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Investigation on Some Applications of Neural Networks in Control of Plants with Variable Parameters*

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I. Introduction

The variations of the plant parameters always worsens the performance indices in a control system and requires more sophisticated control approaches [1,10]. Fortunately, there are but few industrial cases which require continuous adaptation. Then model reference adaptive systems or self-tuning regulators with direct and indirect algorithms, stochastic or deterministic, are designed, which main tradeoffs are still related to the complicated time-consuming calculations, high sensitivity to noise effects, operation mainly in transient modes, problems with convergence rate and stability. More often some other more simple approaches can do. The method of the frozen parameters assumes that for different time intervals the plant preserves its parameters at different but constant for the interval values. The robust approach can ensure a satisfactory control for plants with specified uncertainties. Automatic tuning is a wide spread technique for all standard linear controllers that is repeatedly applied after some time or following the plant parameter changes. Gain scheduling is powerful when the plant parameter variations are related to the change of the operation modes, which can be distinguished by the interval value of associated measured variables. Then the controller is tuned for a finite number of plant parameter sets that determine the plant description for each mode. Finally a table with the operating modes or interval values of the associated variables and the corresponding controller parameters is elaborated. This process often relies on expert knowledge on how to define the various operation modes, to relate them to the measured variables and to the plant parameters. A scheduling table implies discretization in the values of the plant and controller parameter and a finite number of modes considered. By interpolation the dropped information can be restored with a given accuracy.

Neural networks can successfully be implemented in the control of technological processes with variable parameters. There is a number of notions and trials for their

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incorporation in various adaptation algorithms, which usually serve specific purposes or are still far from industrial practice [2, 5, 9, 11, 12]. Moreover, this scanty experience pointed out to some new unsolved problems that arise such as optimal architecture selection, reliability and robustness of real-time training algorithms, self-organization, etc. [6, 8, 11]. Yet, the neural networks application in control of technological processes is a relatively new, rather prospective and fast developing area, which needs further exploration before the elaboration of practical recommendations.

II. Preliminaries

Most technological processes are plants with variable parameters, described by non-stationary differential equations of the following type [10]:

$$a_n(t)\frac{dx^n}{dt^n}+a_{n-1}(t)\frac{dx^{n-1}}{dt^{n-1}}+\ldots+a_0(t)x=b_m(t)\frac{dy^m}{dt^m}+\ldots+b_0(t)y. \qquad (1)$$

The coefficients $a_0, \ldots, a_n$ and $b_0, \ldots, b_n$ are functions of time, analytically or graphically represented, that express the deterioration of the heat exchange with time due to incrustation in heat exchangers, boilers, evaporators, metallurgical ovens and so on, or of the transformation rate in chemical reaction as a result of the catalyst poisoning in reactors, rectification columns, etc. The variety of industrial plants with variable parameters can be classified into the following categories [1, 4, 10]:

– plants with parameter drift that concern low rate parameter changes with regard to the rate of the transient response, as a rule due to aging of the technical equipment and installation and change in the operating conditions;

– plants with batch processes such as oxygen converters, chemical and biochemical reactors, which start the processes under various initial conditions – composition, temperature, etc., of the fed substrates; besides, the exothermic oxidizing reactions introduce additional uncertainties in the description of the elementary chemical, thermal and hydrodynamic processes;

– plants with parameter changes correlated to measurable variables - the changes in the variables result in changes in the mass and heat transfer, in the kinetic and the hydrodynamic parameters; so, the general plant parameters can be expressed as function of the relative plant loading

$$l=\frac{Q}{Q_n}, \qquad (2)$$

where the current and the nominal loading are denoted respectively by Q and Q_n. In general, the inertia, expressed in the time-delay and the main time-constant, increase with decrease of the relative loading. Such single-input-single-output plant can be described by the following parameter differential equation:

$$\sum_{i=0}^{n} a_i[\Psi(t)]\frac{d^i[y(t)]}{dt^i}=\sum_{j=0}^{m} b_j[\Psi(t)]\frac{d^j}{dt^j}x\{t-\tau[\Psi(t)]\}, m\le n. \qquad (3)$$

where the variable coefficients $a_i[\Psi]$ and $b_j[\Psi]$ and the time-delay $\tau[\Psi]$ depend on time via the parameter $\Psi(t)$. Depending on the sense of $\Psi(t)$ there are possibly three cases:

– $\Psi(t)$ is an independent parameter input such as fluid or production rate and then

$\Psi = f[\lambda(t)]$ and (3) is a linear differential equation;

– $\Psi(t)$ depends on the plant output and then $\Psi = f[y(t)]$, the differential equation is non-linear and a parameter feedback appears;

– $\Psi(t)$ depends on the plant input and then $\Psi = f[x(t)]$ and the differential equation is non-linear.

The mathematical description of a plant with variable parameters by means of the parameter equation (3) gives some advantages to the description with non-stationary equation (2), such as:

– the steady state non-linear characteristics $a_i[\Psi]$, $b_j[\Psi]$ that depend on the construction parameters of the installation can be determined experimentally or analytically;

– the relationship $\Psi = \Psi(t)$ can describe all possible plant operating modes

a) for Ψ – a constant, the plant is stationary and the describing differential equation is with constant coefficients;

b) for Ψ – varying about some value Ψ_0, the plant is quasi-stationary and its transfer function parameters can be assumed nearly constant;

c) for $\Psi(t)$ – known deterministic time function equation (3) describes a non-stationary process with deterministic parameter changes;

d) for $\Psi(t)$ – a random time function (3) describes a non-stationary process with stochastic parameter or mode changes.

A more general application of the neural networks in the control of plants with variable parameters is based in the property of the neural networks to reproduce a given non-linear or non-stationary relationship. This can be the relationship between variables and time, implied in the reference model or the linearizing controller for a non-linear plant or between the plant or controller parameters on one side and measured variables or time, on the other side in gain scheduling. The training process of neural networks is based on an advanced intelligent technology for function interpolation and approximation. The neural networks develop in learning generalization, association, and adaptation properties which make them invaluable models. Neural models can account for the simultaneous (parallel) variations of several plant parameters with respect to the change of several variables. This surpasses the possibilities of a table presentation in gain scheduling to reflect more precise and complex relationships. For deterministic relationships the network can be trained off-line and incorporated in the control algorithm thus providing fast controller parameter adjustment.

The aim of the paper is to investigate on the application of neural networks as function approximators in the control, or more specifically in the gain scheduling, of industrial plants with deterministically described parameter changes.

III. Problem formulation

Assume that the plant is described by the following transfer function:

$$W(s,\lambda) = \frac{K_0(\lambda)}{T_0(\lambda)s+1} e^{-s\tau_0(\lambda)} \tag{4}$$

where the gain K_0, the time-constant T_0 and the time delay τ_0 are known deterministic non-linear functions of time via the parameter λ which is an independent measurable variable λ that can in some cases be an estimate of the plant relative loading.

A standard algorithm PI is chosen as most commonly used and easy to tune by well developed simple procedures. According to the Chien-Hrones-Reswick tuning rules [7] that ensure an overshoot of the overall closed-loop system S=20% the controller parameters are determined from:

$$K_p(\lambda)=0,7\frac{T_0(\lambda)}{T_0(\lambda)\tau_0(\lambda)},\ K_i(\lambda)=0,7\,T_0(\lambda). \quad (5)$$

The control is restricted in the range (–10, 10) V.

The problem is to develop a non-linear neural network with one input λ and three outputs K_0, T_0 and t_0 that models the relationships $K_0(\lambda)$, $T_0(\lambda)$ and $t_0(\lambda)$ in order to currently adjust controller parameters according to (5).

IV. Design of gain scheduling control on neural network function approximator

A two-layer neural network with non-linear activation functions in the hidden layer can be off-line trained to perform function approximation using a representative input-target training couple of vectors and applying the backpropagation rule. Thus any deterministic non-linear relationship between continuous values of the measured variables associated to the operating modes, and the corresponding coefficients of the differential equation (1.3), describing the plant, can be produced with given accuracy.

Such a network with K batching input vectors **P** and logistic sigmoid, or else log-sigmoid, activation functions in both layers **F1** and **F2** is shown in Fig.1. The output A of log-sigmoid function is given by:

$$A = \log\text{sig}\,(N, B)=1/(1+e^{-(N+B)}), \quad (6)$$

where N is the function input and B is the bias. It is used to map the input from the interval $(-\infty,+\infty)$ into the interval (0, 1). Other often used with backpropagation non-linear differentiable and monotonic increasing function is the hypertangent sigmoid or tan-sigmoid – $A = h\text{tg}\,(N+B)$, mapping the input from $(-\infty,+\infty)$ to (–1, 1). Occasionally, a linear function can be used when the output is not constrained.

The number of the inputs R corresponds to the number of the number of the mode-related variables, the number of the modes is supposed to be K. While the number of the output layer neurons S_2 depends on the number of the variable plant parameters, the number of the neurons in the hidden layer S_1 can be freely selected in order the optimization problem to have a satisfactory with respect to time and accuracy solution. Typically, the more neurons in the hidden the more powerful the network, the longer the training time, the larger the weight matrices and the bias vectors and the higher the accuracy that can be achieved. Too few neurons, on the other hand, can lead to underfitting while too many neurons can contribute to overfitting, in which the training points are well fit, but the fitting curve takes wild oscillations between these points.

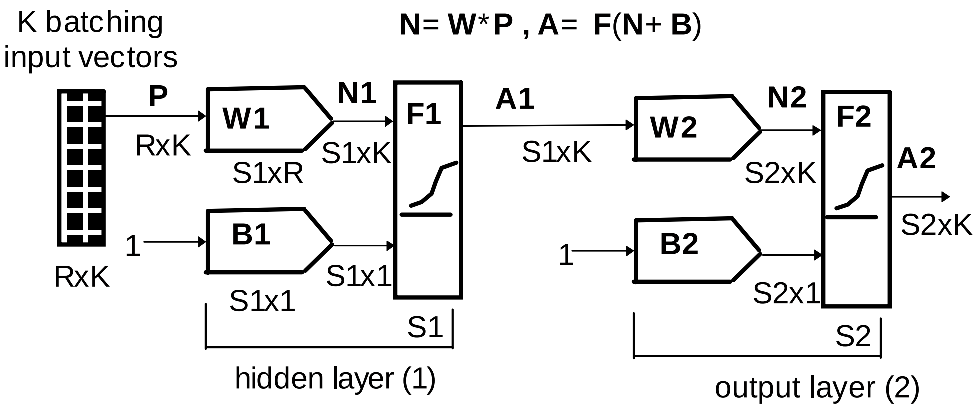

Fig.1

The weight matrices **W1** and **W2** and the bias vectors **B1** and **B2** are being continually adjusted in the direction of the steepest descent with respect to minimization of the sum squared error of the network. Derivatives of error called delta vectors *d* are calculated for the network's output layer and then backpropagated through the network until delta vectors are available for each hidden layer.

The error is the difference *E* between the target *T* vector and the output *A* vectors ($E=T-A$), that corresponds to a given input vector from the batch of input vectors. The steepest descent method is used with adaptive learning rate in order to increase convergence of the gradient procedure in the surroundings of the minimum, to decrease the number of iterations, and to avoid local minima and instability at large rates. Initialization of the network is provided by a random number generator that produces values within the range $(-1, 1)$. The new weights $W_{i,j}$ and biases B_i at the $k+1$ iteration are calculated according to the backpropagation rule:

(7) $$W_{i,j}(k+1) = W_{i,j}(k)+\Delta W_{i,j}(k),\ \ \Delta W_{i,j}(k)=Lr\delta_i(k)\,P_j(k),$$

(8) $$B_i(k+1) = B_i(k)+\Delta B_i(k),\ \Delta B_i(k)=Lr\delta_i(k),$$

where δ_i is the delta vector for the current i layer, P_i is the corresponding input vector, *Lr* is the learning rate. The calculations move from the output to the input layer of the network.

When a desired accuracy is reached in the target points, the network is tested with more input vectors than the ones used in training to see if it has learned to generalize the function it is learning. If the approximated function is smooth and monotonic in-between the target points, the training is considered to have ended successfully. Else, it should be started from different initial conditions, or else the number of the neurons in the hidden layer or the number of hidden layers should be increased. Often more inputs and corresponding targets are added to the training vectors.

A specialized software – the Neural Network Toolbox of the MATLAB package assists the synthesis of the function approximator.

The general block diagram of the gain scheduling control is represented in Fig.2, where *d* is the plant input disturbance, *Y* is the controlled variable, *Yr* is the reference, $f(\lambda)$ is the independent measured variable associated with plant relative loading that effects both the output and the plant parameters. The neural model gives the current plant parameters.

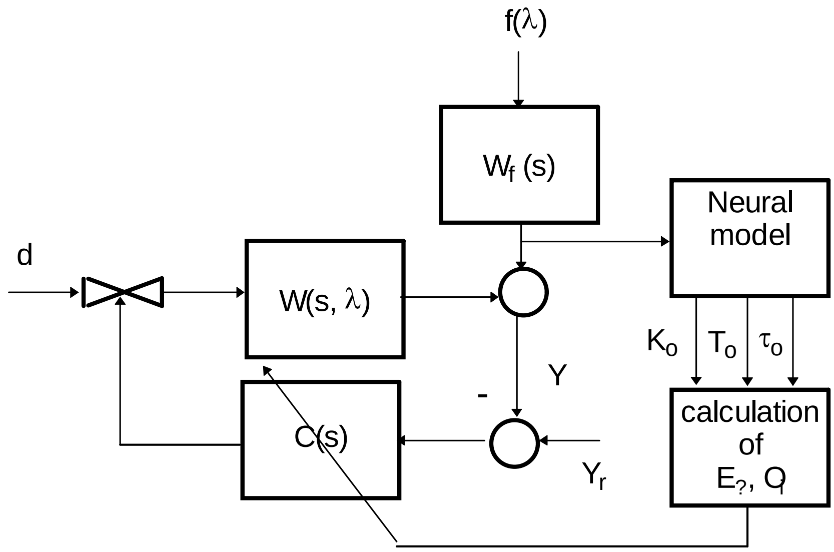

Fig.2

V. Investigation of neural gain scheduling system for the control of heat exchanger

A gain scheduling system is designed for the control of the temperature θ of the heated fluid at the output of a pipe heat exchanger The transient responses of the plant at step increase of the temperature of the heating fluid for different relative loading λ (fluid rate) are experimentally obtained in [4] and given in Fig.3. The relationships $K_\theta(\lambda)$, $T_\theta(\lambda)$ and $t_\theta(\lambda)$, shown in Fig.4, are obtained after Ziegler-Nichols approximation [7] of the transient responses that leads to plant transfer function (4).

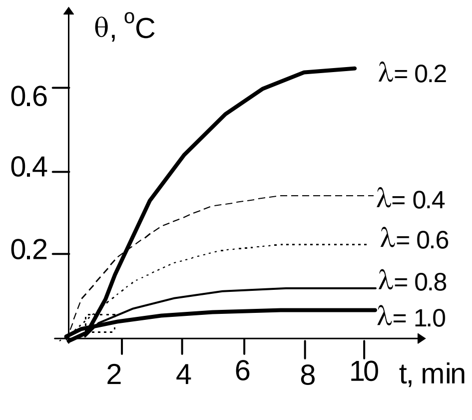

Fig.3

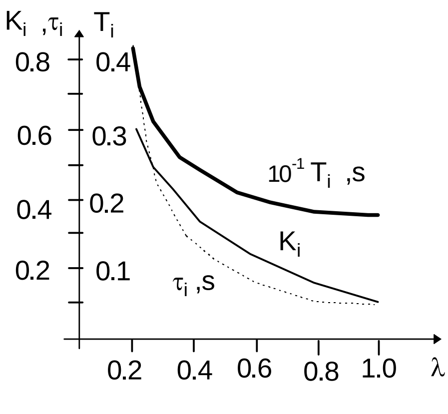

Fig.4

A two-layer log-sigmoid/log-sigmoid neural network with five neurons ($S1$=5) in the hidden layer was successfully trained to model the characteristics from Fig.4, reaching accuracy of 10^{-6} after 20000 epochs and the following weights and biases:

$$\mathbf{W1}=[-35,5253\ 33,9337\ -34,0720\ -37,0186\ -32,6359]^T;$$

$$\mathbf{B1}=[4,5654\ -17,1182\ 8,8747\ 30,8310\ 27,1351]^T;$$

$$\mathbf{W2}=[-4,6023\ -0,6183\ \ 1,5440\ -0,7212\ \ 1,4638$$

$$1,0983\ \ -0,2505\ \ 0,7855\ -1,5403\ 1,7136$$

$$-1,6371\ -0,6764\ \ 2,9320\ -2,9422\ 3,3709];$$

$$\mathbf{B2}=[-1,3706;\ -1,2743;\ -1,5219].$$

A SIMULINK model was proposed, incorporating as S-function the neural model for the relationship of the plant parameters and the relative loading, that is shown in Fig. 5. The change of λ affects the system with a transfer function $W_f(s)=1/(0,1s+1)$. The neural model reproduces the relationships $K_0(\lambda)$, $t_0(\lambda)$ and $10^{-1}\,T_0(\lambda)$ since the plant parameters come out as log-sigmoid function outputs, so they are restricted in the range (0,–1). An amplifier to 10 restores the actual value for T_0. The plant model is revealed in Fig. 6, where the plant parameters are taken from the neural model. The simulation results, produced by a system with an adaptive PI controller and a system with an ordinary PI controller are shown in Fig. 7. The ordinary controller parameters Ti_1=1,54, Kp_1=25,6 are calculated for plant parameters K_0=0,25; T_0=2,2 s; τ_0=0,15 s, taken for λ=0,6.

A comparison shows that the system with an ordinary controller loses stability when λ decreases since the controller does not adapt to the increase of the plant parameters. Besides, the control becomes rather dangerous for the actuator and the valve because of the high frequency oscillations, turning itself almost into an on-off control and consuming a great amount of energy for control. Far too economic and smooth with only few oscillations is the control of the system

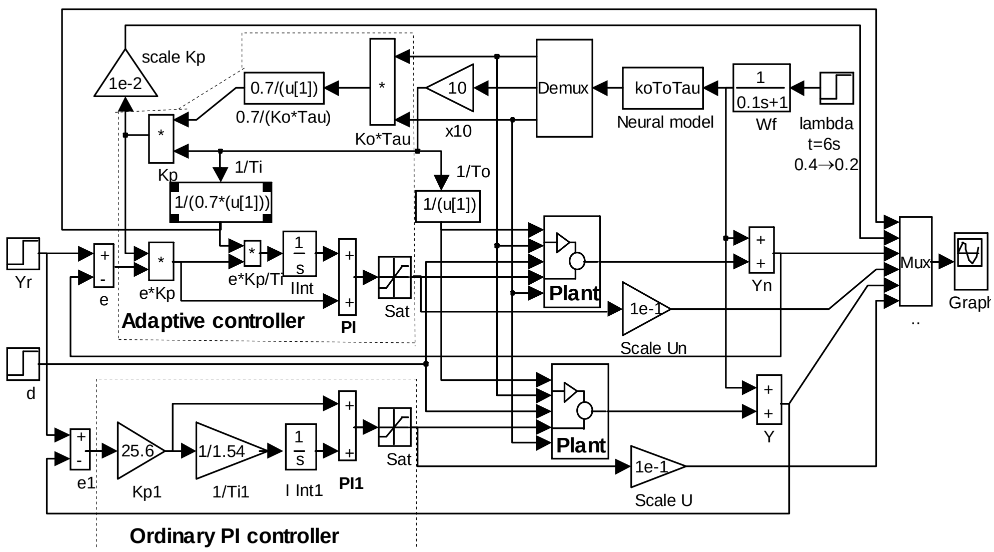

Fig.5

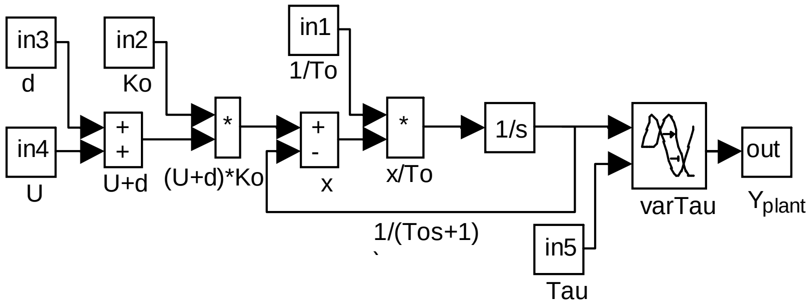

Fig.6

with the adaptive controller, which is explained with the decrease of the proportional and integral gains. The gain scheduling is not effective when the changes of only one of the plant parameters are accounted for. The advantages are guaranteed when the variations of at least two of the plant parameters – K_0 and τ_0 or equally T_0 and τ_0 are considered. Besides, even if the actual plant parameters differ from the calculated by the neural model values, the system with the gain scheduling control preserves stability and performance. This is seen in Fig.8.a. and Fig.8.b. for the same change of λ, after an additive plant parameter drift has been included $q=qnm(1+0,05t)$, where by q is denoted the actual value for the plant gain, the plant time delay and 1/plant time-constant, and by qnm – the corresponding neural model values. The simultaneous increase of the plant gain and the time delay together with the decrease of the time-constant due to drift effects simulates the most unfavourable case with respect to system stability.

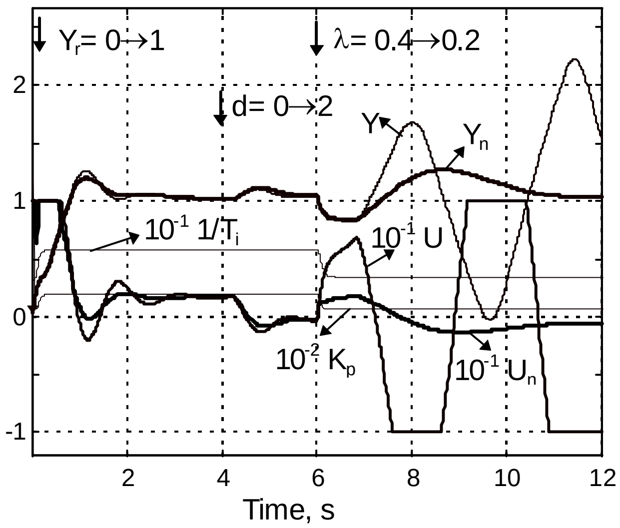

Fig. 7

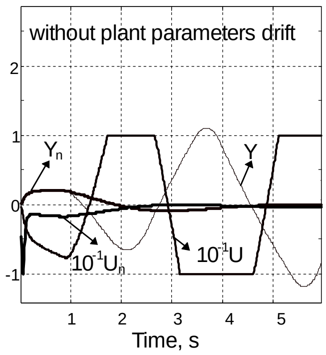

Fig. 8a

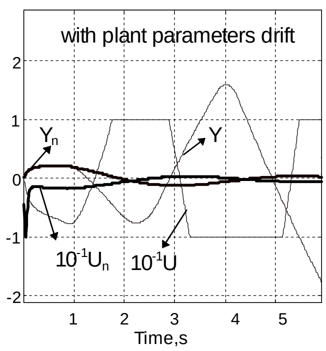

Fig. 8b

VI. Conclusion

A gain-scheduling control based on neural network non-linear function approximator is proposed for plants with variable parameters. A two-layer non-linear network is trained using the backpropagation rules with adaptive learning rate to reproduce the deterministic relationship between the plant parameters and a measured variable associated with their changes. The final neuron model is then incorporated in a PI controller so that the controller parameters follow the plant parameter changes. The procedure is applied for the design of the control of the fluid temperature of a heat exchanger. Closed-loop systems with an adaptive and an ordinary PI controller are simulated using SIMULINK of MATLAB package. The advantages of neural gain scheduling even when the actual plant parameters differ from their values from the neural model are good performance for fast and large parameter changes, economic, smooth and safe for the actuator and the valve control. Investigations show that gain scheduling is effective when the changes in at least two plant parameters are accounted for – the time-delay and the gain or the time-constant.

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Исследования некоторых применений нейронных сетей для управления объектами с меняющимися параметрами

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(Р е з ю м е)

Предложено адаптивное управление объектами при помощи нейронной аппроксимирующей модели, задающей детерминированную нелинейную зависимость параметров от измеряемой переменной. Модель получена после обучения двуслойной сети с логистическими функциями методом обратного распространения для подстройки параметров ПИ регулятора. Процедура применяется к управлению температурой флуида в теплообменнике. Через симмуляции при помощи программы Симулинк получены переходные процессы в системе с адаптивной подстройкой параметров регулятора и показано сохранение показателей качества при быстрых и больших изменений параметров объектов и экономичность управления даже если параметры объекта отличаются от параметров нейронной модели. Исследования показали необходимость в учитывании изменения как в коэффициенте, так и в опаздывании объекта.