilized. Block diagram of the fuzzy PID controller with a 3-D rule base and normalization is shown in (Fig.3).

In this paper, consider the fuzzy inference system to be of Mamdani type [3] where each input and output fuzzy variable has 7 membership functions; for simplicity assume that they have the shape of an isosceles triangle. Example of the membership function layout of the fuzzy input variable is depicted in (Fig.4).

The rule base can be known in advance or be determined together with the parameters of the membership functions.

Consider a beforehand known quasi-linear rule base in which known control rules with fuzzy PID controller are applied, e.g. "*if the control error is large, the change of control action is large*", or "*if the control error is zero and the change of control error (output variable) is zero, change of control action is zero, too*". In this case the rule base contains 343 rules, one rule per each combination of $e(t)$, $dy(t)/dt$, and $d^2y(t)/dt^2$. For defuzzification the center of gravity method has been used.

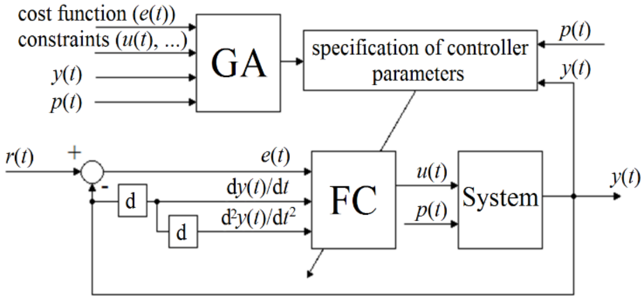

Fig.2. Adaptive switching hybrid control
(FC – fuzzy controller, GA – genetic algorithm, d – derivative,
$p(t)$ –adaptation parameter, $y(t)$ – output variable, $r(t)$ – reference variable).

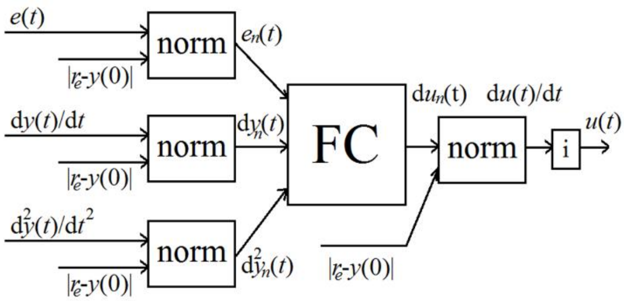

Fig.3. Block diagram of a fuzzy PID controller with 3-D rule base and normalization
(FC – fuzzy controller, i – integration, norm – normalization, r_e – end reference value,
$y(0)$ – initial output value; $e_n(t)$, $dy_n(t)$, and $d^2y_n(t)$ – normalized control error and first and second derivatives of output variable, respectively).

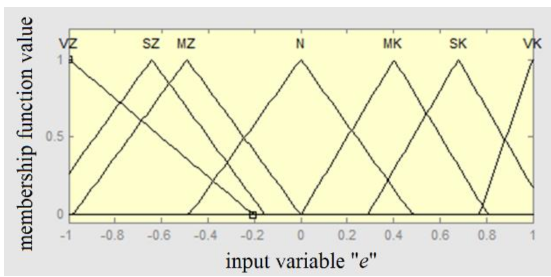

Fig.4. Example of a membership function of a fuzzy input variable
(x – axis: e – control error; y – axis: membership function value).

B. Normalization of Fuzzy Controller Inputs and Outputs

For the fuzzy PID controller normalization is used to get its input and output fuzzy variables in the range <-1; 1>. Input variables are normalized as follows

$$e_n(t) = e(t)/|e(0)| \tag{1}$$

$$\frac{\mathrm{d}y_n(t)}{\mathrm{d}t} = gain_1 . \frac{\mathrm{d}y(t)}{\mathrm{d}t} / |e(0)| \tag{2}$$

$$\frac{\mathrm{d}^2 y_n(t)}{\mathrm{d}t} = gain_2 . \frac{\mathrm{d}^2 y(t)}{\mathrm{d}t} / |e(0)| \tag{3}$$

where $e_n(t)$, $\mathrm{d}y_n(t)/\mathrm{d}t$, and $\mathrm{d}^2y_n(t)/\mathrm{d}t^2$ are normalized values of $e(t)$, $\mathrm{d}y(t)/\mathrm{d}t$, and $\mathrm{d}^2y(t)/\mathrm{d}t^2$, respectively, and $e(0)$ is initial value of the control error for the given reference step change; $gain_1$ and $gain_2$ are parameters of normalization.

Similarly, the output value is obtained from the normalized output of the fuzzy system:

$$\frac{\mathrm{d}u(t)}{\mathrm{d}t} = gain_3 . \frac{\mathrm{d}u_n(t)}{\mathrm{d}t} / |e(0)| , \tag{4}$$

where $\mathrm{d}u_n(t)/\mathrm{d}t$ is a normalized value of $\mathrm{d}u(t)/\mathrm{d}t$ and $gain_3$ is parameter of normalization.

Parameters of normalization $gain_1$, $gain_2$, $gain_3$ are set to selected values to provide fuzzy control in the whole range of fuzzy variables for all operating points at once. They can be proposed also separately together with parameters of the fuzzy system for each selected operating point. In this case, only single values of $gain_1$, $gain_2$, and $gain_3$ are used identical for all operating points and an experimental method is applied to find them.

C. Genetic Control Algorithm

For different operating points (p, y) parameter values of the fuzzy PID controller are designed off-line by genetic algorithm [4].

A chromosome (string) $\bar{x}$ is a set of required parameters of the fuzzy PID controller, which are centers and spreads of membership functions.

Genes of the string are genes of fuzzy variables (fuzzy input variable e, $\mathrm{d}y$, and d^2y, and fuzzy output variable $\mathrm{d}u$), genes of membership functions, and genes of individual parameters of the fuzzy PID controller; the latter ones are the smallest genes and they form the whole string. In population generating, crossovers and mutations, the rules of fuzzy system design are to be taken into account.

At the beginning of the genetic algorithm, the initial population P_0 is generated with a selected number of individuals (strings) in the population. Next steps include repeated chosen number of generations, evaluation of individuals (calculation of the fitness function), selection of the best individuals (group A) and some other individuals (group B) for the new population (generation), and selection of individuals to a working group (group C), their crossover and mutation. The best individual of the last generation is the required set of parameters of the fuzzy PID controller. Block diagram of the genetic algorithm is depicted in (Fig.5).

In the process of individuals' evaluation simulation of the control loop with the fuzzy PID controller is performed; fuzzy controller parameters are determined on the basis of the given string from the population, and closed-loop time responses for upwards and downwards step changes in reference value near the operating point are monitored.

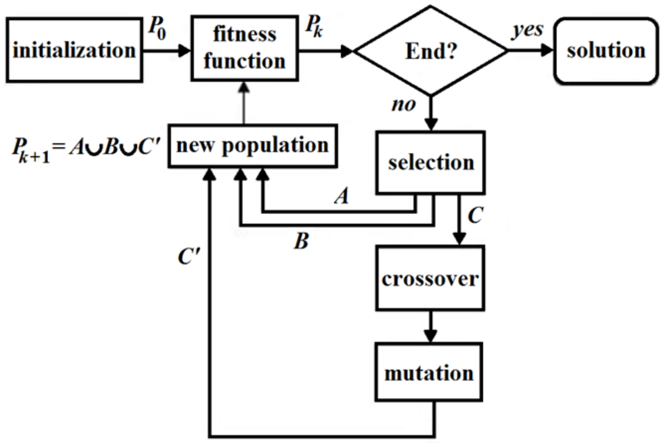

Fig.5. Block diagram of a genetic algorithm
(P_0 – initial population, P_k and P_{k+1} – k-th and k+1-st population,
A – group of best individuals, B – group of other individuals,
C – working group, C' – modificated working group).

Assume that the cost function $J(\bar{x})$ is the integral or a sum of absolute values of the control error (IAE, SAE) for step change in reference value upwards $J_u(\bar{x})$ and downwards $J_d(\bar{x})$; the fitness function $F(\bar{x})$ is the cost function extended with the limitation functions $L_u(\bar{x})$ and $L_d(\bar{x})$ for step change in reference value upwards and downwards, respectively.

Cost function:

$$J(\bar{x}) = J_{\mathrm{u}}(\bar{x}) + J_{\mathrm{d}}(\bar{x}), \tag{5}$$

where

$$J_i(\bar{x}) = \int_{t=0}^{T} \left| e(t, \bar{x}) \right| \mathrm{d}t \tag{6}$$

and i = u, d is index of the step change in reference value upwards and downwards, respectively, J is cost function, e is control error, $\bar{x}$ is a string, T is final observed time and t is continuous time.

Fitness function:

$$F(\bar{x}) = J(\bar{x}) + L_{\mathrm{u}}(\bar{x}) + L_{\mathrm{d}}(\bar{x}), \tag{7}$$

where i = u, d is index of the step change in reference value upwards and downwards, respectively, F is fitness function, J is cost function, L is limitation function and $\bar{x}$ is a string.

D. Adaptation of Fuzzy Controller Parameters

Adaptation of fuzzy controller parameters is realized by switching fuzzy controller parameters based on minimizing the Euclidean distance between the current operating point and operating points for which the parameters were designed.

At the beginning of the adaptation design, operating points are determined for which fuzzy controller parameters will be designed using genetic algorithm described in the previous section. The adaptation consists in finding such an operating point, for which the fuzzy controller parameters were designed in advance and for which the following applies:

$$\left(p(t), y(t)\right) = \min_{p(t),\, y(t)} \left(\sqrt{\left(p(t) - p_i(t)\right)^2 + \left(y(t) - y_i(t)\right)^2} \right) \qquad (8)$$

where $i \in \{1, 2, ..., N_{OP}\}$, and N_{OP} is number of operating points for which the parameter values of fuzzy controller were designed, $(p(t), y(t))$ is the desired operating point, and $p_i(t)$ and $y_i(t)$ are values of adaptation parameter and output variables, respectively, in the i-th operating point.

2 Case Study: Continuously Stirred Tank Reactor

A. Process Description

Controlled process is a textbook model of continuously stirred tank reactor in which the irreversible reactions are A -> B -> C taking place. The feed stream to the reactor is pure species A, and the maximum conversion to product B is desired. The concentration of the product B (C_B) is measured (output variable $y = C_B$ [mol/l]) and the process is regulated by adjusting the temperature T of the reactor directly by a cascaded control system (control action $u = T$ [K]). Adaptation parameter p is a flow F ($p = F$ [l/min]). The system is governed by the equations

$$\dot{C}_A = \frac{F}{V}\left(C_{Af} - C_A\right) - k_1 C_A e^{-E_1/RT} \qquad (9)$$

$$\dot{C}_B = k_1 C_A e^{-E_1/RT} - k_2 C_B e^{-E_2/RT} - \frac{F}{V} C_B \qquad (10)$$

in which the concentrations C_A (concentration of the species A) and C_B are the state variables and the temperature T is the manipulated variable. V is volume of the reactor, C_{Af} is a first value of species A concentration, k_1 and k_2 are first (A -> B) and second (B -> C) reaction rate constants respectively, E_1 and E_2 are activation energies of reactions one (A -> B) and two (B -> C) respectively and R is a gas constant. E_1/R and E_2/R are proportions of molecules that reach activation energy. Values of the parameters are listed in Table I [5].

The steady state input-output response of the CSTR model with the flows p = 0.001, 0.01, ... 1000 l/min are shown in (Fig.6). It can be seen that the system comprises a static nonlinearity for every given p.

TABLE 1. PARAMETERS FOR THE CSTR MODEL.

Param.	**Value**	**Unit**	**Param.**	**Value**	**Unit**
V	100	l	C_{Af}	1	mol/l
k_1	7.2×10^{10}	min^{-1}	k_2	5.2×10^{10}	min^{-1}
E_1/R	8750	K	E_2/R	9700	K

Step responses for upward step changes in input variable are depicted in (Fig.7). Step responses with initial output value $y(0)$ = 0.4 mol/l and various values of adaptation parameter p are shown. By inspection, the controlled system features dynamic nonlinearity.

It can be seen from the figure, that step responses for step changes in input variable upwards with small adaptation parameter p (p = 1 l/min) are slightly nonlinear and the settling time and system gain are large and the larger is adaptation parameter p, the more nonlinear are the step responses and the shorter is the settling time and the smaller is the system gain.

The CSTR is a system with a positive gain, without undershoot, therefore it is appropriate for the control by the proposed adaptive switching hybrid fuzzy PID control with a 3-D rule base.

B. Control Design

The working space was covered by 6 operating points (p, y): (100, 0.5044), (100, 0.3272), (100, 0.1500), (1, 0.5606), (1, 0.3553) and (1, 0.1500).

Parameters of fuzzy PID controller were designed by genetic algorithm for each of these operating points. The parameters of normalization were set to: $gain_1 = 2$, $gain_2 = 0.0333$, and $gain_3 = 1000$. These parameters have been identified in an experimental way, from responses of the system to PID control and by manual fine-tuning.

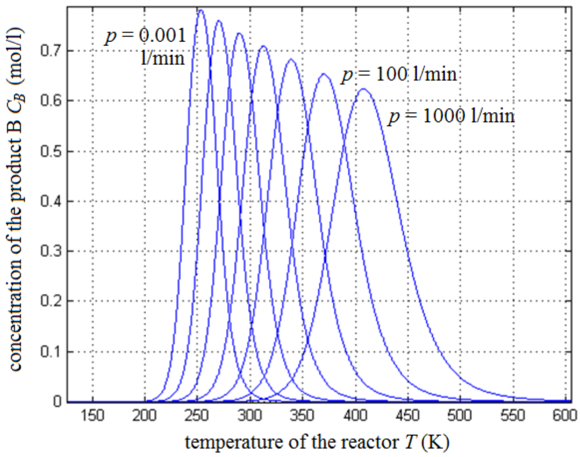

Fig.6. Steady-state input-output response of the CSTR model for different flow values (p).

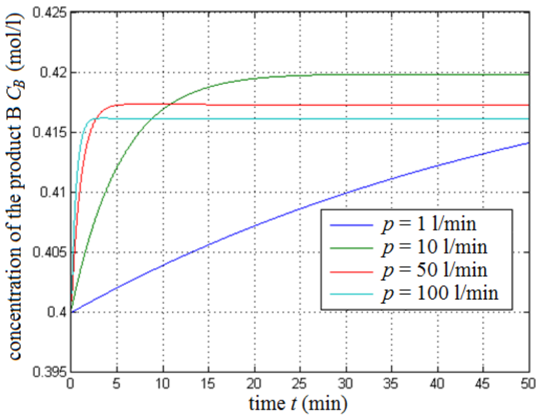

Fig.7. Step responses of the CSTR model for different initial output and flow values $y(0)$ and p, respectively, for upward step changes in input variable.

Furthermore, control parameters were adjusted as follows: sampling time T_s = 0.01 min, simulation time T_{sim} = 50 min, maximum allowed size of control action derivation du_{max} = 600 K, maximum allowed value of overshoot η_{max} = 5%, half value of deadband size δ = 0.5%, and size of step changes in reference value d_{step} = 0.15 mol/l.

Parameters of genetic algorithm were set as follows: number of individuals in population N_i = 10 and number of generations N_g = 10. For working group, there were selected 6 strings: string with the lowest and the second lowest fitness function and 4 strings selected by tournament selection. For new population, there were selected 4 strings: string with the lowest fitness function, one string selected by tournament selection, one by random selection and one new, generated string.

C. Performance Evaluation

The proposed control methodology was tested for reference step change upwards (Fig.8) and downwards (Fig.9).

In (Fig.8) there are shown time responses of controlled output y (concentration of the product B C_B) and control action u (temperature T) for adaptation parameter p = 10 l/min and step change of reference variable r from start reference value r_s = 0.35 mol/l to end reference value r_e = 0.45 mol/l.

In (Fig.9), there are shown time responses of controlled output y and control action u for adaptation parameter p = 80 l/min and step change of reference variable r from r_s = 0.35 mol/l to r_e = 0.3 mol/l.

As it can be seen from the figure, the controlled time is in these cases smaller than 10 seconds and maximum overshoot is under the desired maximum overshoot 5%.

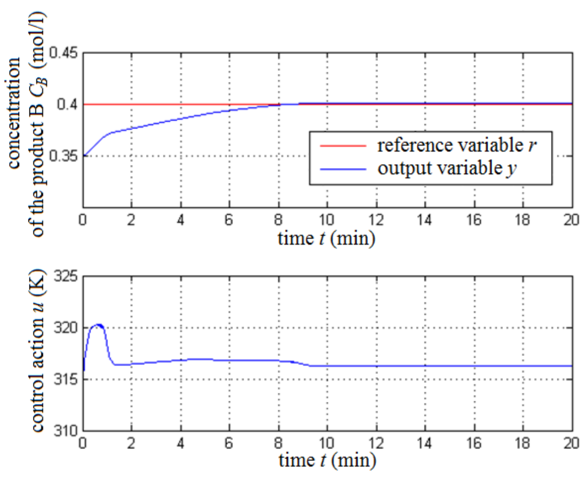

Fig.8. Time responses of controlled output y and control action u for step change of reference variable r upwards (start reference value r_s = 0.35 mol/l, end reference value r_e = 0.4 mol/l, adaptation parameter p = 10 l/min).

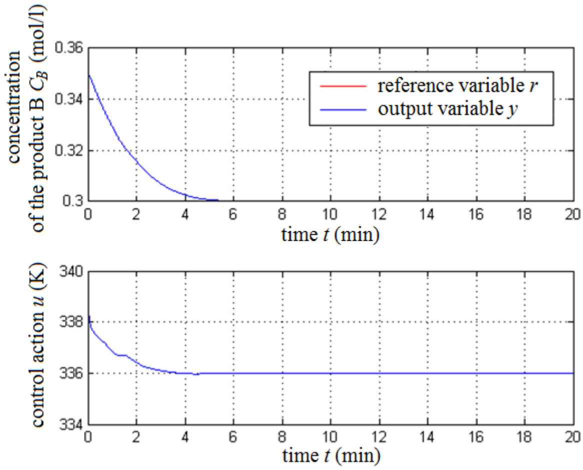

Fig.9. Time responses of controlled output y and control action u for step change of reference variable r downwards (start reference value r_s = 0.35 mol/l, end reference value r_e = 0.3 mol/l, adaptation parameter p = 80 l/min).

Conclusion

Adaptive switching hybrid control is an effective control method that allows controlling nonlinear systems with high-performance control. It provides high quality control at all points of the working space, even if the characteristics of the system in given points are significantly different.

This control methodology and principles based on adaptive switching is open and can be improved and extended to adaptation with continuous change of fuzzy controller parameters, implemented by linear or cubic interpolation, or other type of interpolation or approximation, e.g. artificial neural networks. In the fuzzy controller in addition to the membership functions also the rule base can be optimized. In the fuzzy controller design also the learning ability of the artificial neural networks can be exploited to learn the fuzzy system to existing control by combination of fuzzy systems and artificial neural networks (hybrid soft computing methods).

The proposed methodology can be used for the control of highly nonlinear processes in industries (automotive, robotics, mechatronics, chemical processes, biotechnology etc.).

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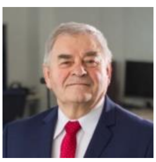

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