МАТЕМАТИЧНЕ МОДЕЛЮВАННЯ В ПРИРОДНИЧИХ НАУКАХ ТА ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ

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FUZZY MODELING IN CONTROL SYSTEMS

The method of synthesis of the control system based on the theory of fuzzy sets has been formulated. The results of the simulation of the system with a fuzzy logical controller and neuro-controller are presented. MATLAB — Simulink, Fuzzy Logic Toolbox — was used to build models and rulebases.

The method of fuzzy adaptation of parameters for regulator's settings is proposed. Modelling results showed that at the constant parameters of the object of regulation, the system with fuzzy regulators and a neuro-controller has better dynamic performance compared to classical systems. An analysis of the work of the fuzzy regulator has been carried out.

***Keywords**: fuzzy PID-regulator, linguistic variable, neuro-controller, fuzzy adaptation block, quality of regulation, transition process.*

Сформульовано метод синтезу системи керування на основі теорії нечітких множин. Наведено результати моделювання системи з нечітким логічним контролером та нейроконтролером. MATLAB — Simulink, Fuzzy Logic Toolbox — використовувався для побудови моделей та баз правил.

Запропоновано метод нечіткої адаптації параметрів для налаштувань регулятора. Результати моделювання показали, що при постійних параметрах об'єкта регулювання система з нечіткими регуляторами та нейроконтролером має кращі динамічні характеристики порівняно з класичними системами. Проведено аналіз роботи нечіткого регулятора.

***Ключові слова**: нечіткий PID-регулятор, лінгвістична змінна, нейроконтролер, блок нечіткої адаптації, якість регулювання, перехідний процес.*

Problem's Formulation

The tasks solved by information systems can in most cases be reduced to a number of typical ones, among which are the following: Classification of images; Approximation of functions; Prediction); Optimization; Regulation — transition and maintenance of the system in the required state.

Regulation is the most complex, and most of the time requires other auxiliary tasks solved. Control systems are, generally, characterized by non-linear dependencies, complex to model dynamics, uncontrollable noises and interferences. The classic Control Theory is based on the idea of linearisation of systems. Hence a more effective approach would be a development of control systems that are based on an adaptive approach, an amalgam of methods from theory of neural networks and fuzzy logic.

Controllers based on this innovative concept are capable of providing higher values of modulation quality in numerous cases in comparison to those of classic controllers. By incorporating fuzzy control algorithm synthesis and technology of neural network building, it is possible to optimise complex control loops without conducting additional comprehensive, mathematical research.

Analysis of recent research and publications

The use of linear proportional–integral–derivative (PID) regulators in non-linear object management systems often results in a poor regulatory process characterized by high re-regulation values, static error and/or transition time.

Analysis of the literature [1—5] showcased that there is a large number of approaches to the problem of synthesis of non-linear object control systems with random signals, and there is no universal controller yet.

Formulation of the study purpose

PID controllers are performing poorly when managing non-linear and complex systems, or when information about the object of management is insufficient. Regulators can be improved in some cases by fuzzy logic, neural networks, and genetic algorithms. These methods are referred to around the world as "soft-computing", emphasizing their difference from "hard-computing", which consists of the ability of the method to operate with incomplete and inaccurate data. A variety of methods can be combined in a single controller: fuzzy-PID, neuro-PID, neuro-fuzzy-PID controllers with genetic algorithms. The main disadvantage of fuzzy and neural network controllers is the complexity of their configuration: the compilation of a base of fuzzy rules and the training of a neural network.

The problem of creating a rule base is one of the key challenges in building a fuzzy logical controller. Different methods are used to solve it: either interviewing an experienced operator, or fixing decisions made by the operator in different situations, or tracking the desired trajectory of control based on any type of considerations.

This paper proposes a fuzzy adaptation of parameters of the PID-controller settings, allowing to take into account the non-linear properties of the object and provide the required quality of regulation when using the search algorithms of the Simulink software package also the synthesis of a neuro-controller with prediction implemented using MATLAB.

Presentation of the main material

An example is the desired trajectory of a closed system with a PID-controller and a third-order object (Fig. 1).

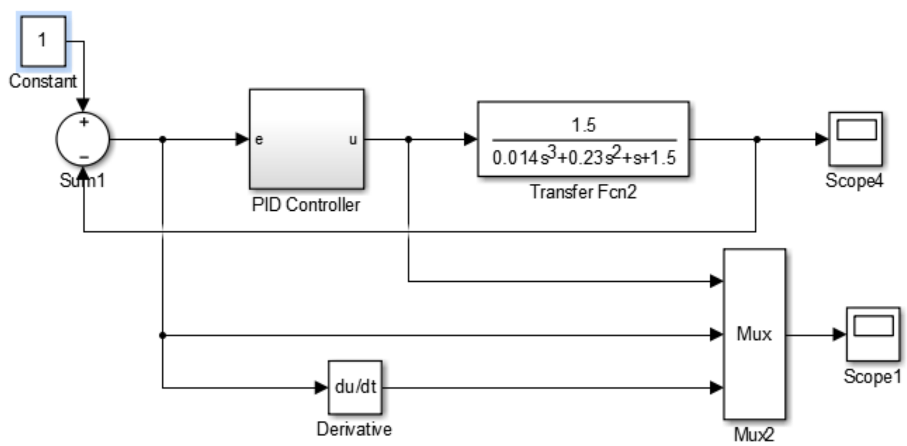

Fig. 1. System with negative feedback and PID-controller

The mathematical model of the system with the PID-controller is researched in terms of transitional processes by "error," "derivative error" and "output" when the task signal jumps and with the constant parameters of the control object (Fig. 2).

Fig. 2 shows transition processes in the system by "error," "derivative error" and "output" (top curve) when the input signal jumps and at the constant parameters of the control object.

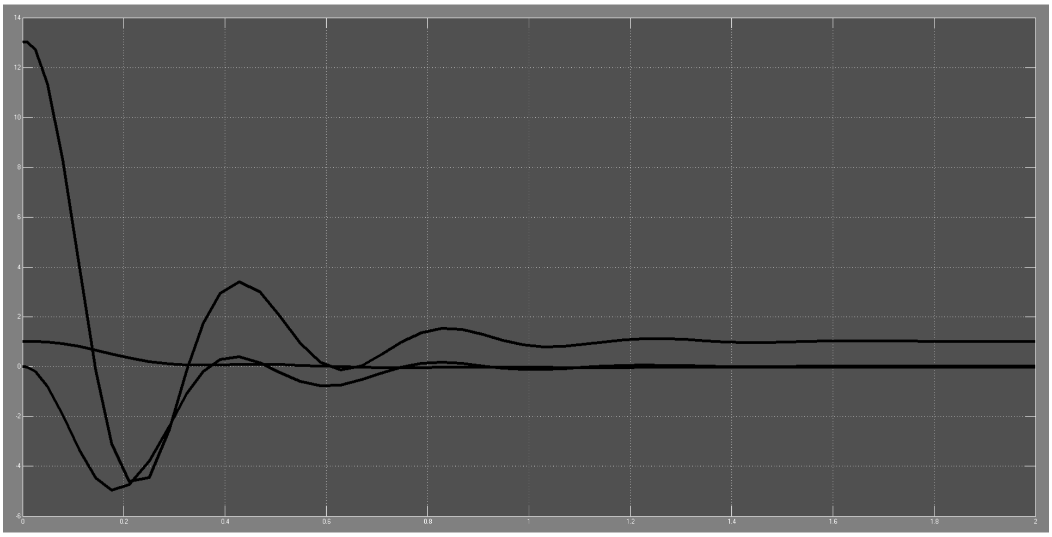

Fig. 2. Transitional processes of the measurable values of input-output of a controller

The fuzzy adaptive PID controller consists of a linear PID controller described by the ratio of

$$u(t) = K_p e(t) + K_i \int_0^t e(t)dt + K_d \frac{de}{dt} \tag{1}$$

and a fuzzy adaptation block proportional to K_p, integral K_i and differential K_d coefficients, that contains input fuzzification operations (error $e = y_0 - y$ and it's speed de/dt), fuzzy rules, fuzzy output and defuzzification operation of three outputs, those are definitions and refinements K_p, K_i, K_d. Variables e and $e' = de/dt$ vary in a range [–3, 3], coefficients: K_p — in range [–0.3, 0.3]; K_i — in range [–0.06,0.06] and accept 7 linguistic values NB, NM, NS, Z, PS, PM, PB (Negative Big, Negative Medium, Negative Small , Zero approaching zero, Positive Small, Positive Medium, Positive Big).

Internal structure of a fuzzy adaptation module

The main steps of building fuzzy rule groups connecting the error e and its derivative e' with three coefficients K_p, K_i, K_d [1]: 1) if e is relatively high, then it should be decreased by increasing K_p and decreasing K_d, as well as decreasing the impact of the integral; 2) if e and e' are acceptable K_p should be decreased until a certain necessary value that would decrease the amounts of re-adjustment and overall influence on the system is reached; 3) If e is very small, K_p and K_i should be increased, to introduce higher stability to the system K_d should be changed so, that any jittering is avoided in the system. if e is too low, we're increasing K_d, if e' is too high, we decrease K_d.

Bases of production rules for coefficients K_p, K_i, K_d are demonstrated in tabl. 1—3. Fuzzy knowledge base rules, with which the proportional coefficient K_p, is refined, the integral coefficient K_i, the differential coefficient K_d are written in the form

R_p^1 : if e is NB, *e*' is NB, then K_p is PB, K_i is PS, K_d is NB,

.... ,

R_p^{49} : if e is PB, *e'* is PB, then K_p есть NB, K_i есть PB, K_d есть PB.

Table 1. Base of production rules of coefficient K_p

e / *de/dt*	**NB**	**NM**	**NS**	**Z**	**PS**	**PM**	**PB**
NB	PB	PB	PM	PM	PS	Z	Z
NM	PB	PB	PM	PS	PS	Z	NS
NS	PM	PM	PM	PS	Z	NS	NS
Z	PM	PM	PS	Z	NS	NM	NM
PS	PS	PS	Z	NS	NS	NM	NM
PM	PS	Z	NS	NM	NM	NM	NB
PB	Z	Z	NM	NM	NM	NB	NB

Table 2. Base of production rules of coefficient K_i

e / **de/dt**	**NB**	**NM**	**NS**	**Z**	**PS**	**PM**	**PB**
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NM	NM	NS	Z
NS	Z	NS	NM	NM	NS	NS	Z
Z	Z	NS	NS	NS	NS	NS	Z
PS	Z	Z	Z	Z	Z	Z	Z
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PS	PS	PS	PB

Table 3. Base of production rules of coefficient K_d

And / **the/dt**	**NB**	**NM**	**NS**	**Z**	**PS**	**PM**	**PB**
NB	NB	NB	NM	NM	NS	Z	Z
NM	NB	NB	NM	NS	NS	Z	Z
NS	NB	NM	NS	NS	Z	PS	PS
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PS	PM	PB
PM	Z	Z	PS	PS	PM	PB	PB
PB	Z	Z	PS	PM	PM	PB	PB

The rule base was built in the FIS-editor with a fuzzy conclusion on the Mamdani algorithm (Fig. 3).

Closed loop control system in dynamic mode package in a Simulink MATLAB window, containing the fuzzy PID-controller adapter block, as well as a control object with the transfer function (Fig. 1), is shown in Fig. 4. Initial values of the coefficients are $K_e = 1, K_{de} = 1, K_{p0} = 1, K_{i0} = 1, K_{d0} = 1$. $K_e = 1$.

The structure of the PID-controller, presented in fig. 5. To set up a fuzzy PID regulator to optimize and improve the quality of the transition process, you can use the Response Optimization block by triggering the Check Step Response Characteristics optimization window, which sets the necessary parameters to be automatically configured.

In the process of optimizing the "Response Optimization Options" window, you can install and use several search algorithms in succession. Once the optimization is complete, the "Design Optimization" window displays a schedule of the optimal transition process.

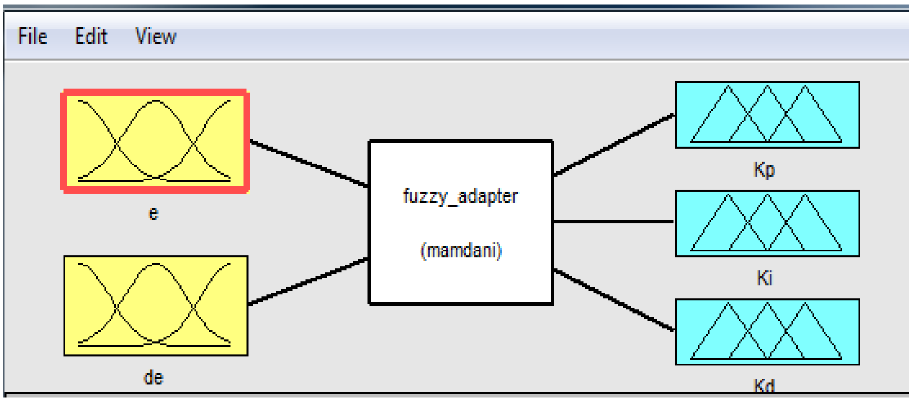

Fig. 3. Upper part of the FIS-editor window

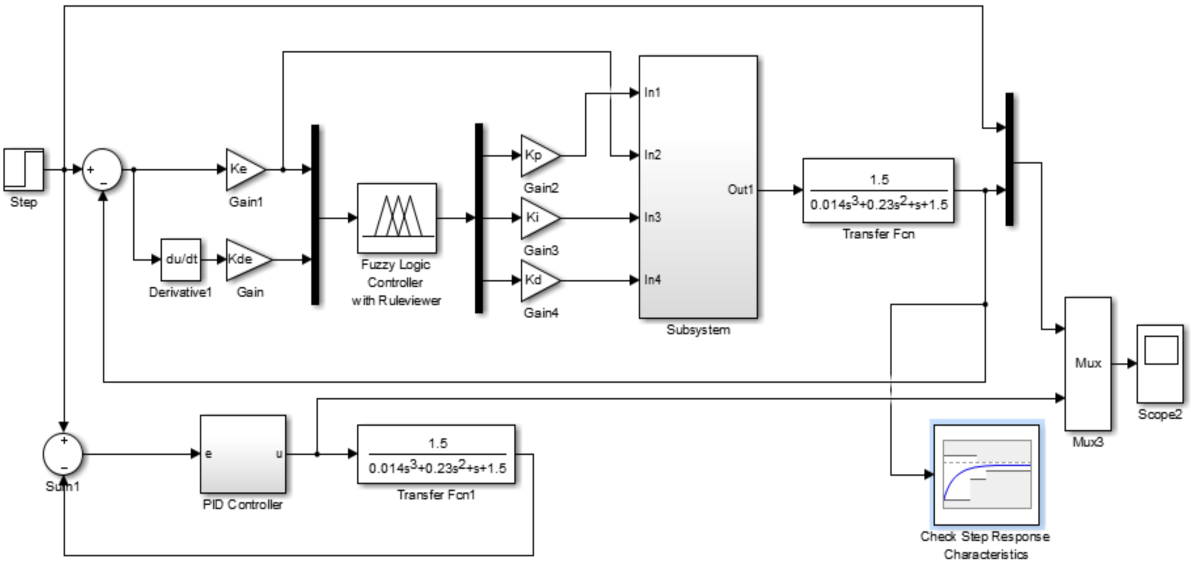

Fig. 4. A system with fuzzy adaptive PID-management and PID-Controller

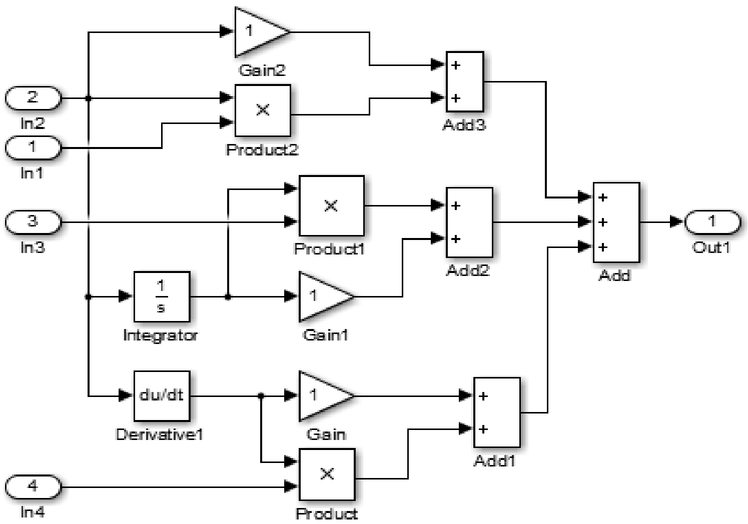

Fig. 5. Customized PID-regulator scheme

Neural controller design

The work [6] describes three neurocontrollers: NN Predictive Controller; a controller based on the autoeggression model with a moving average NARMA — L2 Controller; Model Reference Controller effective controller is the NN Predictive Controller. The regulator uses a model of a non-linear controlled object in the form of a neural network in order to predict its future behavior. The regulator calculates a control signal that optimizes the volume's behavior at a given time interval. The design of the neurocontroller consists of two stages: the stage of identification of a managed object and the stage of synthesis of the control law. During the identification phase, a model of a controlled object in the form of a neural network is developed, which is used for the synthesis of the regulator at the synthesis stage.

Synthesis of the NN Prediction Controller neurocontroller uses files placed in the toolbox/nnet/nncontrol catalog of toolbox/nnet nncontrol the SIMULINK system, which can be broken down into three groups: one-dimensional optimization functions, SIMULINK models, auxiliary functions: Sfunxy2 — a function for output of graphs; Nncontrolutil is a support that enables private functions from the SIMULINK system to be accessed; Nnident.m is a feature used in identifying an object in the private catalog that provides a GUI, a learning sample, and network creation and training.

On fig. 6 shows the structural circuit of the neural network system along with the fuzzy adaptive and classic PID-regulator developed by SIMULINK. This structure includes a controllable process unit and a NN Predictive Controller unit, as well as reference step signal generation units. The NN Predictive Controller is activated by the double click of the left mouse button.

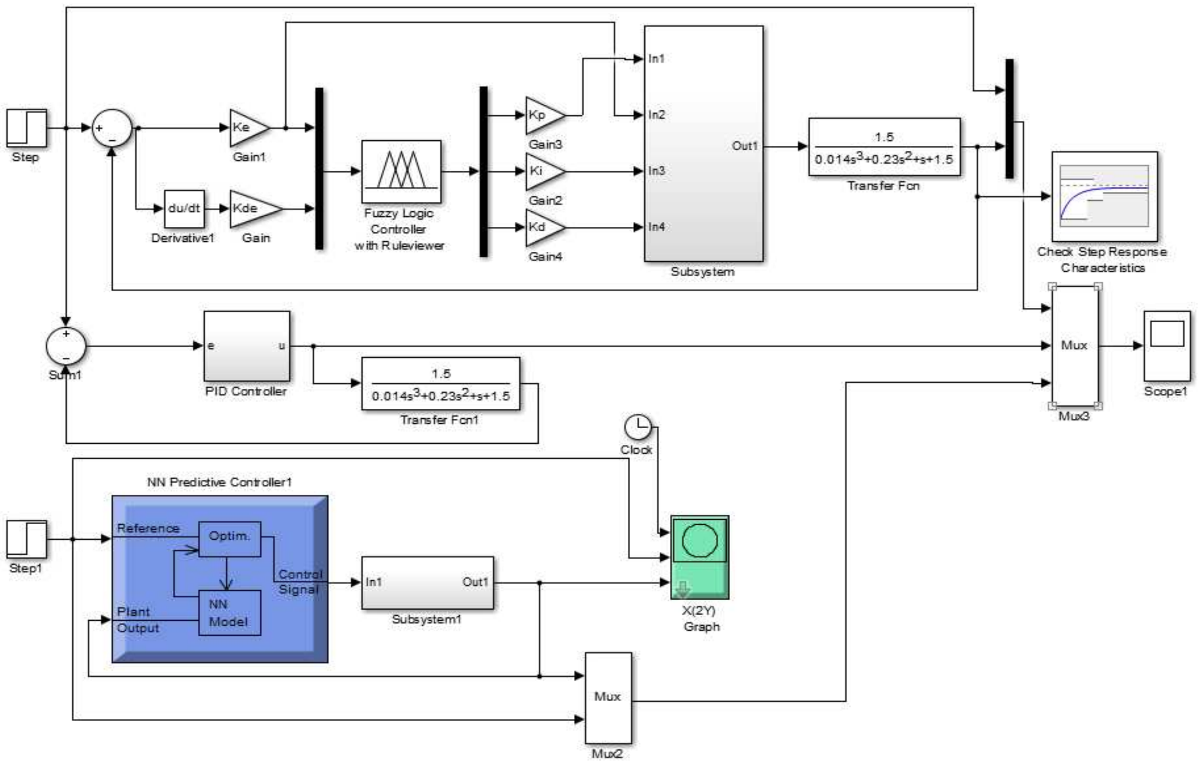

Fig. 6. Witha tink-black circuit of a fuzzy adaptive PID-regulator, a neural network regulator and the classic PID-regulator

After the appearance of the user GUI window — Neural Network Predictive Control and set the controller parameters. E. build his neusse-modern model using the plant Identification special procedure.

The identification procedure requires the task of the following parameters: the size of the hidden layer of the detected neurons, the tact of discreteness in seconds, the number of lag elements at the entrance and exit of the model, the length of the training sequence (the number of points of removal of information), the maximum and minimum values of the input signal, the maximum and minimum values of the output signal.

This window is versatile and can be used to build neural network models for any dynamic object that is described by the Simulink model. In our case, it is a non-linear dynamic model of the third order. n Epochs n function With the Browse button, you can choose any model available. If the model should be used to set up the controller, it should be created before the controller is calculated. You may also need to create a new model of the object if the designed controller is not functioning well.

Choosing the Generate Training Data procedure will result in the launch of a training sequence generation program at 1600 c for the model under study. The program generates training data by impacting a number of random step signals on the Simulink managed process model.

When the training sequence is finished, it is suggested either to accept the data generated (Accept Data) or to abandon it (Reject Data). If the data is accepted, the app returns to the Plant Identification window. Training of the neural network model will begin. After completing the training, the results are displayed on the graphs, where the results are built accordingly on the training and control set.

The current state is marked in the Plant Identification window by "training is complete." You can generate or import new data, continue learning, or save results by selecting OK or Apply buttons. As a result, the parameters of the neural network model of the managed process will be introduced into the NN Predictive Controller block of the Simulink system.

Then they return to the Neural Network Predictive Controller window and set optimization parameters: Gost Horizon is the upper limit in the quality indicator(Nz7, the lower limit is fixed and is 1), the upper clog limit when assessing control power (NNq2), the weight factor for the control power component (z0.05), the one-dimensional search option, setting the threshold for quality reduction (), choosing the one-dimensional search procedure (the csrhbac procedure was chosen — the search with reverse run), the number of iterations per 1 tact of the discrete is equal2. $\alpha = 0.001$ Introduce the regulator's parameters into the NN Predictive Controller block by pressing the OK or Apply buttons and start modeling by selecting the Start option from the Simulation menu.

From fig. 7 It can be seen that the output of the system control facility with fuzzy adaptive PID control and neurocontroller has less overregulation and the number of fluctuations, i.e. the quality of regulation.

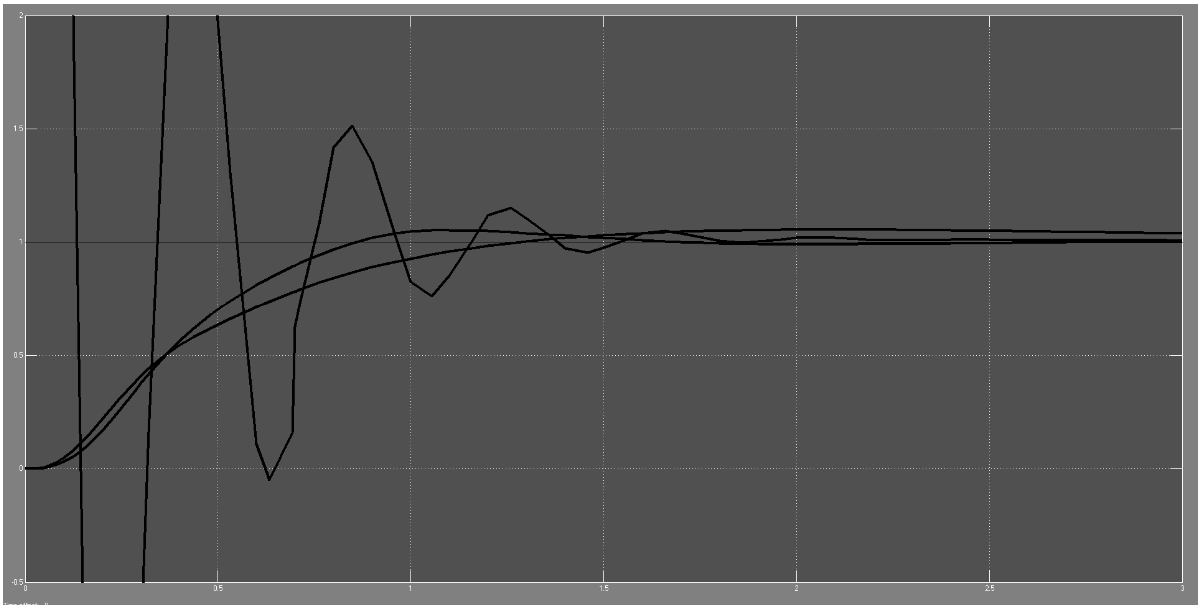

Fig. 7. Transitional processes of output with PID, adaptive fuzzy and neural controller

Conclusion

This work considers issues of constructing and adjusting a fuzzy adaptive PID-controller, consisting of a block of fuzzy adaptation of fuzzy coefficients of the linear PID-controller, as well as a neurocontroller with prediction. As the results of the simulation showed, at the constant parameters of the object of regulation of the system with fuzzy regulators and neurocontrollers have the best dynamic indicators compared to classical systems. At the same time, both in the classical and in the system with a fuzzy regulator, the time of reaching the output of a given value is about the same.

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НЕЧІТКЕ МОДЕЛЮВАННЯ В СИСТЕМАХ УПРАВЛІННЯ

Дранишников Л.В.

Реферат

Застосування лінійних пропорційно-інтегрально-диференціальних (ПІД) регуляторів у системах управління нелінійними об'єктами найчастіше призводить до низької якості процесу регулювання, що характеризується великими значеннями перерегулювання, статичною помилкою та/або часом перехідного процесу.

Системи управління характеризуються, як правило, нелінійними залежностями, складною для моделювання динамікою, наявністю неконтрольованих шумів та перешкод. Класична теорія управління базуються на ідеї лінеаризації систем. Тому найефективнішою є розробка систем управління на основі адаптивного підходу у поєднанні з методами теорії штучних нейронних мереж та нечіткої логіки.

Регулятори, побудовані з урахуванням цієї інноваційної концепції, часом здатні забезпечити вищі показники якості перехідних процесів проти класичними регуляторами. Застосовуючи технологію синтезу нечітких алгоритмів управління, технологію побудови нейронних мереж можна провести оптимізацію складних контурів регулювання без проведення всебічних математичних досліджень.

У роботі сформульовано методику синтезу системи управління на основі теорії нечітких множин. Наведено результати імітаційного моделювання системи з нечітким логічним контролером та нейроконтролером. При побудові моделей та бази правил були використані засоби MATLAB — Simulink, Fuzzy Logic Toolbox.

Результати моделювання показали, що з постійних параметрах об'єкта регулювання системи з нечіткими регуляторами і нейроконтроллером мають кращі динамічні показники проти

класичними системами. Запропоновано метод нечіткої адаптації параметрів налаштування регулятора.

На підставі отриманих результатів моделювання обрано раціональні алгоритми управління для нечіткого регулятора з шумом у вхідному каналі. Виконано аналіз роботи нечіткого регулятора. Розглянуто основні процеси, що відбуваються у нечіткому висновку у нечітких системах управління.

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