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APPLICATION OF HYBRID NETWORKS IN THE ADAPTIVE CONTROL SYSTEMS OF HEAT POWER OBJECTS

Application of the fuzzy neural apparatus is proposed for finding optimal values of PI regulator parameters in the adaptive control systems of heat power objects. Efficiency of the proposed intelligent adaptive system is shown as compared with the traditional adaptive ACS.

Key words: *parametric identification; harmonic oscillator; optimization; hybrid network; PI regulator.*

Current importance

As a rule, functional algorithms of automated control systems (ACS), developed at the design stage, differ considerably from the optimal parameter values of traditional regulators. It is explained by the imperfectness of mathematical models of the objects represented both in an analytical (often too simplified) and experimental forms. It is difficult to obtain mathematical models of the control systems of functioning complex objects experimentally as well as of those operating in remote or automatic modes. These difficulties are connected with the influence of external and parametric disturbances, some of which are of non-stationary nature and cannot be controlled.

Taking the above-mentioned into account, the developed APCS (automated process control systems) require readjustment accompanied with lower quality of the control process, which involves additional consumption of material resources. As frequent works on setting up ACS at the time of commissioning as well as during subsequent operation (when tasks and loads are changed) are required, organizational problems arise during their implementation. For example, the number of control system circuits to be adjusted at a modern heat power object may reach several tens, which makes it almost impossible to provide high-quality and rapid manual execution of the work by a limited number of the employees from the operational personnel [1, 2]. For example, a boiler working in a regulated mode responses to fluctuations of thermal and electrical loads of turbines, i.e. it is involved in regulating the overall thermal and electrical loads of the station and, as a result, is affected by non-stationary external and internal disturbances. It should be noted that dynamic characteristics of the control areas of HPS (heat power station) power unit undergo significant changes during the launching process. As a rule, dynamic parameters of these characteristics, determined for the initial stage of start-up, differ significantly from those determined for the final stage of start-up or for normal operation. For example, the steam temperature delays τ along the steam boiler pipeline via the regulatory channel are much larger and the gain k is much smaller at the initial stage of start-up compared with the final stage of start-up and the normal mode. Due to the transition from fuel firelighters to the main fuel and changes of the thermal unit circuit, automatic adjustment of the majority of technological parameters can not be implemented by regular controls during start-up, even if you change their settings and tasks [2]. For this purpose start-up or firelighter ACS are used. The latter are distinguished from the regular ones by the presence of devices for remote changing of the regulator settings (K_r, T_c) by the experienced expert operator.

The above-mentioned shows that application of intelligent control systems of complex multi-mode heat power objects (control loops of HPS steam boilers) has become an urgent and necessary measure of improving efficiency of the fuel-and-energy complex management in general.

Structure of the regulation object

As a regulation object, ACS of the superheated steam temperature of HPS drum boiler was considered [1, 2]. The superheater control task was to provide given temperature conditions in the steam path of the boiler. The steam temperature was changed by increasing or decreasing the amount of water injected into the desuperheater to stabilize the temperature setpoint at the output of steam superheater (Fig. 1).

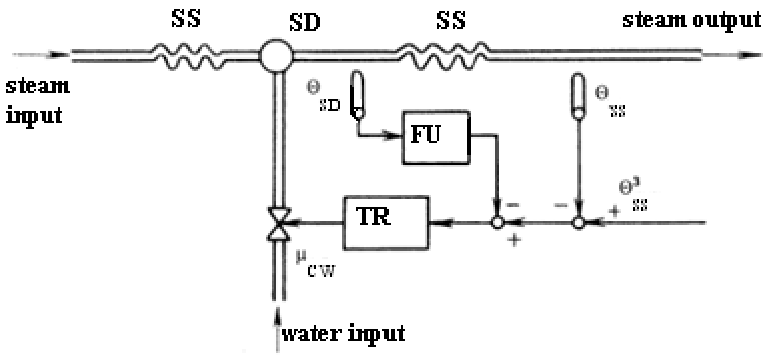


Fig. 1. ACS of the overheated steam temperature: SS – steam superheater, SD – steam desuperheater, FU – signal formation unit (differentiator), TR – temperature regulator, $\Theta_{S.D.}$ – steam temperature after desuperheater, $\Theta_{S.S.}$ – steam temperature after steam superheater, $\Theta^{з}_{S.S.}$ – the task

In the thermal power engineering of Ukraine a typical cascade system for superheated steam temperature regulation is mostly used (fig. 2). The cascade ACS includes a control circuit of PI regulator and an additional contour for measuring the controlled quantity formed in BF unit. The practice of such system application shows that significant changes in the flow rate of the steam entering the turbine require manual re-setting of the control loop coefficients to achieve the desired temperature. In fact, this is an important objective indication that the control system operation takes place under a priori uncertainty conditions. Analysis of the superheater performance shows that the control object has a variable transport lag value, its dynamical properties depend strongly on the oxygen content in the outgoing gases, pollution of the heating surfaces as well as the operation mode factors – the load, the type and grade of fuel used, the state of heating surfaces, excess air, etc. Besides, obtaining a mathematical model of the steam superheating temperature is usually associated with the approximation of acceleration curves, obtained experimentally, so that mathematical description will be a priori inaccurate.

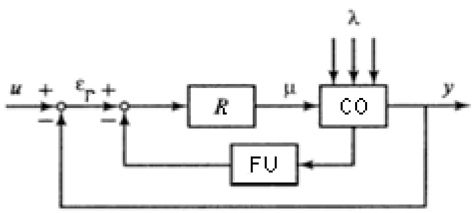


Fig. 2. Cascade ACS: R – regulator, CO – control object, u – task, λ – external disturbance, ε_r - error, μ – control action, y – output parameter.

Literature review

The study of scientific publications in the field of adaptive ACS of heat and power systems [1 - 3] led to the conclusion that the traditional methods of active identification and associated algorithms are widely used for calculating the optimal settings of PI and PID regulators by analyzing CFC of the objects or auto-oscillation mode. For example, these approaches are used in Russian adaptive controllers Remikont and Protar. It should be noted that for the steam temperature ACS under consideration auto-oscillatory process is invalid due to the process procedure requirements as the temperature deviation from the norm can lead to a premature wear of the turbine equipment. Thus, there arises a scientific problem of finding optimal object identification methods in the cases of changing load and the algorithms for calculating the settings of PI regulators, taking into account the expert opinion, in order to ensure the expected transient process (overshoot G <30%, the degree of attenuation Ψ = (0,75 - 0.95) with a minimum regulation time T_r.

At present, scientific approaches related to the use of intelligent systems are very popular in the theory of adaptive control [4 - 6]. These systems successfully implement the experience and knowledge of experts (fuzzy regulators) as well as possess the self-learning ability (neural controllers). Joint or combined use of these areas gave rise to the emergence of a new scientific trend of hybrid, or fuzzy neural networks (FNN) [4]. Consideration of this technology as applied to identification and adaptation of the superheated steam temperature ACS is an important current scientific problem.

The goal of the paper. The goal of this paper is development and training of hybrid networks in order to determine the optimal values of PI regulator settings in cascade ACS of the superheated steam temperature under changing load conditions of the object (adjusting mode) and in the presence of start-up mode.

Development of the functioning algorithm for the adaptive ACS of superheated steam temperature

The authors proposed a structure of the hybrid adaptive control system (fig. 3). In fig. 3 the following designations are introduced: *K* – object transfer coefficient, *T* – object time constant, *τ* – delay, *n* –order of the object, *y* – output parameter.

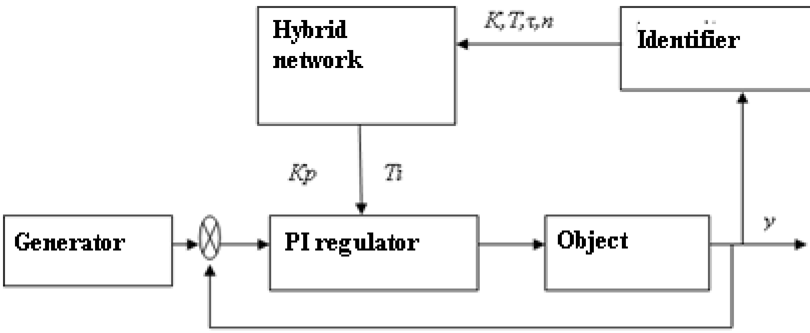


Fig. 3. The structure of adaptive ACS

The structure of PI regulator adaptive setting is based on the application of frequency identification methods and finding optimal PI regulator settings by the hybrid network. Application of the frequency methods has made it possible to provide interference immunity of the algorithm and rational organization of the active experiment using the functioning system in terms of maintaining the stability region. Identification was conducted by applying two different-frequency sinusoidal signals from the generator to the system input, the frequencies belonging to a significant range [7]. Structure of the object transfer function consists from several inertial links with the lag of $W(s) = \frac{K}{(T(s)+1)^n} e^{\tau(s)}$, the values varying over time within a definite range depending on the load type or on the steam boiler operating mode. The identifier determines values of the object parameters and its order. These values are further used by the optimizer in the form of a neural fuzzy network operating according to the algorithm of Sugeno [2 – 3] for searching the optimal values of PI regulator settings (K_r, T_c). The hybrid network training should be conducted taking into account the opinions of expert fitters of ACS.

Object identification and calculation of the optimal PI regulator parameters

In order to determine the values of the four object parameters (*K, T, τ, n*), It is proposed to use a harmonic oscillator that estimates CFC of the object at two different frequencies belonging to a significant range. Taking into account real equations:

$$\left.\begin{aligned} A_1 &= \frac{K}{(\beta^2\tau^{\ 2}\omega^2{}_1+1)^{0,5n}}; \\ A_1 &= \frac{K}{(\beta^2\tau^2\omega^2{}_2+1)^{0,5n}}; \\ \varphi_1 &= \text{-}arctg(\beta\tau\omega_1)\text{ - }\tau\omega_1\,; \\ \varphi_2 &= \text{-}arctg(\beta\tau\ \omega_2)\text{ - }\tau\omega_2 \end{aligned}\right\},$$

the solution of which for the known frequencies, amplitudes and phase shifts: A_1, A_2, ω_1, ω_2, φ_1, φ_2 – makes it possible to find the parameter values of the object transfer function. The time constant $T = \beta\tau$. It was assumed that the identifier has found the following parameter values for the transfer function of the investigated object via the control channel [1, 2]: $W(s) = \dfrac{8{,}27}{(3{,}05s+1)^3}e^{\ 0{,}93}$. The optimal values of PI regulator settings were calculated using MathCAD program (fig. 4).

It should be noted that PI regulator settings, calculated using the proposed method, required manual corrections since a number of the obtained fading transient processes did not meet the given criteria (the first deviation and the regulation time). To obtain a test sampling (a matrix of the neural fuzzy network training) of the optimal parameter values for PI regulator of the cascade ACS, a computer experiment was conducted using MatLab (Simulink) software with manual correction of the settings of K_r and T_c. Parameter values of the object transfer function were changed taking into account different modes of the steam boiler operation (nominal, economical, starting, stopping, regulation and peak modes) [7]. Experimental results are presented in table 1.

Table 1

Optimal PI regulator settings for n=3 and parametric disturbance action on the object (load variations)

K_{ob}	0,5	1	5	15	5	12	4,43	7,05	11,9	13,7
T_{ob}	1,5	3	4	4	1,5	1,5	2,48	1,5	1,5	3,4
τ	0,5	1	1,5	1	0,5	0,5	0,92	0,5	0,5	0,7
K_r	1,34	0,99	0,49	0,146	0,135	0,031	0,22	1,92	0,031	0,021
T_i	1,91	5,55	40,63	20,4	1,92	1,58	6,61	0,1	1,58	3,55

Mathcad-document

PI regulator setting calculation by the auxiliary function

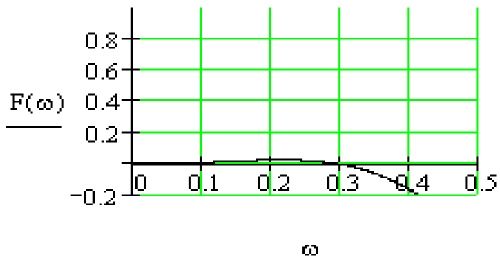
Entry of the oscillation index $M := 1.55$

Entry of the object parameters $k_\mu := 8.27$ $T_\mu := 3.05$ $\tau := .93$ $W_\mu(\omega) := \dfrac{k_\mu \cdot e^{-\tau\omega\cdot j}}{(T_\mu \cdot j\cdot\omega + 1)^3}$

Building the plot of the auxiliary function

$\omega_{end} := .5$ $n := 500$ $\Delta\omega := \dfrac{\omega_{end}}{n}$ $\omega := \Delta\omega, 2\cdot\Delta\omega .. \omega_{end}$

$\phi_\mu(\omega) := \arg(W_\mu(\omega))$ $A_\mu(\omega) := |W_\mu(\omega)|$ $F(\omega) := \dfrac{-\omega\cdot M}{A_\mu(\omega)\cdot(M^2 - 1)}\cdot(M\cdot\sin(\phi_\mu(\omega)) + 1)$



Finding the frequency of the auxiliary function maximum

$\omega := .35$ Given $\omega \ge .2$ $\omega \le .4$

$\omega_{res} := \mathrm{Maximize}(F, \omega)$

$\omega_{res} = 0.213$ $F(\omega_{res}) = 0.022$

Finding optimal parameters of the regulator and building AFC

$A_{res} := A_\mu(\omega_{res})$ $k_p := -M^2\cdot\dfrac{\cos(\phi_\mu(\omega_{res}))}{(M^2 - 1)\cdot A_{res}}$ $T_i := \dfrac{k_p}{F(\omega_{res})}$ $W_r(\omega) := k_p\cdot\left(1 + \dfrac{1}{T_i\cdot\omega\cdot j}\right)$

$W(\omega) := W_\mu(\omega)\cdot W_r(\omega)$ $\Phi(\omega) := \dfrac{W(\omega)}{1 + W(\omega)}$ $A(\omega) := |\Phi(\omega)|$ $\omega_{end} := 2$ $\Delta\omega := \dfrac{\omega_{end}}{n}$

$\omega := \Delta\omega, 2\cdot\Delta\omega .. \omega_{end}$

Optimal values

$k_p = 0.124$ $T_i = 5.649$

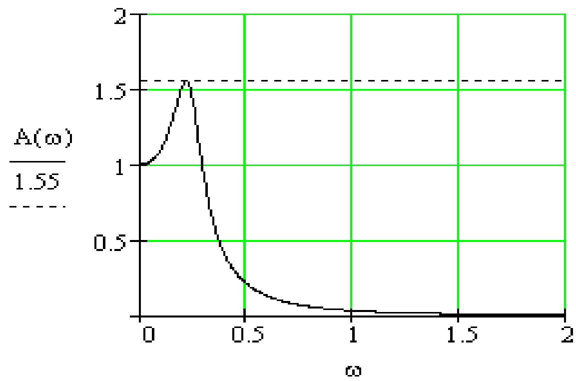


Fig. 4.Calculation of optimal values of PI regulator settings

Development of the fuzzy neural system

Fuzzy neural network (FNN), or a hybrid network (HN), is a multi-layer neural network without feedback [3]. The inputs of such network (K, T, τ) are represented in the form of linguistic variables (small, average and high values). In Matlab (ANFIS) program the process of building an adaptive neural fuzzy inference system was conducted (fig. 5) for approximating the dependence that represents a casual relationship between K, T, τ and K_r, T_c. Proceeding from recommendations [5, 6] and computer experiments in MatLab (Fuzzy Logic Toolbox) environment, the type of membership functions (trapezoidal and triangular), describing the input values, was chosen [4]. During training the number of cycles we used was equal to 40 and the selected method of instruction – back error propagation [5].

Thus, the hybrid network implemented mapping of PI regulator parameters according to the regulation object characteristics: $S^k = f(x^k) = f(x_1^k, x_2^k, ..., x_n^k)$, $k = 1, 2, \dots N$ in the presence of training set $((x^1, y^1), \dots, (x^N, y^N))$ given in table 1.

For simulating an unknown function f Sugeno algorithm was used with the knowledge base of the following type: Π_i : IF x_1 is A_{i1} И x_2 is A_{i2} И x_l is A_{in}, THEN $T_C = S_i$, i=1, 2, …, m, where A_{ij} – fuzzy sets of a triangular form, describing the expert statements (small (S), average (A), big (B)), S_i – output values of the regulator. The degree of truth μ of rule i is determined by the operation of conjunction. The fuzzy system output was determined by the center of gravity method [3]:

$$T_{ik} = \frac{\sum_{i=1}^{m} \mu_i S_i}{\sum_{i=1}^{m} \mu_i}.$$

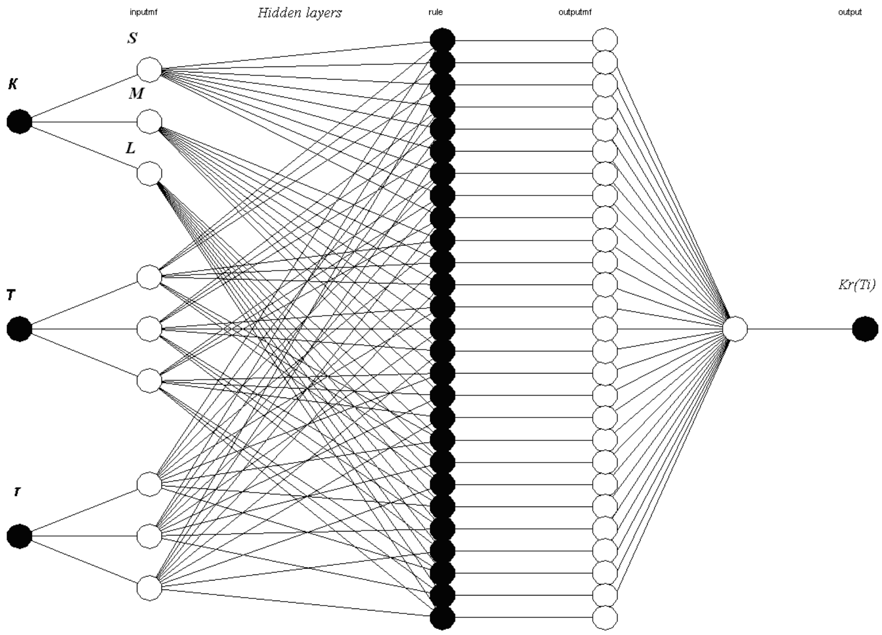


Fig. 5. Structure of the proposed hybrid network

After the hybrid network training and supplying the values of the object parameters (K_{ob} = 8,27; T_{ob} = 3,05; τ = 0,928) to its input (these values are not represented in the test sampling of table 1 and are determined as a result of active identification), the network recommended the following values of PI regulator settings: T_c = 5,15; K_r=0,12, while those determined using a traditional CFC method (fig. 4) were K_r =0,21, T_c = 5,649.

Computer experiments on approbation of the values of the adaptive PI regulator settings

Using MatLab (Simulink) software [8], models of the cascade ACS were elaborated (fig. 2). They include PI regulators and third-order inertial objects with time delay (a steam superheater model via the regulation channel) with a non-linear element (restriction on the control action) (fig. 6). A single jump was supplied to the system input. If the values of the transfer function parameters are changed in the cases of power unit transition to a peak or a start-up mode (when the action of parametric disturbances is simulated) and new values of the object parameters are established K_{ob} = 13,7; T_{ob} = 5,4; τ = 1,1, HN recommended the following settings: K_r = 0,81; T_c = 6,33, and a traditional frequency method by an auxiliary function - K_r=0,021; T_c = 3,55. Substitution of these values into Simulink software scheme has made it possible to obtain the following transient processes (fig. 7):

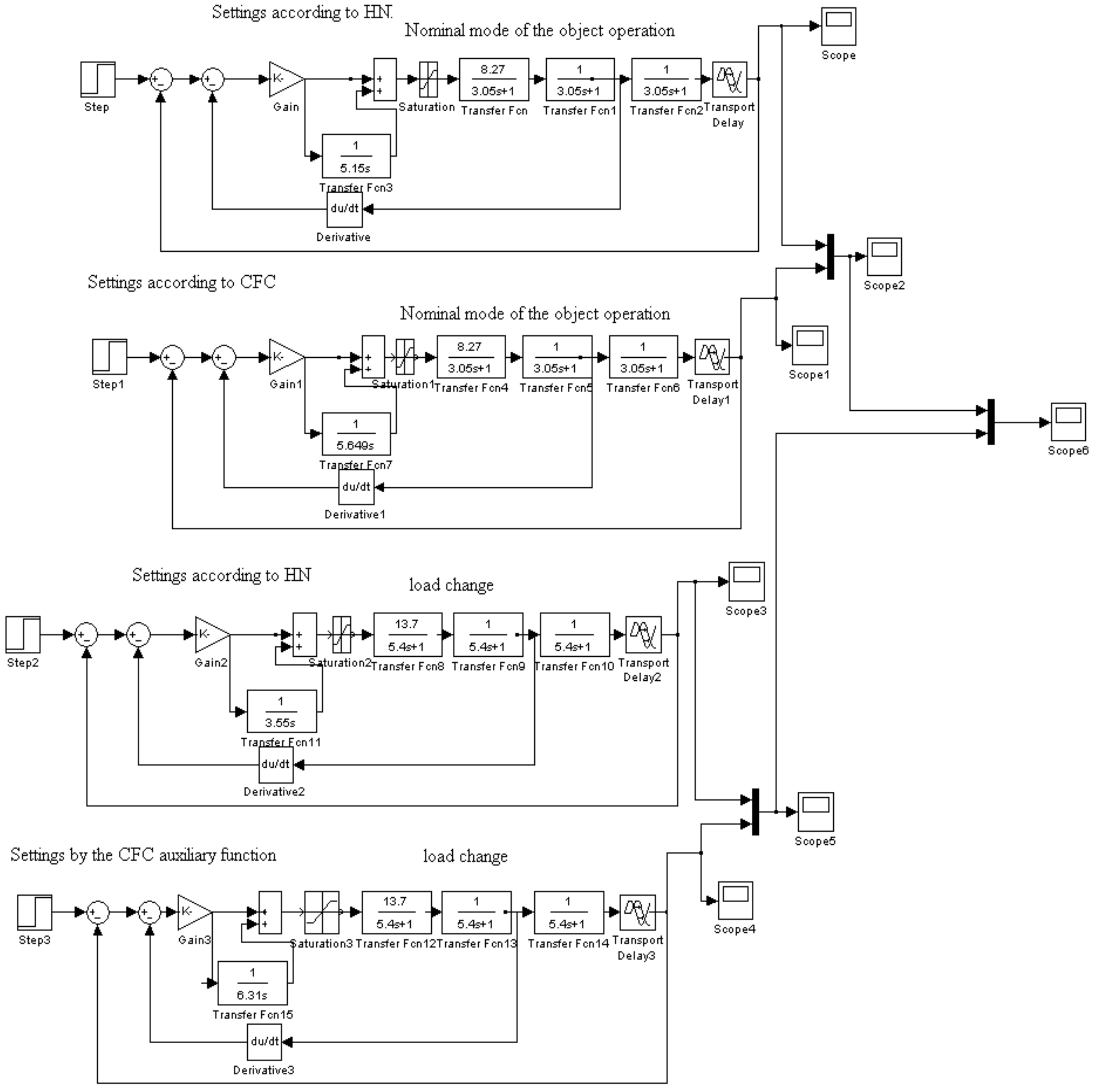


Fig. 6. The circuit of adaptive ACS with PI regulators and non-linear elements (Saturation)

From the analysis of the transient processes of fig. 7 (1, 2) it could be concluded that under nominal or stable operating conditions of the object the hybrid and traditional PI regulators demonstrated the same quality indicators (regulation time T_r = 45s). However, under the influence of parametric disturbances (3, 4) the hybrid system had shorter regulation time (T_{r1} = 138 s) as compared with the traditional adaptive ACS (T_{r2} = 173 s), the hybrid ACS overshooting G^{hb} = 28% while that of a traditional ACS G^{tr} = 50%, the degree of fading for the hybrid ACS Ψ^{hr} = 0,91, for the traditional Ψ^{tr}= 0,68, i.e. the proposed ACS is optimal and energy-saving while the traditional cascade ACS requires additional adaptation.

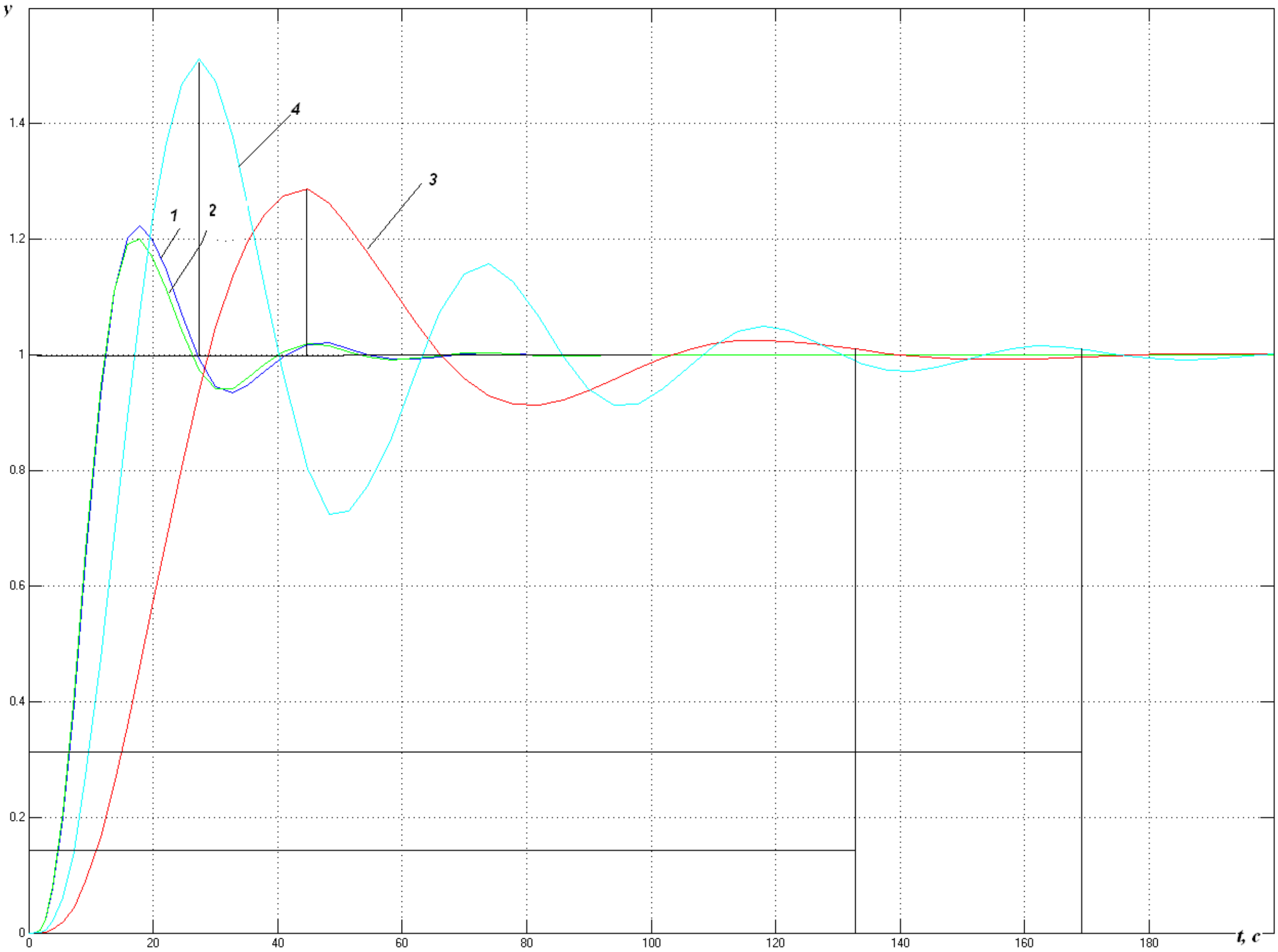


Fig.7. Transient processes over the regulation channel : 1 – for a traditional ACS and 2 – for the fuzzy neural ACS (under nominal load), 3 – for the fuzzy neural ACS and 4 – for a traditional ACS (under changing load).

Conclusion

Computer experiments using MatLab (Simulink) software with varying values of the object transfer function parameters (while simulating peak and start up modes of the steam boiler) have demonstrated that the traditional adaptive approach is ineffective in a number of cases (ineffective ACS) in contrast to the algorithm of HN, the transient processes of which proved to be optimal. From the obtained results it can be concluded that the proposed intelligent adaptive ACS of the overheated steam temperature has the following advantages over traditional methods of adaptation according to CFC and auto-oscillations, which are currently used in ACS of HPS:

1) fast process of finding optimal PI regulator settings for cascade ACS with the ability of their approximation and extrapolation as well as under the action of uncertain disturbances;

2) smaller first deviation and shorter transient process of regulation;

3) the possibility of the cascade ACS optimal operation under all the modes of the steam drum boiler operation;

3) the possibility to use different ACS with PD- and PID regulators during the adaptation processes in thermal power engineering.

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