Genetic Algorithms for Control System Design Applications

Ivan Sekaj,

Dipl. Ing. ✉ Dept. of Automatic Control Systems, Faculty of Electrical Engineering and Information Technology, Slovak University of Technology Ilkovičova 3, 812 19 Bratislava, Slovakia 💻sekaj@kasr.elf.stuba.sk

1. Abstract

The paper describes genetic algorithms application for control system design and for dynamic system model identification. The approach is based on the search for the multivariable function global optimum with cost functions which consist of dynamic system simulation and integral performance criterion evaluation. The proposed methods are demonstrated on design examples of control structures under PID controllers for single input – single output (SISO) and multi input – multi output (MIMO) systems as well as on an example of a selftuning control structure for a 2x2 system. A real-time identification example is presented, too.

Keywords: dynamic system, control design, system identification, adaptive control, genetic algorithms

2. Introduction

In the design of control systems there are commonly used mathematical models of controlled systems and controllers. Based on these models, the control system parameters use to be designed by means of analytical approaches with respect to the required static and dynamic system behaviour. However, the state-of-the-art of computers enables also another way of dynamic systems design which is based on computer simulations. In this paper, a optimisation approach is presented which uses parametric simulations in connection with genetic algorithms (GA). Due to this approach, the task of the optimal design of the dynamic control system is transformed to the search for global minimum of a (static) multivariable function. In this paper an approach is shown which can be used for dynamic system identification and optimal controller parameters design using GA-based optimisation techniques.

The aim of the control system design consists in guaranteeing the required static and dynamic closed-loop behaviour. Usually, this behaviour is represented by means of the well-known concepts referred to in the literature: maximum overshoot, settling time, damping or using different integral control performance criterions [3,4 and others]. Without loss of generality let us consider a simple feedback control loop (Fig. 1) with either a PID controller described by the transfer function $S_{PID}(s)=P+I/s+Ds$ or a PI controller having the transfer function $S_{PI}(s)=P+I/s$, respectively. The parameters P, I and D (proportional, integral and derivative gain) are to be optimised.

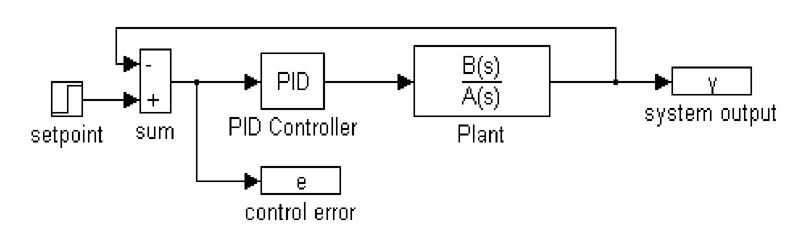

Fig. 1. Simple control loop with PID controller

For the simplicity let us now consider an example with the plant which is described by the transfer function

$$S(s) = \frac{2}{(s+1)(s+2)(s+5)} \tag{1}$$

to be controlled using the PI-controller. The integral control performance criterion "Absolute Control Error" (IAE) is considered

$$IAE = \int_0^T |e(t)| dt \tag{2}$$

where e is the control error ($e=y-w$, y-system output, w-setpoint) and T is the evaluated time interval. This expression can be evaluated after the dynamic control process simulation, in our case in the Matlab/Simulink environment [7] . The goal is to find the controller parameters P and I from the bounded intervals (P_{min}, P_{max}) and (I_{min}, I_{max}), which guarantee the minimum of the IAE. The graphical representation of this control performance criterion for the system (1) represented by the function $G_{IAE}=F(P,I)$ is depicted in Fig. 2. Each point of this surface (with the selected step) is the result of simulation and the performance criterion evaluation. This simple 2-D search problem can be solved also via conventional optimization techniques [5], however, in case of more complex control structures with multiple parameters or for controller structures for MIMO systems generally a complex n-dimensional optimization problem is considered.

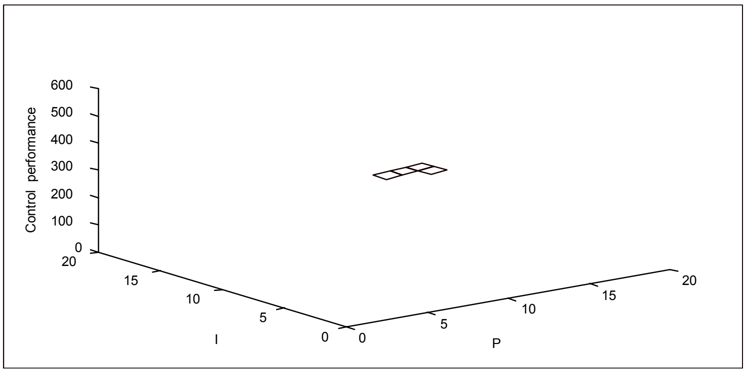

Fig. 2. The surface of the IAE criterion for a PI controller with the system (1)

3. GA-based controller design

For solving the above mentioned problems the GA-based optimization approach has been used [1,2,and others]. The simulated dynamic system may be complex and can include different linear or nonlinear parts. The only limitation is the computation time.

Now, for the illustration, the GA will be applied to the simple PID controller design. The space of all possible solutions - sets of the three PID parameters ("chromosomes") - is $(P_{min}, P_{max}) \times (I_{min}, I_{max}) \times (D_{min}, D_{max})$ which is a subspace of R^3 . From all possible solutions we have to find the best one from the point of view of the selected performance criterion. An outline of the used genetic algorithm is as follows: The first step is the generation (random or by the user) of the start parent population of *n* chromosomes and their fitnes function calculation. Each chromosome represents a string *{P,I,D},* which consists from the 3 controller parameters: proportional, integral and derivative gain. The objective function values, which are called „fitness“are calculated for each string using dynamic system simulations and a selected (integral performance) criterion, e.g. (2). From the *n* chromosomes the best *b* ones are without any change moved to the next generation. Next a new „reproduction“ group of *n-b* chromosomes selected either according to their fitness values, or randomly selected, or selected combining both methods, etc. are used for crossover and mutation operations. After this a new parent population of *(n-b)+b=n* chromosomes is completed. This algorithm will be repeated unless the fitness function of the best string in some population fulfills the predefined condition or until the predefined number of populations is put into life. Fig. 3 depicts the step responses of the controlled system (1). The responses relate to the best chromosomes of the PID controller in the 1st, 10th, 30th, 50th, 70th and the 100th population, respectively. A fundamental effect on the dynamic system behaviour has the choice of the cost function (control performance criterion). Usage of (2) normally causes relatively fast control responses with some small overshoots. If necessary to damp the overshoot or the oscillations, it is possible to insert under-integral terms containing absolute values of the first or second order control error derivatives

$$J = \int_0^T \alpha|e(t)| + \beta|e'(t)| + \gamma|e''(t)| dt \tag{3}$$

where α,β,γ are weight coefficients. Good results can be obtained also with the criterion

$$J = \alpha\eta + (1-\alpha)t_r \tag{4}$$

where η is the overshoot, t_r is the settling time and α is the weight coefficient.

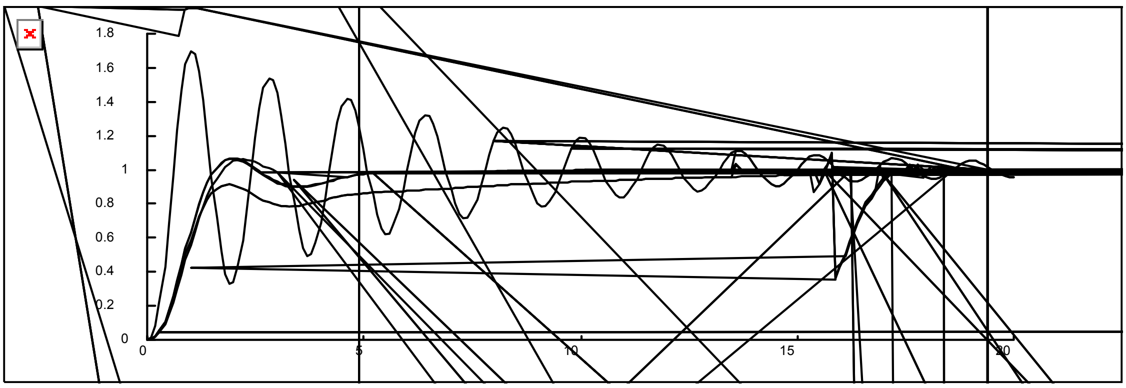

Fig. 3. Evolution of the PID contoller parameters using GA

An efficient extension of the cost function leading to non-oscillatory transient responses, is the use of a condition which minimizes the number of the step response inflexion points. The reference response y_r tracking can be achieved via minimization of the criterion

$$J = \int (y_r(t) - y(t))^2 dt$$

The input energy optimization can be carried out using the criterion

$$J = \int (\alpha e^2(t) + (1-\alpha)u^2(t))dt$$

where u is the control signal. In the Fig. 4 there are closed-loop responses under a PID controller and the system

$$S(s) = \frac{(s+0.2)}{(s+0.25)(s+0.9)(s+1.5)(s+5)}$$

for which the following criterions have been used: a) IAE (2); b) criterion (3) with $\alpha = 3, \beta = 2, \gamma = 1$; c) IAE extended with the condition of minimum number of inflexion points in the step response;

d) criterion (4) with $\alpha = 0.5$.

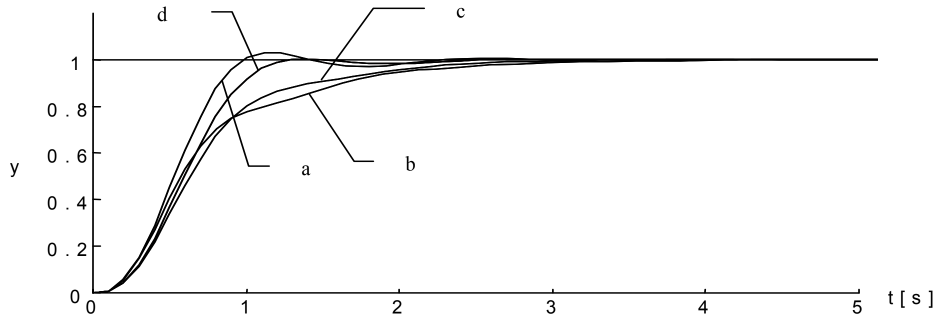

Fig. 4. Step responses using different cost functions

4. Applications

The above mentioned GA-based approach can be used for various design tasks. The next example deals with the system identification. Consider a linear system which is represented by a transfer function *S(s)=B(s)/A(s)* with the unknown coeficients b_0, b_1, ... , b_m and a_0, a_1,, ... , a_n , which is encoded into the chromosome in the form [b_0, b_1, ... , b_m , a_0, a_1,, ... , a_n]. For this purpose let us use the standard cost function

$$J = \int (y_m(t) - y(t))^2 \, dt$$

where y is the system output and y_m is the model output. An example of GA – based identification of a servosystem speed from real-time intut/output data is depicted in Fig.5.

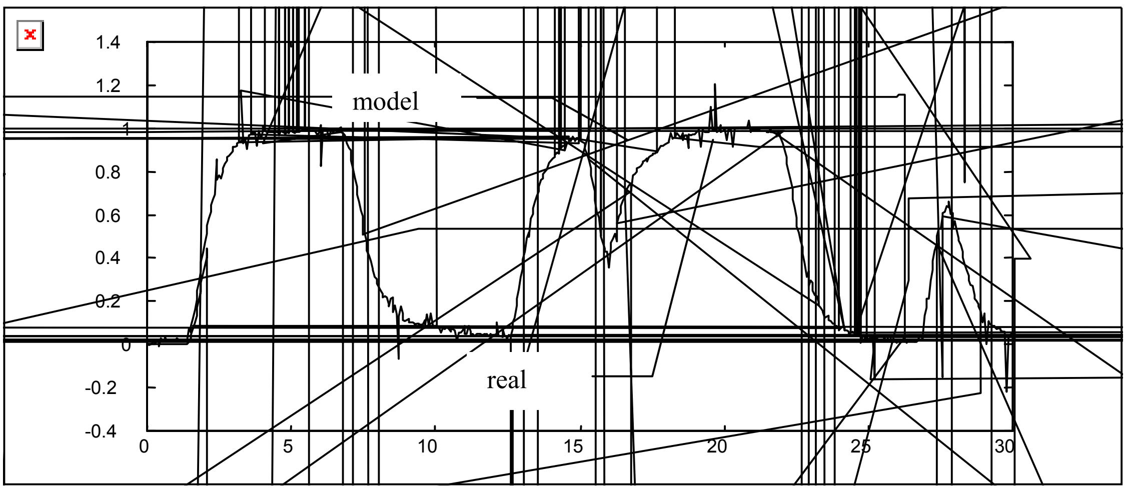

Fig. 5.GA-based identification of a servosystem

Both tasks, the identification and the controller design, can be used for construction of a selftuning controller. In the next example such an adaptive control structure has been used for the control of a two-input two-output system with interactions between the subsystems (Fig.6). Beside the linear parts the system contains also saturations and a transport delay. After setpoint changes for the PID controllers (Fig.7) in the 1^{st}, 60^{th} or the 30^{th} and 90^{th} second respectively the systems S_{11}, S_{21}, S_{12},S_{22} have been identified and then the two PID controllers are designed. Then the new controller parameters are retuned. The better control performance after this adaptation process is evident in next setpoint changes. For all partial models S_{ij}, the following 2^{nd} order transfer function has been used

$$S_{ij}(s) = \frac{b_{ij1}s + b_{ij0}}{a_{ij2}s^2 + a_{ij1}s + 1}, \qquad \text{where i and j are 1 or 2}$$

The chromosome for the identification has the form

$$[b_{11,1}\ b_{11,0}\ \ a_{11,2}\ \ a_{11,1}\ a_{11,0} \ldots\ldots\ a_{22,0}\ \ \tau\ ]$$

where τ is the transport delay of the system S_{11} . The chromosome contains 17 parameters. The used cost function in this case is

$$J = \int \left((y_{1m}(t) - y_1(t))^2 + (y_{2m}(t) - y_2(t))^2 \right) dt$$

where y_{1m} and y_{2m} are model outputs and y_1 and y_2 are system outputs. The chromosome for the two PID controller design is in the form

$$[P_1\ I_1\ D_1\ P_2\ I_2\ D_2]$$

and in the GA-based procedure the following cost function has been used

$$J = \int_0^T \left(|e_1(t)| + |e_2(t)| \right) dt$$

where e_1 and e_2 are the control errors for PID_1 and PID_2, respectively .

The last example shows the GA approach applied for the parametrization of a neuro-PID controller (Fig. 8) in the closed loop with a nonlinear process

$$y'' + 5y' + 3y + 2y^3 = 3u(1 + y)$$

which dynamics depens on the working point y. The chromosome consists from weights and biases of a three-layer perceptron neural net. The fitness represents the evaluation of some of the above-mentioned integral criterions. The closed-loop responses are depicted in Fig. 9.

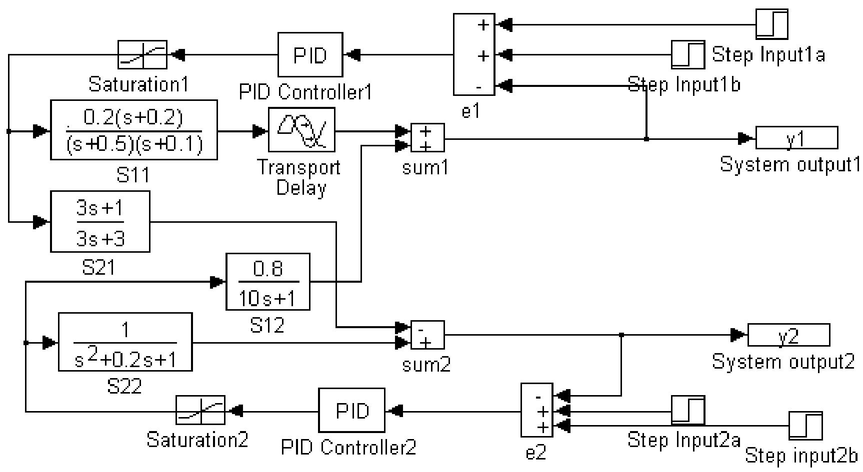

Fig. 6. Two input - two output system under the decentralized PID control structure

f–r□□ **7.** Adaptation process of the selftuning control structure for the 2x2 system

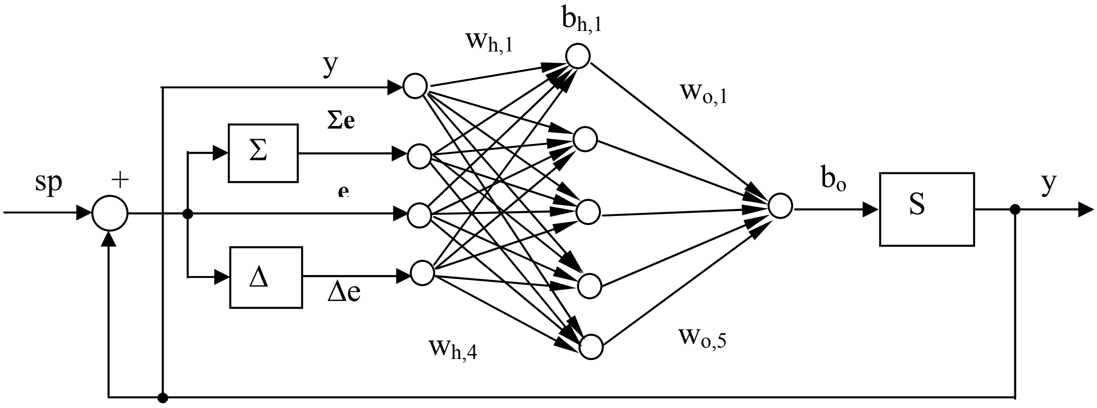

Fig. 8. Nonlinear neuro-PID controller with a 3-layer perceptron net

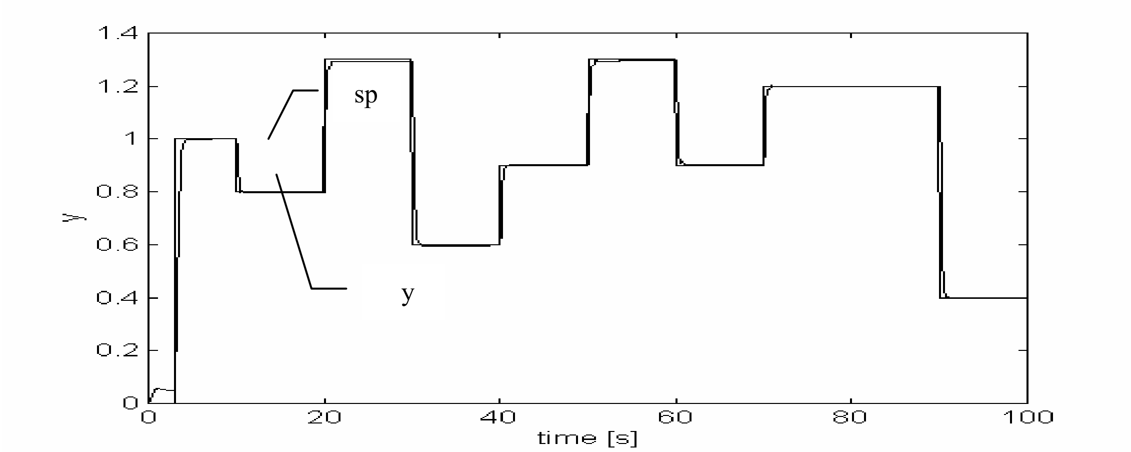

Fig. 9. Step responses of the closed loop with neuro-PID and a nonlinear system

5. Conclusion

This paper deals with genetic algorithms-based optimization pocedures used for the design of various control system structures with PID controllers, for system identification, for selftuning controllers as well as for a neuro-PID controller. This approach based on parametric simulations can be used also for the design of general dynamic systems practically without any limitations on their type and number of their inputs and outputs. The only limitation is the computation time and the computation effort. The presented approach has been successfuly applied in the controller design as well as in system identification tasks for linear, nonlinear, stable, unstable, nonminimum-phase systems, systems with control action limitations, SISO and MIMO systems, fuzzy systems or neural nets as well.

6. References

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