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ADAPTIVE CONTROLLER FOR NONLINEAR DYNAMIC NON-STATIONARY STOCHASTIC PLANT BASED ON REAL TIME NEO-FUZZY-MODEL

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ABSTRACT

For the plant identification we have used an adaptive model based on the neo-fuzzy-neuron, which has rather simple architecture of the zeroth order Takagi-Sugeno-Kang neuro-fuzzy system type and is characterized by high learning rate and simplicity of both software and hardware implementation. Using adaptive control approach the controller based on neo-fuzzy-model with generalized minimum variance and constraint on the control energy is proposed. The advantage of the proposed controller is a convergence rate increasing due to quasi linearity of its structure, which allows to control the nonlinear non- stationary processes. The experiments were carried out on the real technical task, included the process of wood drying modeling and control. Using the proposed adaptive controller allows to increase the quality of the wood drying process providing the required humidity level or the electric power consumption constraints.

***Index Terms*—** Controller, neo-fuzzy-neuron, generalized minimal variance, constraint on the energy

1. INTRODUCTION

The effectiveness of adaptive identification, control, prediction, pattern recognition is substantially depended on the quality of mathematical object model. In the most cases the model construction was performed based on bench mode modeling of data obtained in the experiment. Therefore the most perspective in this case can be adaptive models which are capable to change their parameters as well as their structure in real time. The idea of an optimal model structure has been taken as a principal of the scientific field known as the inductive modeling. At the same time, a fairly wide spread for the solution of the same tasks has the computational intelligence methods based on combining a hybrid neural networks, a fuzzy inference systems and evolutionary algorithms. Therefore combining of the computational intelligence methods (neuro-fuzzy-, wavelet-neuro-fuzzy-, neo-fuzzy- systems) can improve the quality of the decision problem of adaptive identification, control, forecasting, etc.

In the paper the model construction of the non- stationary nonlinear dynamic plant based on the neo-fuzzy neuron are considered. At that the quality of adaptive identification depends not only on the applied learning algorithm parameters and the number of membership functions, which can change during the model design in real time.

2. NEO-FUZZY-MODEL

Let us consider a nonlinear dynamical non-stationary stochastic plant, which is defined by the nonlinear autoregressive model with exogenous input (NARX model) in the form

$$\begin{aligned} y(k) &= f(y(k-1), u(k-1)) + \xi(k) = \\ &= f(x(k)) + \xi(k), \end{aligned} \tag{1}$$

where $y(k)$ is the output signal, $u(k)$ is the control signal, $\xi(k)$ is the stochastic noise component with zero mathematical expectation and bounded variance in current discrete time instant $k = 0, 1, 2, \ldots$; $f(\bullet)$ is some bounded nonlinear function unknown in the general type; $x(k) = (y(k-1), u(k-1))^T \equiv (x_1(k), x_2(k))^T$.

For the plant (1) identification in real time we use an adaptive model based on the neo-fuzzy-neuron [1, 2], which has rather simple neuro-fuzzy architecture of the zero order Takagi-Sugeno-Kang system type [3] and is characterized by high tuning rate and simplicity of both software and hardware implementation.

It should be noted, that the authors of neo-fuzzy neuron prof. T. Yamakawa with colleagues successfully used it for the filtering, forecasting and restoration signal problem solving, and in [4, 5] the neo-fuzzy neuron was used for the adaptive nonlinear controller synthesis.

Let us introduce into consideration the model of the plant (1) based on neo-fuzzy neuron in the form

$$\begin{aligned}\widehat{y}(k) &= F(y(k-1), u(k-1)) = \\ &= \sum_{i=1}^{2} f_i(x_i(k)) = \\ &= \sum_{i=1}^{2}\sum_{h=1}^{m} \mu_{ih}(x_i(k)) w_{ih}(k-1),\end{aligned} \tag{2}$$

where the function $f_i(x_i(k))$ describes the output signal of i-th nonlinear synapse in the k-th current time instant

$$f_i(x_i(k)) = \sum_{i=1}^{2}\sum_{h=1}^{m} \mu_{ih}(x_i(k)) w_{ih}(k-1), \tag{3}$$

μ_{ih} is an h-th membership function of the i-th input, $w_{ih}(k-1)$ is an h-th tuning synaptic weight of the i-th nonlinear synapse in the previous time instant $(k-1)$.

The membership functions are accepted of the triangular type and such as, that they satisfy to the conditions of Ruspini partitioning

$$\sum_{h=1}^{m} \mu_{ih}(x_i(k)) = 1, \tag{4}$$

that is

$$\mu_{ih}(x_i) = \begin{cases} \dfrac{x_i - c_{i,h-1}}{c_{i,h} - c_{i,h-1}}, x_i \in [c_{i,h-1}, c_{i,h}], \\ \dfrac{c_{i,h+1} - x_i}{c_{i,h+1} - c_{i,h}}, x_i \in [c_{i,h}, c_{i,h+1}], \\ 0, x_i \notin [c_{i,h-1}, c_{i,h+1}], \end{cases} \tag{5}$$

where c_{ih} is the center of h-th membership function of i-th input.

Fig. 1 shows the example of such membership functions, at that the interval of signal variation x_i is supposed to be a-priori known $[x_{i,\min}, x_{i,\max}]$.

It is easy to see, that in general case every nonlinear synapse is m-rules fuzzy base

$$\begin{aligned} &IF \quad x_i \quad IS \quad X_{ih} \\ &THEN \quad f_i = w_{ih}, \quad h = 1, \ldots, m, \end{aligned} \tag{6}$$

where X_{ih} is a fuzzy set, defined by the membership function μ_{ih} .

The structure of neo-fuzzy model (2) of the plant (1) is shown on the fig. 2, where NS_i is a nonlinear synapse, z^{-1} is time delay element, $e_I(k) = (y(k) - \widehat{y}(k))$ is the identification error.

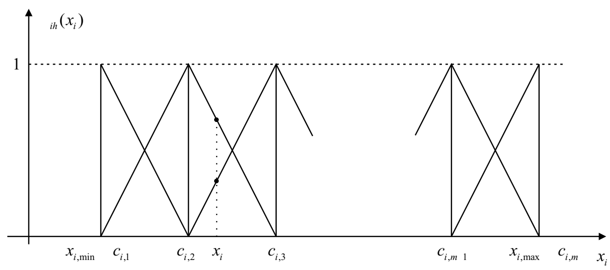

Fig. 1. The membership functions satisfying Ruspini partitioning.

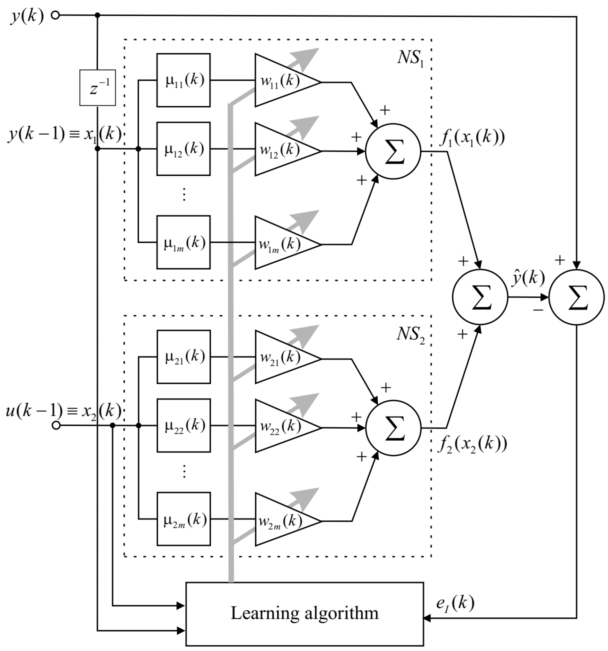

Fig. 2. Neo-fuzzy model of the controlled plant.

3. THE NEO-FUZZY MODEL PARAMETERS TUNING

The synaptic weights tuning in real time can be done both based on conventional gradient optimization algorithm [1, 2], and by adaptive procedure with improved following and filtering properties [6, 7]

$$\begin{cases} w(k) = w(k-1) + r^{-1}(k) e_I(k) \mu(k), \\ r(k) = \alpha r(k-1) + \|\mu(k)\|^2, \\ \quad 0 \le \alpha \le 1, \end{cases} \tag{7}$$

where $w(k) = (w_{11}(k), w_{12}(k), \ldots, w_{1m}(k), w_{21}(k), \ldots, w_{2m}(k))^T$, $\mu(k) = (\mu_{11}(x_1(k)), \mu_{12}(x_1(k)), \ldots, \mu_{1m}(x_1(k)), \mu_{21}(x_2(k)), \ldots, \mu_{2m}(x_2(k)))^T$, $e_I(k) = y(k) - \hat{y}(k)$.

The membership functions, as usual, are selected as fixed and equidistant, at that in every current time instant due to condition (4) only two neighbouring functions can be fired, for example, $\mu_{i,h}(x_i(k))$ and $\mu_{i,h+1}(x_i(k))$.

Therefore, the equation (3) can be rewritten in the form

$$
\begin{aligned}
f_i(x_i(k)) =&\mu_{i,p}(x_i(k))w_{i,p}(k-1)+\\
&+\mu_{i,p+1}(x_i(k))w_{i,p+1}(k-1)=\\
&=\frac{c_{i,p+1}-x_i(k)}{c_{i,p+1}-c_{i,p}}w_{i,p}(k-1)+\\
&+\frac{x_i(k)-c_{i,p}}{c_{i,p+1}-c_{i,p}}w_{i,p+1}(k-1)=\\
&=\Delta c^{-1}(c_{i,p+1}-x_i(k))w_{i,p}(k-1)+\\
&+\Delta c^{-1}(x_i(k)-c_{i,p})w_{i,p+1}(k-1),
\end{aligned}
\tag{8}
$$

where $\Delta c=(c_{i,p+1}-c_{i,p})=(c_{i,p}-c_{i,p-1})$, p is the index of the active fuzzy interval.

Introducing the notation

$$
\begin{cases}
a_i(k-1)=(w_{i,p+1}(k-1)-\\
\quad -w_{i,p}(k-1))(c_{i,p+1}-c_{i,p})^{-1}=\\
\quad =\Delta c^{-1}(w_{i,p+1}(k-1)-w_{i,p}(k-1)),\\
b_i(k-1)=(c_{i,p+1}w_{i,p}(k-1)-\\
\quad -c_{i,p}w_{i,p+1}(k-1))(c_{i,p+1}-c_{i,p})^{-1}=\\
\quad =\Delta c^{-1}(c_{i,p+1}w_{i,p}(k-1)-\\
\quad -c_{i,p}w_{i,p+1}(k-1)),
\end{cases}
\tag{9}
$$

we can rewrite the equation of nonlinear synapse (3) in simple linear form

$$f_i(x_i(k))=a_i(k-1)x_i(k)+b_i(k), \tag{10}$$

what will allow in the sequel to use conventional adaptive control theory for the controller synthesis.

4. ADAPTIVE CONTROLLER WITH GENERALIZED MINIMAL VARIANCE

Let's introduce into consideration the control criterion with generalized minimal variance

$$J(k)=(y^*(k+1)-y(k+1))^2+\rho u^2(k), \tag{11}$$

that using (10) can be rewritten in the form

$$
\begin{aligned}
J(k)=(y^*(k+1)-a_1(k)y(k)-b_1(k)-\\
-a_2(k)u(k)-b_2(k))^2+\rho u^2(k),
\end{aligned}
\tag{12}
$$

where $y^*(k+1)$ is the desired value of the reference signal, $\rho\geq 0$ is the penalty coefficient, which sets energy "cost" of the control signal.

Solving differential equation

$$\frac{\partial J(k)}{\partial u(k)}=0, \tag{13}$$

one can be obtain the adaptive control law in the form

$$
\begin{aligned}
u(k)=(y^*(k+1)-a_1(k)y(k)-b_1(k)-\\
-b_2(k))(a_2^2(k)+\rho)^{-1}a_2(k),
\end{aligned}
\tag{14}
$$

what is modification of the well-known Clarke-Gawthrop algorithm [8]. It is easy to see that when $\rho=0$ we obtain the modification of conventional adaptive Aström–Wittenmark controller [9]

$$
\begin{aligned}
u(k)=a_2^{-1}(k)(y^*(k+1)-a_1(k)y(k)-\\
-b_1(k)-b_2(k)).
\end{aligned}
\tag{15}
$$

5. ADAPTIVE CONTROLLER WITH THE CONSTRAINT ON THE ENERGY

The selection of the parameters ρ in criterion (11) is performed as a rule on the intuitive level or in the experimenting with control plant model process.

Since the task considered here is solved based on computational intelligence methodology, it is quite natural to require that this parameter is automatically defined by the controller.

In [10] it was proposed to solve adaptive control tasks under additional constraint on the control energy in the form

$$u^2(k)\leq U^2, \tag{16}$$

where U^2 is some threshold, which can not be exceeded in the plant control process.

Introducing the Lagrange function

$$L(k)=(y^*(k+1)-y(k+1))^2+\lambda(u^2(k)-U^2) \tag{17}$$

(here λ is the positive Lagrange undetermined multiplier) and solving the standard Kuhn–Tucker equations system by the Arrow–Hurwitz–Uzawa procedure [3], one can obtain the control law in the form

$$
\begin{cases}
u(k)=a_2(k)(y^*(k+1)-a_1(k)y(k)-\\
\quad -b_1(k)-b_2(k))(a_2^2(k)+\lambda(k))^{-1},\\
\lambda(k+1)=[\lambda(k)+\\
\quad +\eta_\lambda(k)(u^2(k)-U^2)]_+
\end{cases}
\tag{18}
$$

(here $\eta_\lambda(k)>0$ is a parameter of the gradient search increment, $[\lambda]_+=max\{0,\lambda\}$).

The second recurrent relation (18) can be also rewritten in the form [10]

$$
\begin{aligned}
&\lambda(k+1)=\lambda(k)+\eta_\lambda(k)\frac{u^2(k)-U^2}{U^2},\\
&0<\eta_\lambda(k)<1.
\end{aligned}
\tag{19}
$$

Thus, except the adaptive identification loop and eigen controller, the adaptive control system contains additional loop [11, 12, 13] of the parameter $\lambda(k)$ tuning, which sets the energy constraints on the control signals.

The fig. 3 shows the structure of the adaptive intelligent controller based on neo-fuzzy-model.

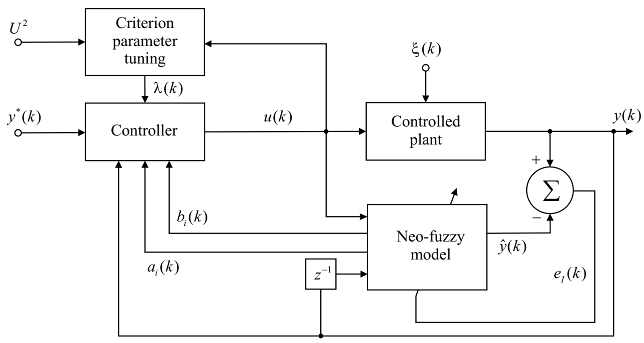

Fig. 3. Adaptive controller based on neo-fuzzy models with constraint on the energy.

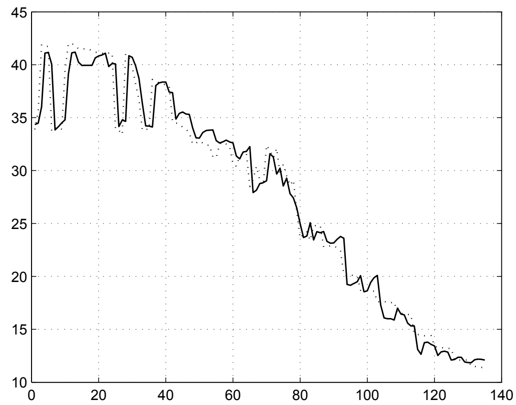

Fig. 4. Results of the wood drying process identification (20).

6. EXPERIMENTAL RESULTS

The experimental simulation was performed using different non-stationary dynamical process.

The fist experiment has performed on the real data, describing the process of the wood drying process. The wood drying process is quite different from other similar wood processing large duration and high energy costs and at the same time is essential in the woodworking industry. The wood drying problem is not completely solved, ignoring the fact that successfully used different methods and equipment. Untimely or inadequate the wood desiccation leads to a rank reduction of the term fitness of wooden structures, as well as the huge costs wood. The quantity and quality of the wood drying process depend on the correct choice and validity environmental parameters as close as possible to a specified level, which depends on the state of the material (its humidity and inner properties). Generation of the optimal operating practices, achievement of the required quality level of the wood drying is an topical problem today, one solution which is the mathematical models synthesis that enable to control the humidity and the development of the inner qualities of the material. The data was obtained from 7 humidity sensors and 1 temperature sensor, which located on the wood timber and was averaged for the further processing [14]. The mathematical model of the wood drying process was obtained based on neo-fuzzy neuron (Fig. 2) and its learning algorithm (7) in bench mode.

The neo-fuzzy neuron has in this task two nonlinear synapses. The number of learning parameters is 10. Fig. 6 shows the adaptive identification of wood drying process.

The table 1 shows the comparative analysis of the identification process based on neo-fuzzy-neurons with the results of the linear and polynomial models. Thus as it can be seen from experimental results the mathematical model based on neo-fuzzy neuron with triangular membership function ensures the best quality in the sence of determination coefficient (DC) in comparison with conventional linear and polynomial models.

Table 1. The results of wood drying process identification.

Mathematical model	DC
Neo-fuzzy neuron model	0.998
Linear model	0.873
Polynomial model (second-order)	0.921
Polynomial model (third-order)	0.932

In the second experiment we evaluated the performance of the developed controller on the well-known benchmark nonlinear plant [15] described by the equation

$$y(k+1) = \frac{y(k)}{1+y^2(k)} + f(u(k)). \qquad (20)$$

The control law (18-19) was used to make the output of the plant (20) follow a random step-wise setpoint (Fig.5) and a sine wave setpoint (Fig.6). The plant output was disturbed with normally distributed random sequance.

The neo-fuzzy model learning was performed based on the sample set generated based on equation (20) with the control signals $f(u(k)) = u^3(k)$ and $u(k) = cos(2\pi k/25) + cos(2\pi k/2)$ for $k = 1 \dots 2000$. After 2000 steps the learning process was stopped. The dynamic object 20 with the same control signals for $k = 2501 \dots 3000$ and $f(u(k)) = u^3(k)$ and $u(k) = sin(2\pi k/250) + sin(2\pi k/10)$ for $k = 3001 \dots 3600$ was used as the test data for emulation.

The neo-fuzzy model had 2 inputs for the signals $y(k)$, $u(k)$, and contained 5 membership function per input. The total number of tuned weights was 10. These weights were adapted online using the procedure (7) with $\alpha = 0.99$. For the proposed control low, we chose the initial value of parameter $\rho = 0.15$.

The simulation was carried out for 1000 time steps. The neo-fuzzy model was identified and simultaneously used to compute the control action. The resulting plots are shown in Fig.5 (for the random step-wise setpoint) and Fig.6 (for the sine wave setpoint).

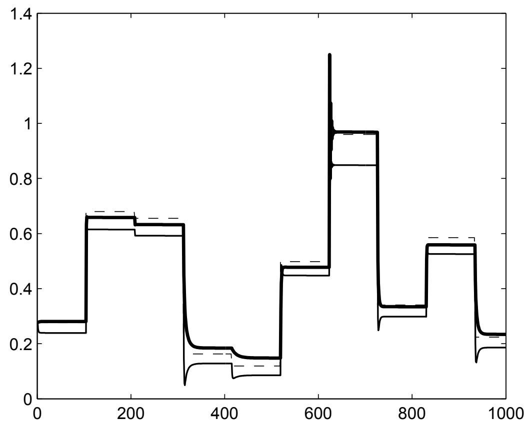

Fig. 5. Simulation results: plant output (thick solid line), model output (thin solid line), and random step-wise setpoint (doted line).

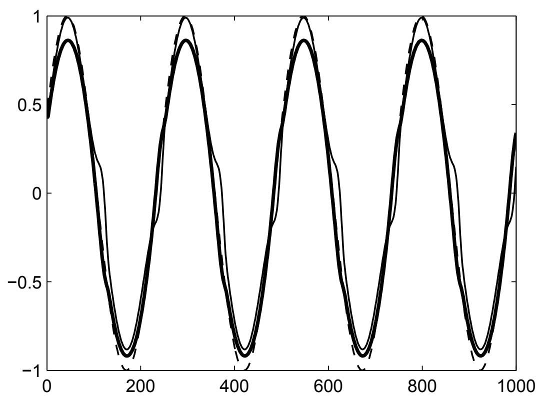

Fig. 6. Simulation results: plant output (thick solid line), model output (thin solid line), and sine wave set-point (doted line).

7. CONCLUSION

In this paper the adaptive identification process based on neo-fuzzy neuron is considered. Using adaptive control methods the intelligent controller based on neo-fuzzy model with generalized minimum variance and constraint on the power with the on-line parameter definition is proposed. The advantage of the proposed controller is a rate increasing obtained due to quasi-linearity of its structure, which allows to control the nonlinear non-stationary processes in real time.

The experiments were carried out on the real technical plant, included modeling and controlling the process of wood drying.

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