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OPTIMIZATION OF SYSTEM PARAMETERS CONTROLLING ELECTRIC FURNACE TEMPERATURE USING GENETIC ALGORITHMS

OPTYMALIZACJA PARAMETRÓW UKŁADU STEROWANIA TEMPERATURĄ PIECA ELEKTRYCZNEGO Z WYKORZYSTANIEM ALGORYTMU GENETYCZNEGO

Abstract

The optimization of the parameters of the electric furnace temperature control was considered. The optimization was executed using genetic algorithms. The model takes into account nonlinearity, which is connected with the penetration of heat. Also, it is connected with losses of heat due to convection and radiation. The genetic algorithm determines the selection of parameters of the mathematical model in which the system accurately reproduces the input action.

Keywords: genetic algorithm, individual, population, mutation, target function, electric furnace

Streszczenie

W artykule przedstawiono optymalizację parametrów układu sterowania temperaturą pieca elektrycznego. Optymalizacja odbywa się za pomocą algorytmu genetycznego. Model pieca uwzględnia nieliniowości związane z przenikaniem ciepła oraz stratami ciepła przez konwekcję i promieniowanie. Algorytm genetyczny określa parametry modelu matematycznego, dla których system maksymalnie dokładnie odtwarza sygnał wejściowy.

Słowa kluczowe: algorytm genetyczny, osobnik, populacja, mutacja, funkcja celu, piec elektryczny

The authors bear full responsible for the text and quotations.

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1. Introduction

The electric furnace is a very common object in various technical and household systems; therefore, the control of its temperature is of great practical importance. The temperature control system was created for electric furnaces – this raises questions regarding the estimation of its dynamic properties, in particular, its inertia. The first step which is necessary to reach this point is to create a mathematical model of furnaces' temperature control systems which has the ability to perform the physical process in the most adequately way. Certainly, such a system will be nonlinear and inertial because the mathematical model will be reduced to the system of nonlinear differential equations. To adequately perform the physical processes in the furnace, it is recommended to write the differential equations in partial derivatives. This is due to the spread of temperature in time and space. The independent variables of this model are spatial coordinates and time. In this article, the spatial variables are not considered it is limited by the time. This makes it possible to record a mathematical model of the furnace using the usual derivatives. Such a simplification distorts the true picture of the physical process. However, it is possible to carry out a quantitative assessment of the dynamic work of the system using such a model. Finally, the control system is described by a system of nonlinear differential equations. The reason for the nonlinearity of these equations is the dependence of the parameters of the current furnace temperature and the heater. In particular, the electrical resistance of the heater is also nonlinearly dependent on temperature. As the temperature increases, electrical resistance also increases. However, if the temperature varies slightly, it could be considered as a constant.

Electric furnaces are objects with many parameters, these are time constants, structural factors and parameters furnace heater. It is characterized by a significant number of variables, as a result, it creates a large space of search. Therefore, there is no way to enumerate all solutions in a reasonable time. This leads to the application of a genetic algorithm in solving optimization problems. For efficient operation of the temperature control of an electric furnace, it is necessary to optimize its parameters. In genetic algorithms, during the modelling of parametric optimization target function is used. In this case, such a function is representative of the difference between the desired results and those that are available. If we are interested in the output signal of the system, it should be a difference between the desired output signal and the available output signal. In an electric furnace, the output of the system changes its temperature over time.

We are dealing with two independent mathematical models. The first independent mathematical model reflects the change in time of the state variables of the system. It is based on the nonlinear dynamic equation in ordinary derivatives and on being solved by numerical methods. The second independent mathematical model using evolutionary methods selects the parameters of the system, so the dynamic characteristics of the system should be close to the desired. For each new set of numerical values of parameters we have an absolutely independent task, which is related to the other set. Therefore, this algorithm is easy to parallelise, which enables improving its performance.

2. Analysis of publications

To determine the optimal parameters of control systems a variety of approaches are used. The most widely used two directions. In the first direction neural Networks are used. The second direction is based on genetic algorithms and the other. The cause of using depends on the particular problem and its adaptation to a specific method. The minimax methods are known, but they are cumbersome and often determine only a local optimum.

In [1] the problem of modelling nonlinear control systems is considered. The structured nonlinear parameter optimization method (SNPOM is a structured nonlinear parameter optimization method), which is adapted to the radial basis function (RBF is a radial basis function) of network is proposed. This is non-linear model of parameters' optimization depending partly on Levenberg–Marquardt method for nonlinear optimization of parameters. Compared with some other algorithms, SNPOM accelerates the computing convergence of searching process of parameters' optimization models RBF type. In [2] the procedure for implementing the Taguchi's method for electromagnetic optimization problems is shown. Optimization procedure is used for the development of antenna arrays. Compared with traditional methods of optimization, Taguchi's method is easy to implement and it quickly reaches the optimal solutions. In [3], the numerical optimization combined with finite element (FE – finite element), which plays an important role in the development of electromagnetic devices is performed. The parametric description of the investigated objects executed and the optimization problem is formed. Special attention is paid to the symbolic description of the model to minimize computation time and process of definition the optimization task. In [4] the new optimization algorithms for the optimal configuration of controllers PI, belonging to a class of second-order processes with integral component and variable parameters are proposed. Sensitivity analysis relatively to the parameters' changing of controlled process leads to increased sensitivity of the model. The increase in output sensitivity function through the integral criterion of absolute error in determining the objective functions and related optimization problems are solved by the systems Particle Swarm Optimization (PSO) and Gravitational Search Algorithms (GSA).

In [5] a concept for the optimization of nonlinear functions using the methodology of cluster particles represented. The evolution of multiple paradigms is shown but attention is focuses on the implementation of one of them. The measurement of productivity paradigm, including nonlinear function of optimization is described the process of neural network training is suggest. The relationship between the particle and cluster optimization using genetic algorithms is described. In [6] an optimization task that contains gaps, nonlinearity or high dimension is performed. It is difficult to solve it using conventional numerical methods because it requires high time costs. The tool that solves this problem using optimization particle Games Gaming Particle Swarm Optimization (GPSO) is suggested. This algorithm is implemented on the hardware using the graphics processor (GPU). The paper used this utility to optimize the allocation of radio resource. This study is a powerful tool that can be used to solve various disciplinary optimization tasks such as training of artificial neural networks, function maximization/minimization for universal plug and play mobile communication systems, and planning. A nonlinear mathematical model of electric furnace which will be explored is given in [7].

3. The mathematical model of control system

To adjust the temperature in the furnace, a conventional analogue closed linear stabilising system with automatic control (Fig. 1) and with full original information can be used. This system works in such a way: action u , which was setting, comes to the difference scheme, where it is deducted from the voltage u_{MT} output proportional to the temperature of the furnace. The resulting difference is amplified by an electronic amplifier (EA) and fed to the motor (M) shaft through a reduction gear (RG) which is connected to a potentiometer (PT). The potentiometer is a part of the scope of the heating furnace element (OE) and a change in its resistance leads to a change of temperature in the furnace t_{EO} . The temperature using the measuring transducer MT is converted into a voltage that is fed to the difference scheme. Time will be denoted as τ . To simplify the model, it is necessary to suggest the assumption that the measuring transducer has a linear characteristic. Its parameters are chosen to achieve the desired temperature and its output voltage must be equal to setting action. In such a case, the amplifier input voltage will be at zero and the motor will not rotate. The system will go into equilibrium.

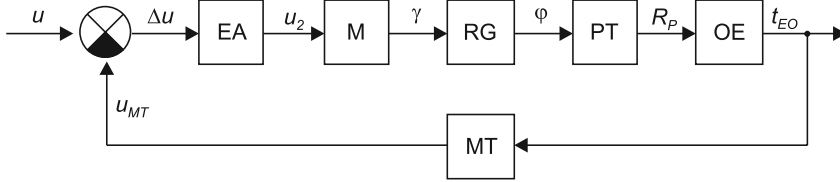


Fig. 1. The functional scheme of the automatic temperature control in an electric furnace

The mathematical model of the system's elements is considered. Linear and nonlinear elements are presented.

Electronic amplifier. This element in comparison with motor, furnace can be considered as having no lag. Therefore, it is described by the algebraic equations:

$$u_2 = \begin{cases} 0, & \text{if } |\Delta u| < u_{\min} \\ K_E \Delta u + u_0, & \text{if } u_{\min} < |\Delta u| < u_{\max} \\ u_{2\max}, & \text{if } |\Delta u| > u_{\max} \end{cases} \quad u_0 = -K_E u_{\min}, \quad \Delta u = u - u_{MT} \quad (1)$$

DC motor. This refers to electromechanical devices and it is described by differential equations of the fourth order:

$$\frac{di_a}{d\tau} = S_a u_a - T_a u_f + E_a, \quad \frac{di_f}{d\tau} = -T_f u_a + S_f u_f - E_f, \quad \frac{d\omega}{d\tau} = (c\Phi i_a - M_R) / J, \quad \frac{d\gamma}{d\tau} = \omega \quad (2)$$

where:

$$S_a = 1 / (L_a + L_{af} L_{fa} / L_f), \quad T_a = S_a L_{af} / L_f, \quad E_a = S_a (L_{af} r_f i_f / L_f - c\omega\Phi - \Delta u - r_a i_a), \\ T_f = S_a L_{fa} / L_f, \quad S_f = (1 - L_{fa} T_a) / L_f, \quad E_f = (L_{fa} E_a + r_f i_f) / L_f.$$

- L_a – the total inductance of the consecutive circuit's armature,
- L_f – the inductance of exciting winding,
- L_{af}, L_{fa} – mutual inductances of the circuit's armature and the circuit of excitation,
- r_a, r_f – active resistances of the circuit's armature and the circuit of excitation,
- ω – the angular velocity of motor armature,
- γ – the angle of rotation,
- Φ – the magnetic flux of motor,
- c – the constitutive constant of motor armature,
- Δu – the voltage drop in the brush contact,
- J – the moment of inertia of the rotor motor,
- M_R – the moment of resistance.

In consideration of saturation compensated motors of electromagnetic conductor it is possible to approximate the curve of magnetization. In the unsaturated motor it is:

$$\Phi = L_f i_f / w_f \quad (3)$$

To receive the equations of DC motor with series excitation, equation (2) must be supplement by conditions:

$$i_a = i_f = i_M, \quad u_C = u_a + u_f \quad (4)$$

Solving (2) and (4) together, the equation of DC motor with series excitation will be obtained:

$$\frac{di_M}{d\tau} = S_a u_a - T_a u_f + E_a, \quad u_f = \frac{(T_f - S_a) u_C + E_f - E_a}{T_a - S_a + T_f - S_f}, \quad u_a = u_C - u_f. \quad (5)$$

Reducer. The reducer's equation is described by the linear dependence:

$$\varphi = \gamma / i \quad (6)$$

where i is a coefficient of reduction.

Potentiometer. This element is also a linear element without lag that converts the rotation angle φ in the resistance of the resistor regulator:

$$R_p = k_p \varphi \quad (7)$$

where R_p, k_p are the resistance and coefficient of conversion resistor's regulator.

An electric heating element. In Figure 2, a scheme of an electric heating element with a resistance R_p is shown. This is powered by voltage U through resistor regulator R_p .

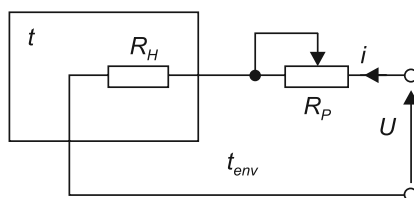


Fig. 2. A scheme of electric heating element

The temperature t is a managed quantity of the furnace. In this scheme, the control value is the resistance R_p . The values, which are disturbing are voltage U , an environment temperature t_{env} and a resistance heater R_H . According to the law of energy conservation, such an equation can be formed [7]:

$$A_E = \dot{A}_H + \dot{A}_{env} \quad (8)$$

where:

- A_E – the elevated heat,
- \dot{A}_H – the energy, which is expended to replace the thermal state of the heater,
- \dot{A}_{env} – the energy, which is removed from the control object into the environment.

Considering that for an infinitely small time interval, $d\tau$ voltage of net U , resistance of heater R_H and resistor of control R_p remain the same, it is possible to determine the elevated energy using this time:

$$A_E = i^2 R_H d\tau = \frac{U^2 R_H}{(R_H + R_p)^2} d\tau \quad (9)$$

where i is the current flowing through the heater. In turn:

$$A_H = c_t m dt \quad (10)$$

where:

- c_t – the specific heat of the material object,
- m – the mass of the object,
- dt – the change in temperature.

The energy, which is removed from the facility into the environment, is determined by the cost of the heat transfer, convection and heat's radiation and dissipation:

$$A_{env} = \lambda_H S_H (t - t_{env}) d\tau + \kappa_r S_r (t^4 - t_{env}^4) d\tau \quad (11)$$

where:

- λ_H – a coefficient of heat,
- S_H – an equivalent heat's transfer surface,
- κ_r – a coefficient of radiation,
- S_r – an equivalent surface of radiation:

$$S_H = \frac{\lambda_S S_S (t_S - t_{env})}{\lambda_H (t - t_{env})}, \quad S_r = \frac{\kappa_S S_S (t_S^4 - t_{env}^4)}{\kappa_r (t^4 - t_{env}^4)} \quad (12)$$

where:

- S_S – the actual surface of the object,
- t_S – the temperature on the surface of this object,
- λ_S, κ_S – the heat transfer coefficient and the radiation furnace surface.

By substituting (9)–(12) (8) and dividing this result by $\lambda_H S_H d\tau$ dynamic equations, an electric heating element is obtained:

$$\frac{c_l m}{\lambda_H S_H} \frac{dt}{d\tau} + t = \frac{U^2 R_H}{\lambda_H S_H (R_H + R_P)^2} + t_{\text{env}} - \frac{\kappa_r S_r}{\lambda_H S_H} (t^4 - t_{\text{env}}^4) \quad (13)$$

Time constant is $T_1 = c_l m / (\lambda_H S_H)$. The final form of the equation, which will be integrated by the Runge–Kutta's method in modelling process:

$$\frac{dt}{d\tau} = T_1^{-1} \left(\frac{U^2 R_H}{\lambda_H S_H (R_H + R_P)^2} + t_{\text{env}} - \frac{\kappa_r S_r}{\lambda_H S_H} (t^4 - t_{\text{env}}^4) - t \right). \quad (14)$$

Measuring converter. A thermocouple is used to measure the temperature, which in the first approximation can be considered as a linear element without lag:

$$u_{MT} = k_{MT} t \quad (15)$$

where k_{MT} is a coefficient of measuring transducer.

4. The implementation of the genetic algorithm

The mathematical model of the explored control system is nonlinear, it is therefore impossible to use analytical methods of parametric optimization. The appropriate modification of the genetic algorithm, which takes into account all the features of the model was performed. In order to evaluate the results of optimization which were obtained, the following fitness function was used: $F_{\text{fitm}} = \sum_i |t_i - t_0|$, where t_0 is the given temperature, t_i is the temperature of the heating element.

For the fitness function, a sum of absolute means of differences between input and output values in the range of output value outside the statistical error of the control system is taken. For simplicity, it is considered that the transition process was completed when the resulting value is included in the limit of static error system. Be considered more adaptable individual with a lower value of the fitness function. This objective function does not account for the duration of the transition process; therefore, the result cannot be the best of the possible solutions in the terms of speed heating of furnace.

Genetic methods, which according to their nature are stochastic methods, are based on the analogy with the natural evolutionary process. Genetic methods do not impose additional requirements to the expression of the fitness function – at each iteration, it works with multiple solutions. This provides an opportunity to circumstance the whole research space in comparison to making it possible in most cases a more detailed comparison with gradient methods of multidimensional nonlinear unconstrained optimization. Genetic method predicates a ways out of local extremes.

The fitness function is one of the most influential factors on the effectiveness of the genetic algorithm because it determines the aim of algorithm. In the case of an incorrect algorithm's default it will get to a local extremum. It appears as effective data or it can be taken as a result of work because sometimes a local extremum can be better than primary data. Additionally, the genetic algorithm can reach the extremum at the circumference

of the point. The aim of the genetic algorithm is to search the following values of the model's parameters under which the fitness function value is equal to zero or it is close to zero. System's parameters which will be changed by the genetic algorithm are: k_{AI} which is the amplification factor of electronic amplifier; k_{OF} is the displacement of strengthening of output quantity for input signals, its amount exceeds the threshold value; u_{min} is the threshold of sensibility if it will be exceeded the input signal becomes strengthening.

For the implementation of the optimization model, the algorithm of classic GA is simplified. Such simplifications are permissible due to the small number of chromosomes (system parameters, which are selected by the algorithm) and because of ease of the control system's mathematical model. In the simplified algorithm, the crossover's operator mutation of parental individuals is absent. The parameters of the new individual will be accidentally generated based on the parents' parameters, which are monogamous.

This simplified modification of the algorithm consists of the following stages:

- 1) The creation of initial population.
- 2) The calculation of adaptability for each species.
- 3) The selection of individuals according to adaptability. Some amount is selected, which is set by GA working.
- 4) The condition algorithm's work completion is checking.
- 5) If condition 4 is not satisfied, the generation of a new population based on the best selected is executed using mutation operation and it returns to condition 2.
- 6) If condition 4 was executed, the best individuals from the generated population would be selected. It would be the result of the algorithm's work.

Graphical interpretation of modification of the algorithm is shown in Fig. 3.

Before the program starts, it is necessary to establish the following parameters:

- the mathematical model of the control system (amplifier, engine, gearbox, heating element),
- genetic algorithm (number of generations and populations, the percentage of people who will be selected by a better indicator of adaptation),
- limits of changes in these parameters.

After the process of necessary constant reading program will calculate some service information, which is necessary for it proper work. It includes the primary parameters of the algorithm and a set of launching at the environment of execution. Only after this procedure can the important stage of work of the genetic algorithm will begin. It is a process of creation of primary population individuals. At this stage, all individuals of the first generation are successively created. During the population's individual creation, an accidental choice of the meanings of changeable parameters is occurred at the limits of the whole range of changes, which includes the changing from minimal meaning of the parameter to maximum with some stage. The meanings for whole parameters, which are selected by the algorithm are chosen in a such way that it is not depending from one another. to run the process in runtime. Only then begins an important stage of the genetic algorithm – creating initial population of individuals. At this stage, all individuals of the first generation are consecutively created. When creating an individuals of population, the selection of values of variable parameters within the entire range of variation from minimum to maximum

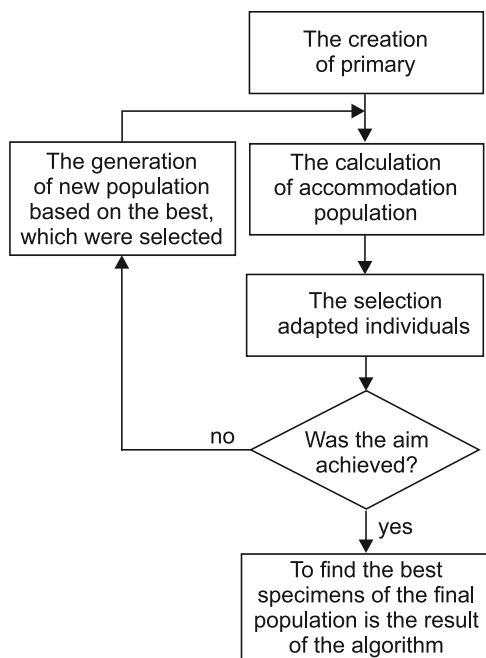


Fig. 3. The scheme of genetic algorithm's modification

setting, with a certain step is happened. Chosen values for all parameters are selected by algorithm, regardless of each other.

After creating the population for each individual held the launch of a mathematical model with a set of input parameters is occurred. In the process of modelling in iterative form fitness function for the individual is calculated. If the method for pre-set parameters was divergent, fitness function would take the maximum value for a variable of double type of C++.

After the process of fitness function meaning calculation for all individuals of generation individuals are sorted according to this value in ascending order. This means that the most adapted individuals will be at the beginning. Since the beginning of the sorted list sorted according to the prescribed percentages correlation some amount of the best individuals is chosen. Based on this, these new individuals will be generated. One of the best individuals passes in to the next generation. The rest places in generation are stuffed by new individuals, which creation is based on the best selected individuals.

When creating some new species, the mutation operator is used. For example, we have only 30 individuals out of 100; therefore, they become the basis for a new population which in turn will also have 100 individuals. 30 individuals using mutation will form 70 its descendants. The principle 'the best can get better' is established. So, the best individual will have the largest amount of descendants. The rest will have an equal amount of descendants but its division will begin from the best. This means that the worst of the 30 individuals will be able to get the child in the least. The creation of descendants occurs

sequentially, skirt all the population. If we had an equal number of new and old persons, each old individual would have the descendants. If the percentage value of new individuals was less than 50, an opportunity to get descendants would have only the best individuals. The worst individuals will not get such an opportunity at all. The principle of mutation work is described in detail.

Firstly, the possible range of variation for each of the parental settings is calculated. It is a constant percentage of the whole spectrum, for example it is 10%. This means if k_{AI} has a general spectrum of changing from 1 to 10, the parent individual will receive the meaning of parameter, which is equal to 5.7. For the descendants, the variation of this value is within the limits from 5.2 to 6.2. The values of descendant's parameters will be changed randomly according to the possible limits of change. The important point of mutation is to reduce the possible range of descendant's parameters from 5–30% in the transition to the next generation. Thus, in each subsequent generation, descendant's mutation decreases, this gives an opportunity to receive the optimal meaning of the parameters and to reach the global minimum of fitness-function. Therefore, detached after mutation we will get a new generation of primary amount. A block diagram of a simplified implementation of the algorithm is shown in Fig. 4.

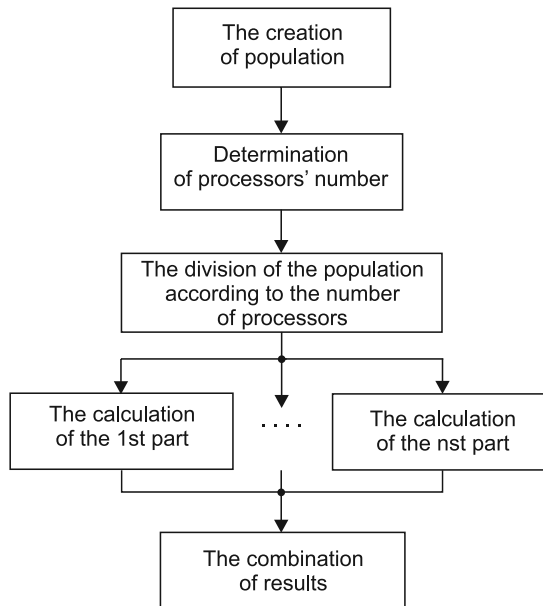


Fig. 4. The scheme of parallel computation of genetic algorithm

As a result of the program, we will get an individual with optimal parameters and a fitness function. Through substituting the values of optimal parameters in the mathematical model, it is possible to reproduce the work of the control system and estimate its results. As a significant amount of the genetic algorithm occurs randomly, multiple runs of a program will give different, but similar results.

The calculation for each individual of generation is not dependent from the others. It can be separated as detached flows, which will occur on the separate nucleus or flows of the processor's nuclear. The increase of productivity from the parallel computation is directly proportional to the number of logical processors (in the case of OS family of Windows NT).

5. Analysis of the genetic algorithm results

In computer simulations modes of the control system the following values of parameters are used:

$$h = 0.04c, \tau_m = 3000c, t_0 = 150^\circ\text{C}, P_{pm} = 75 \Omega, i = 1500, k_E = 5, k_{Emin} = 1, k_{Emax} = 10, \\ u_0 = 1 \text{ V}, u_{0min} = 0, u_{0max} = 4 \text{ V}, u_f = 15 \text{ V}, r_a = 0.025 \Omega, r_f = 200 \Omega, L_a = 0.00467 \text{ H}, \\ L_f = 110.8 \text{ H}, L_{fa} = L_{af} = 10^{-5} \text{ H}, N_f = 2470, c = 70.8 \text{ N}\cdot\text{m}/(\text{Wb}\cdot\text{A}), M_R = 0.2 \text{ N}\cdot\text{m}, \\ J = 0.2 \text{ N}\cdot\text{m}\cdot\text{s}^2/\text{rad}, c_t = 20 \text{ N}\cdot\text{m}/(\text{Wb}\cdot\text{A}), \lambda_H = 1 \text{ Wt}/(\text{m}^2\cdot\text{K}), S_H = 1 \text{ m}^2, m = 10 \text{ kg}, \\ U = 220 \text{ V}, R_H = 40 \Omega, t_{env} = 20^\circ\text{C}, k_r = 10^{-6} \text{ Wt}/(\text{m}^2\cdot\text{K}^4), S_r = 10^{-5} \text{ m}^2.$$

During the application of the genetic algorithm, it was observed that for some number of species, it was impossible to calculate the function performance goals due to the error of calculation's implementation of output parameters of the mathematical model. A large number of errors occurred in calculations on the first generation and significantly decreased in the following calculations. This gives the opportunity to implement the conclusion that calculation errors arise in some sets of input parameters – this causes divergence of the mathematical model. There are two sorts of errors:

- 1) The transition process is too long. The output value during the time of integration was not included in the limits of static error of the system.
- 2) The divergence of integration of differential equations by the Runge–Kutta's method is a periodic character of the output value or its value can be too large.

The first type of error indicates instability or unsatisfactory work of the control system with pre-set parameters. The duration of the entrance action is too long, this is unacceptable. Using standard parameters, such action occurs within the limits of the chosen integration time. To detect this type of error, it is enough to look at the meaning of the output value or to receive an appropriate flag of position of output value in the limits of the static system's errors. This flag is reset at the beginning of the simulation and at each curve's intersection of the output value of the lower or upper limit of static error on the output of this limit, and it is set when the output curve of value crosses the upper or lower limit one more time in the limits of the system.

The second type of errors led to differences in the method of Runge–Kutta. The meanings of value, which were given by the method of Runge–Kutta, were too large. These meanings are featured in differential equation. To exclude such errors, the meanings of values are checked at every step. If at least one of them is too big (limit is set with regard to system settings 10^{-5}), the simulation was stopped.

Thus, in the first generation the exclusion of most false sets was occurred because of the large variation of parameters and diverse species composition. In the next generation, a suitable individuals were modified, so the possibility of a false set with each generation was decreased.

By trial of the genetic algorithm's run, the most successful spread range of input parameters was chosen. It was occurred setting on a large range of change of a large number of individuals of the first population and a small number of generations.

The research of the genetic algorithm occurred using such schemes:

- 1) The percentage change of new persons using a constant amount and population amount.
- 2) The change in population size using constant number of generations and the percentage of selection.
- 3) The change of generations using constant number and percentage of selection.

The work of GA was explored using the first scheme. The amount of generations is 4. The quantity is 10 individuals. The results of algorithm work using different percentage of selection are shown beneath.

Table 1

The results of GA's research according to the first scheme

The percentage of selection	τ_{TP} [s]	t_{oc} [°C]	F_{fitn}
0.4	941	70	416 137
0.5	917	66	377 676
0.6	977	74	447 802
0.7	903	63	362 498
0.8	955	68	482 823

Using the results of testing for the specified amount of population and the quantity of generation, there are two of the most optimal percentage of selection 0.5 and 0.7. Using this meaning of percentage, the results of optimization will be the best.

The GA's work was explored according to the second scheme. The amount of the generation is 5, the percentage of selection is 0.6.

Table 2

The results of GA's research according to the second scheme

The quantity	τ_{TP} [s]	t_{oc} [°C]	F_{fitn}
10	932	74	444 343
20	928	66	389 021
30	902	63	362 069
40	907	64	367 882

Using the results of testing for the specified amount of population and the quantity of generation, there is one the most optimal percentage of selection is 30. Using this meaning of percentage, the results of optimization will be the best.

The GA's work was explored according to the third scheme.

The amount of population is 30, the percentage of selection is 0.6.

Using the 4 population: the duration of transient process is $t_{TP} = 959$ s; the process of over control is $t_{OC} = 70^\circ\text{C}$; the process of adaptability is 417 060. Using 6 generations: the duration of the transition process is $t_{TP} = 913$ s; the duration of over control process is $t_{OC} = 64^\circ\text{C}$; the process of adaptability is 373 231. Using 7 generations: the duration of the transition process is $t_{TP} = 912$ s; over control is $t_{OC} = 64^\circ\text{C}$, the process of adaptability is 373 258. The results of using 8 and more generation are repeated. Therefore, there is no sense to increase the quantity of generations. In pre-set conditions, GA gives the best result using 6 generation.

After investigating the modes of the GA's work, it is possible to choose the best. It will have these parameters the population size is 50 individuals, the number of generations is 6, the percent selection is 0.7.

The calculated curves of the transitional process of furnace's temperature are shown in Fig. 5. Curve 1 corresponds to the regime of parametric optimization, curve 2 corresponds

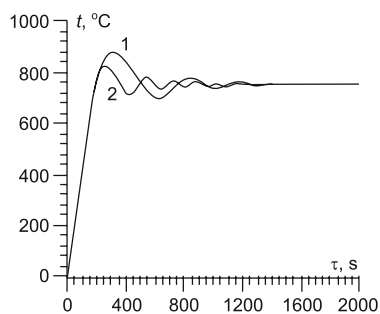


Fig. 5. The transitional process' curves of furnace temperature before optimization (curve 1) and after optimization (curve 2)

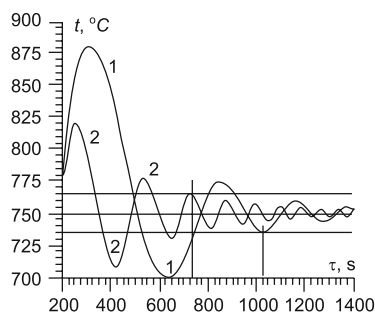


Fig. 6. The fragment of Fig. 5 in scaled-up

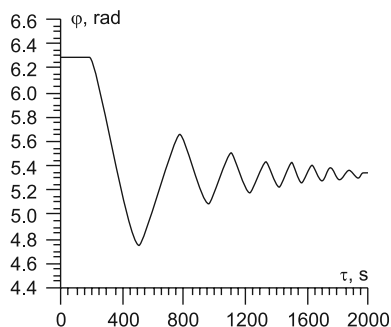


Fig. 7. The transitional process' curve of angle rotation of the potentiometer before parametric optimization

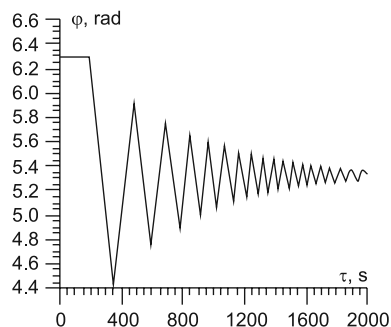


Fig. 8. The transitional process' curve of angle rotation of the potentiometer after parametric optimization

to the regime which exists after parametric optimization of genetic algorithm. To see the essence of the process in Fig. 6, better a fragment in Fig. 5 is shown on a larger scale. The established error is 2%. It is 15°C from the nominal temperature, which is 750°C. The area of this error, which was shown in Fig. 6, are performed by two horizontal lines. As we can see, curve 1 is the zone of error at time 1025 s before parametric optimization. Instead of it, curve 2 comes into this zone more quickly, in particular at time of 730 s after parametric optimization. In conclusion, it is possible to confirm that after parametric optimization, the time of transitional process decreases to 295 s. The overshoot is also decreased from 130°C to 70°C, it is almost doubled. However, the frequency of fluctuations in furnace's temperature doubly increase around factory defaults, which is 750°C.

In Figure 7 the calculated curve of transitional process of angle rotation of the potentiometer is shown before parametric optimization. In Figure 8, the curve is shown after parametric optimization. The fluctuation of the rotation angle of potentiometer occurs around factory default, which is 5.33 rad.

6. Conclusions

A mathematical model of electric furnace of temperature control which takes into account the nonlinear characteristics of the object is proposed. The energy losses from the furnace because of direct heat transfer and radiation are taken into account. Using a genetic algorithm, it is shown that it is possible to determine the optimum parameters of the electronic amplifier. This provides the ability to reduce the transition process to 295°C and to reduce overshoot at 60°C. Thus, the mathematical model of the system modes is determined as universal and ease of algorithms.

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