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ARTIFICIAL INTELLIGENCE

Design of Robust Knowledge Bases of Fuzzy Controllers for Intelligent Control of Substantially Nonlinear Dynamic Systems: II. A Soft Computing Optimizer and Robustness of Intelligent Control Systems

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Abstract—The structure of intelligent control system (ICS) is analyzed, and the interrelations with conventional problems of the theory and practice of application of control systems are described. The analysis of the results of simulation of typical structures of intelligent control systems has allowed us to establish the following fact. The application of the technique of designing (presented in Part I), which is based on a fuzzy neural network (FNN), does not guarantee in general that the required accuracy of approximation of the training signal (TS) will be reached. As a result, under an essential change of external conditions, the sensitivity level of the controlled plant (CP) increases, which, on the whole, leads to a decrease in the robustness of the intelligent control system, and, as a consequence, to a loss of reliability (accuracy) of achieving the control goal. To eliminate the specified drawback of the neural network, a soft computing optimizer (SCO), which uses the technique of soft computing and allows one to eliminate the drawback, is applied, which results in an increase in the robustness level of the structure of the intelligent control system. The structure of the soft computing optimizer, which contains as a particular case the required configuration of an optimal fuzzy neural network, is considered. The main specific features of the functional operation of the soft computing optimizer and the stages of the process of designing robust knowledge bases (KB) of fuzzy controllers (FC) are described. The methodology of joint stochastic and fuzzy simulation of automatic control system based on the developed tool of the soft computing optimizer is discussed in order to test the robustness and to estimate the limiting structural capabilities of intelligent control systems. The efficiency of the control processes with application of the soft computing optimizer is demonstrated by particular typical examples (benchmarks) of models of dynamic controlled plants under the conditions of incomplete information about the parameters of the structure of the controlled plant and under the presence of unpredicted (abnormal) control situations. Examples of industrial application of robust intelligent control systems in actual control systems designed based on the soft computing optimizer are presented. Practical recommendations for improving the robustness level of intelligent control systems by using new types of computations and simulation are given

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INTRODUCTION

Engineering methods of control theory and the technique of designing automatic control systems were formed in the past century. In particular, the foundations of stochastic and adaptive control of complex dynamic systems (in general, with variable structure) under conditions of information uncertainty were developed.

The next step in this direction was the development of principles of simulation and design of fuzzy automatic control systems under uncertainty conditions that take into account the individual specific features of the behavior of chosen trajectories of the controlled plant [1]. This design methodology was based on the theory of linguistic approximation and fuzzy inference (L. A. Zadeh and others) for developing robust knowledge bases of intelligent fuzzy controllers [2, 3]. Within the framework of the specified methodology of designing control laws based on physical methods (information–thermodynamic and quantum–relativistic methods of describing controlled plants and control processes [4]), in the mid 1970s, the background of the technique of designing intelligent automatic control systems was developed [5–8].

Remark 1. One of the most important elements of science intensive information technology of designing intelligent control systems is the development of the methodology and the corresponding software–hardware support of the processes of testing and evaluating the robustness level of the designed structure of the intelligent control system (as a measure of sensitivity to various external and internal random perturbations acting both on the controlled plant and in the measurement channels or control loops). The topicality of the solution to this problem is dictated by practical control tasks addressed by many researchers [2, 3, 9–12].

An increase in the complexity of the structures of controlled plants and difficulties in predicting unexpected (abnormal) control situations only stresses the topicality of this problem and draws attention to it. Such problems are referred to as the so-called problem of "System of Systems Engineering" that studies in a general form complex structures of automatic control systems with different levels and scales of integration and/or priority data exchange between subsystems in order to establish global (necessary and sufficient) conditions for reliable autonomous operation of the controlled plant in the external environment.

Remark 2. In a number of cases, in the experience of designing automatic control systems, linearized models of controlled plants are applied. However, under this approach, the adequacy of the relation between the physical parameters of the controlled plant and the parameters of its linearized model is frequently lost. In this paper, in the optimization of the structure and the parameters of an intelligent control system, we consider nonlinear models of controlled objects. Note that the effect of nonlinearities on the dynamics and on the controllability of the controlled object in the control laws is taken into account by the gains of a fuzzy PID controller. Thus, by methods of soft computing, the effect of nonlinearities in the controlled plant is compensated by varying dynamically the proportionality coefficients in the classical PID controller with global negative feedback (GNF).

In practice, controlled plants are under conditions of uncertainty connected with the effect of both external and internal random factors. The ability of automatic control systems to react adequately to one or another change in the parameters of the external environment that is not given in advance in designing the automatic control system characterizes the level of learning, adaptation, and robustness of processes and the ability to learn and adapt itself. Frequently, the methods of the theory of robust control are not able to solve general control problems under the presence of uncertainty described in the form of a certain stochastic process with definite (in general, unknown) statistical characteristics (probability distribution functions). A number of approaches to the solution of this problem based on iterative randomized algorithms were developed in [10, 11].

In this paper, the evaluation of sensitivity and the improvement of the robustness level is reached, in particular, by using algorithms of nonlinear forming filters for reproducing realizations (informatively represented chosen trajectories) of stochastic interactions with given characteristics (see the Appendix). In the course of optimization of the parameters of automatic control systems, this approach of stochastic simulation is used together with the method of fuzzy simulation in order to achieve the required control quality irrespective of the particular implementation of the perturbing stochastic action. We consider the methodology of joint stochastic and fuzzy simulation of automatic control systems based on the developed tools of the soft computing optimizer with the aim to test the robustness and estimate the limiting structural capabilities of intelligent control systems. The efficiency of control processes with application of the soft computing optimizer is demonstrated by particular typical examples of models of dynamic controlled plants under the conditions of uncertainty of information about the parameters of the controlled plant and under the presence of unpredicted (abnormal) control situations.

Thus, in connection with the fact that within the framework of the classical approach to designing automatic control systems it is not possible to improve the control quality and the robustness level of the control laws obtained, the problem of development of methods of mathematical simulation of algorithms for intelligent control of nonlinear dynamic systems based on soft computing and software tools for their support still remains topical. It is these problems to which this paper is dedicated.

Since the main point in the design of intelligent control systems is the stage of forming the corresponding knowledge base [1, 3], the design of a knowledge base with a required robustness level, under unpredicted control situations, allows one to establish in a general form the correspondence between the conditions of functioning of the controlled plant and the required robustness level of the intelligent control system.

In this paper, we focus the main attention on the description of particular results of designing knowledge bases and simulating intelligent control systems with essentially nonlinear controlled plants with a randomly variable structure and stimuli (control goals). In this case, the aim of this work is to determine the robustness levels of control processes that ensure the required reliability and accuracy indices under the conditions of uncertainty of the information employed in decision-making. First of all, we consider the evolution of typical structures of intelligent control systems, their specific features, advantages, and disadvantages from the point of view of design and application of intelligent control systems.

1. SPECIFIC FEATURES OF DESIGNING THE STRUCTURES OF ROBUST INTELLIGENT CONTROL SYSTEMS

One of the main tasks of designing an intelligent control system consists in providing that the developed (chosen) structure possesses the required level of control quality and robustness (supports the required indices of reliability and accuracy of control under the conditions of information uncertainty). Note that one of the most important and hard-to-solve problems of designing intelligent control systems is the design of robust knowledge bases that allow the intelligent control system to operate under the conditions of information uncertainty. The core of technique for designing robust knowledge bases of fuzzy controllers is generated by new types of computing and simulation processes [3, 7, 9].

Recently, the application of the structures of intelligent control systems based on new types of computations (such as soft, quantum, etc., computing) has drawn the ever-increasing attention of researchers [1–9, 11–13]. Numerous investigations conducted have shown that they possess the following points of favor:

retain the main advantages of conventional automatic control systems (such as stability, controllability, observability, etc.);

have an optimal (from the point of view of a given control objective functional) knowledge base, as well as a possibility of correcting it and adapting it to the changing control situation;

guarantee the attainability of the required control quality based on the designed knowledge base;

are open systems, i.e., they allow one to introduce an additional objective functional for control and constraints on the characteristics of the control process.

One of the main problems of modern control theory is to develop and design automatic control systems that meet the three main requirements: stability, controllability, and robustness [2, 3, 9–11]. The listed quality criteria ensure the required accuracy of control and reliability of operation of the controlled plant under the conditions of incomplete information about the external perturbations and under noise in the measurement and control channels, uncertainty in either the structure or parameters of the controlled plant, or under limited possibility of a formalized description of the control goal.

This problem is solved in three stages.

(1) The characteristics of stability of the controlled plant are determined for fixed conditions of its operation in the external environment.

(2) A control law is formed that provides the stability of operation of the controlled plant for a given accuracy of control (according to a given criteria of the optimal control).

(3) The sensitivity and robustness of the dynamic behavior of the controlled plant are tested for various classes of random perturbations and noise.

These design stages are considered by modern control theory as relatively independent. The main problem of designing automatic control systems is to determine an optimal interaction between these three quality indices.

For robust structures of automatic control systems, a physical control principle can be proven that allows one to establish in an analytic form the correspondence between the required level of stability, controllability, and robustness of the control [1–3, 8, 12]. This allows one to determine the required intelligence level of the automatic control system depending on the complexity of the particular control problem.

Example 1. Let us consider in short the main physical principles of control processes that allow one to establish the interrelation between the qualitative dynamic characteristics of the controlled plant and the actuator of the automatic control system: stability, controllability, and robustness of control. For this purpose, we employ the informational and thermodynamic approaches that join by a homogeneous condition the criteria of dynamic stability (the Lyapunov function), controllability, and robustness [2]. Consider a dynamic controlled plant given (in a general form) by the equation

$$\frac{dq}{dt} = \varphi(q, S(t), tu) \qquad (1.1)$$

where q is the vector of generalized coordinates describing the dynamics of the controlled plant; $S(t)$ is the generalized entropy of dynamic system (1.1); u is the control force (the output of the actuator of the automatic control system); and t is the time. The necessary and sufficient conditions of asymptotic stability of dynamic system (1.1) are determined by the physical constraints on the form of the Lyapunov function, which possesses two important properties represented by the following conditions:

(1) This is a strictly positive function of generalized coordinates, i.e., $V > 0$.

(2) The complete derivative in time of the Lyapunov function is a nonpositive function, $\frac{dV}{dt} \le 0$.

By conditions (1) and (2), as the generalized Lyapunov function, we take the function [12]

$$V = \frac{1}{2}\sum_{i=1}^{n} q_i^2 + \frac{1}{2}S^2, \qquad (1.2)$$

where $S = S_p - S_c$ is the production of entropy in the open system "CP + controller"; $S_p = \Psi(q, \dot{q}, t)$ is the production of entropy in the controlled plant; and $S_c = \Upsilon(\dot{e}, t)$ is the production of entropy in the controller (actuator of the automatic control system). It is possible to introduce the entropy characteristics in Eqs. (1.1) and (1.2) because of the scalar property of entropy as a function of time, $S(t)$ [2].

Remark 3. It is worth noting that the presence of entropy production in (1.1) as a parameter reflects the dynamics of the behavior of the controlled plant and results in a new class of substantially nonlinear dynamic automatic control systems. The choice of the minimum entropy production both in the controlled plant and in the fuzzy PID controller as a fitness function in the genetic algorithm allows one to obtain feasible robust control laws for the gains in the fuzzy PID controller [8]. The entropy production of a dynamic system is characterized uniquely by the parameters of the nonlinear dynamic automatic control system, which results in determination of an optimal selective trajectory from the set of possible trajectories in optimization problems [2, 3, 12].

The first condition is fulfilled automatically. Assume that the second condition $\frac{dV}{dt} \le 0$ holds. In this case, the complete derivative of the Lyapunov function (1.2) has the form

$$\frac{dV}{dt} = \frac{1}{2}\sum 2\dot{q}_i q_i + \frac{1}{2}2S\dot{S} = \sum_{i=1}^{n}\dot{q}_i q_i + S\dot{S}$$

$$= \sum_{i=1}^{n} q_i \varphi(q, S, t, u) + (S_p - S_c)(\dot{S}_p - \dot{S}_c).$$

Thus, taking into account (1.1) and the notation introduced above, we have

$$\underbrace{\frac{dV}{dt}}_{\text{stability}} = \underbrace{\sum_{i=1}^{n} q_i \varphi(q, (\Psi - \Upsilon), t, u)}_{\text{controllability}} + \underbrace{(\Psi - \Upsilon)(\dot{\Psi} - \dot{\Upsilon})}_{\text{robustness}} \le 0. \quad (1.3)$$

Relation (1.3) is a generalization of the results of [1, 8, 12] and relates the stability, controllability, and robustness properties.

Remark 4. The presence of entropy production in the motion equations of the controlled plant is the principal distinction of (1.3) from the corresponding formula of [1–3, 8, 12]. The practical application of control law (1.3) to conventional problems such as the estimation of accuracy (roughness) of the linearization of models of controlled plants, observability of the parameters of control processes, etc., was considered in [2, 3, 12]. We note that the term $\sum_i q_i \dot{q}_i$ characterizes an additional opportunity to work with a physical model of the controlled plant without a mathematical model, using directly the measurement of the indices of dynamic behavior of the controlled plant. In this case, we have a generalization of the black-box model of the controlled plant. Other approaches of entropy analysis of dynamic systems were described in [14–17].

Equation (1.3) joins in an analytic form different measures of control quality such as *stability, controllability*, and *robustness* supporting the required reliability and accuracy. Consequently, the interrelation between the Lyapunov stability and robustness described by Eq. (1.3) is the main physical law for designing automatic control systems. This law provides the background for an applied technique of designing knowledge bases of robust intelligent control systems (with different levels of intelligence [2, 3]) with the use of soft computing. In concluding this section, we formulate the following conclusions.

1. The introduced physical law of intelligent control (1.3) provides a background of design of robust knowledge bases of intelligent control systems (with different levels of intelligence) based on soft computing.

2. The technique of soft computing gives the opportunity to develop a universal approximator in the form of a fuzzy automatic control system, which elicits information from the data of simulation of the dynamic behavior of the controlled plant and the actuator of the automatic control system.

3. The application of soft computing guarantees the purposeful design of the corresponding robustness level by an optimal design of the total number of production rules and types of membership functions in the knowledge base [3, 18].

Figures 1 and 2 present typical criteria for control quality, their interrelations with different types of computations and simulation types, as well as the hierarchy of levels of control quality depending on the required level of intelligence of the automatic control system.

Figure 3 presents the main components and their interrelations in the information design technology (IDT) based on new types of computing (soft and quantum). The key point of this information design technology is the use of the method of eliciting objective knowledge about the control process irrespective of the subjective experience of experts and the design of objective knowledge bases of a fuzzy controller [3, 18], which is principal component of a robust intelligent control system. The output result of application of this information design technology is a robust knowledge base of the fuzzy controller that allows the intelligent control system to operate under various types of information uncertainty.

2. EVOLUTION OF OPTIMIZATION PROCESSES AND STRUCTURAL ANALYSIS OF INTELLIGENT CONTROL SYSTEMS

Optimal control problems for substantially nonlinear and globally unstable controlled plants were studied under the presence of stochastic perturbations of various types (a set of typical essentially nonlinear oscillators were considered as controlled plants). With the help of the developed system of stochastic simulation, the limiting capabilities of classical automatic control systems based on the use of the actuator in the form of a conventional PID controller were determined (Table 1, position 1). As a result of the conducted investigation, the following fact was established: classical automatic control systems based on a PID controller with constant gains frequently do not cope with the control problem in the case of globally unstable and essentially nonlinear controlled plants subjected to

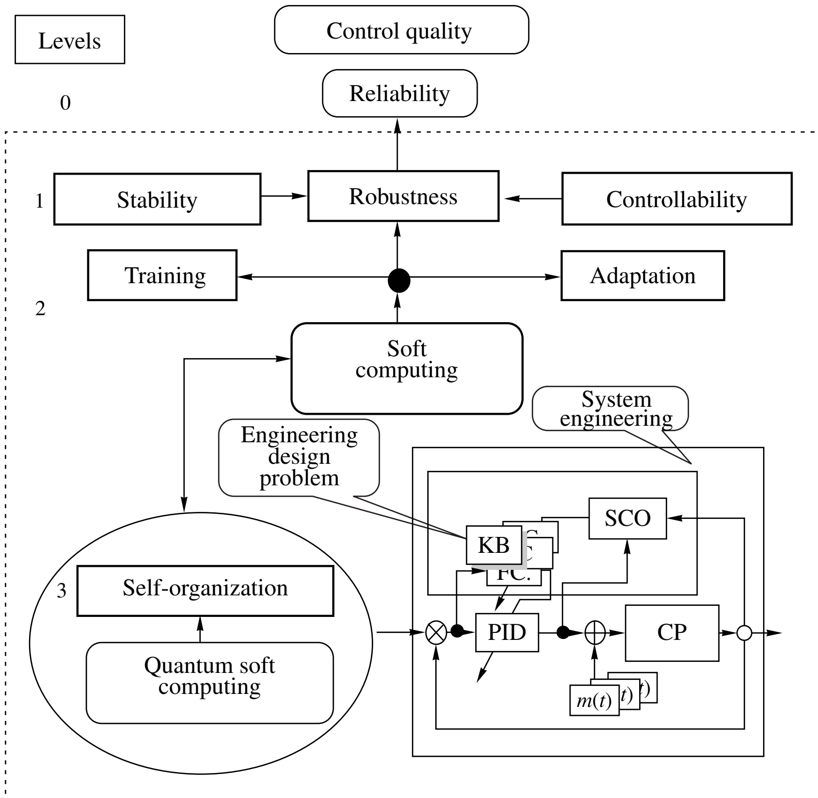


Fig. 1. The interaction between the types and hierarchical levels of control quality criteria.

non-Gaussian (e.g., Rayleigh) statistical noise, as well as under the presence of time delays in the measurement and control channels.

This fact can be explained by the following circumstances. Classical automatic control systems are based on the global-negative-feedback principle and the method of compensation of the control error. However, in complex controlled plants (mentioned above), it is not sufficient to take into account the result of optimization according to only one quality control index, such as the minimum of control error. Therefore, in the practice of designing intelligent control systems for complex controlled plants, the following problem arises: *How will we introduce in the control system other additional control quality indices?*

For example, among these criteria we have the criterion of minimum entropy production in the automatic control system itself mentioned above (taking into account the heat loss and loss of useful work in the object and control system), as well as other more complex vector control quality indices.

It is practically impossible to solve this problem with the help of design of a standard PID controller with constant gains. The limited opportunities of realization of complex quality control indices in classical automatic control systems, especially in the control cases specified above, provide a stimulus for developing intelligent control systems based on the use of control strategies formulated by a human expert (in complex unpredicted situations of control and decision making).

In this paper, the control quality indices are considered in this case as components of vector fitness function of the corresponding genetic algorithm in the soft computing optimizer.

2.1. Generations and Evolutions of the Typical Structures of Intelligent Control Systems

Table 1 presents the generalized evolution of the development and formation of the structures of intelligent control systems, their specific features, and their advantages and disadvantages, as well as the levels of control quality belonging to these structures.

At the first stage, for simulating human–machine control strategies, so-called soft computing was used. Soft computing is based on set theory and fuzzy inference [1–3]. For example, the structure of position 1 of Table 1 is transformed to an expert control system (ES) by growing step by step the constituent blocks in the classical version of the automatic control system (in this case, by introducing a block of fuzzy inference) (Table 1, position 2) [2] and is an example of the first generation of intelligent control systems.

Thus, the first generation of intelligent control systems was considered as expert systems with knowledge

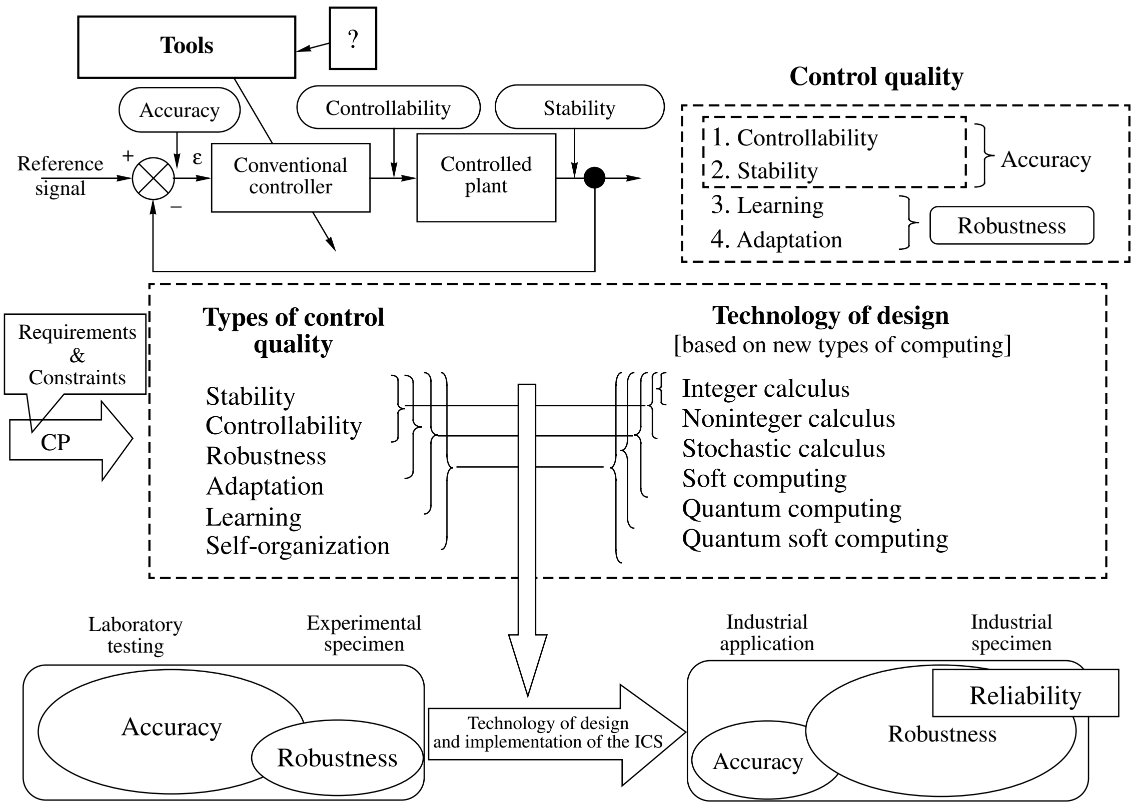


Fig. 2. The interrelation between the control quality criteria, types of intelligent computing, and simulation in designing robust KBs of the FC.

representations different in depth. The main role in these expert systems was played by the quality of the knowledge base, which depends on the experience and subjective knowledge of the human expert. However, in the case when the control of globally unstable and substantially nonlinear controlled plants is subjected to complex stochastic noise, it is difficult even for an experienced human operator to choose an optimal (from the point of view of control quality) knowledge base of the fuzzy controller. This problem is a bottleneck of all first (and the following modifications) intelligent control systems [2, 3]. Therefore, the use of expert systems as a tool for knowledge acquisition and formation of knowledge bases (as the background for designing intelligent control systems) has not resulted in the expected essential success (although there are many example of industrial application [5, 19]) because of the complexity of control plants and the subjective nature of the information provided by an expert.

From the point of view of design technology, the main problem of application of intelligent control systems of the first generation was their weak adaptivity to changes in the parameters of controlled plants (e.g., caused by the fact that the structure of the controlled plant is getting older or by sharp change of the external environment), as well as the low robustness of control laws obtained. For solving such problems, intelligent control systems of the second generation were developed with a deeper knowledge representation, using the technique of so-called soft computing, which joins in a single chain genetic algorithms, fuzzy neural networks, and fuzzy controllers. This has allowed one to eliminate the subjective expert opinion at the stage of forming the structure and parameters of the knowledge base of the fuzzy controller. In turn, the development of intelligent control systems based on soft computing has generated several approaches to forming the structures of knowledge bases. It was planned initially to form a certain rather rough training signal (TS) from the genetic algorithm and to acquire the knowledge base by approximating the obtained training signal on fuzzy neural networks. The structure of intelligent systems of the second generation is formed by introducing a block containing genetic algorithms and fuzzy neural networks in the structure of intelligent control systems of the first generation (Table 1, position 3).

Then, the second generation of intelligent control systems began to use a new form of feedback, called a global intelligent feedback (GIF) [1, 3, 8, 12, 18] represented in Table 1 (position 4). This gives the opportunity to acquire objective knowledge directly from the dynamic behavior of the controlled plant and the actuator of the automatic control system. The GIF loop contains a genetic algorithm for obtaining information

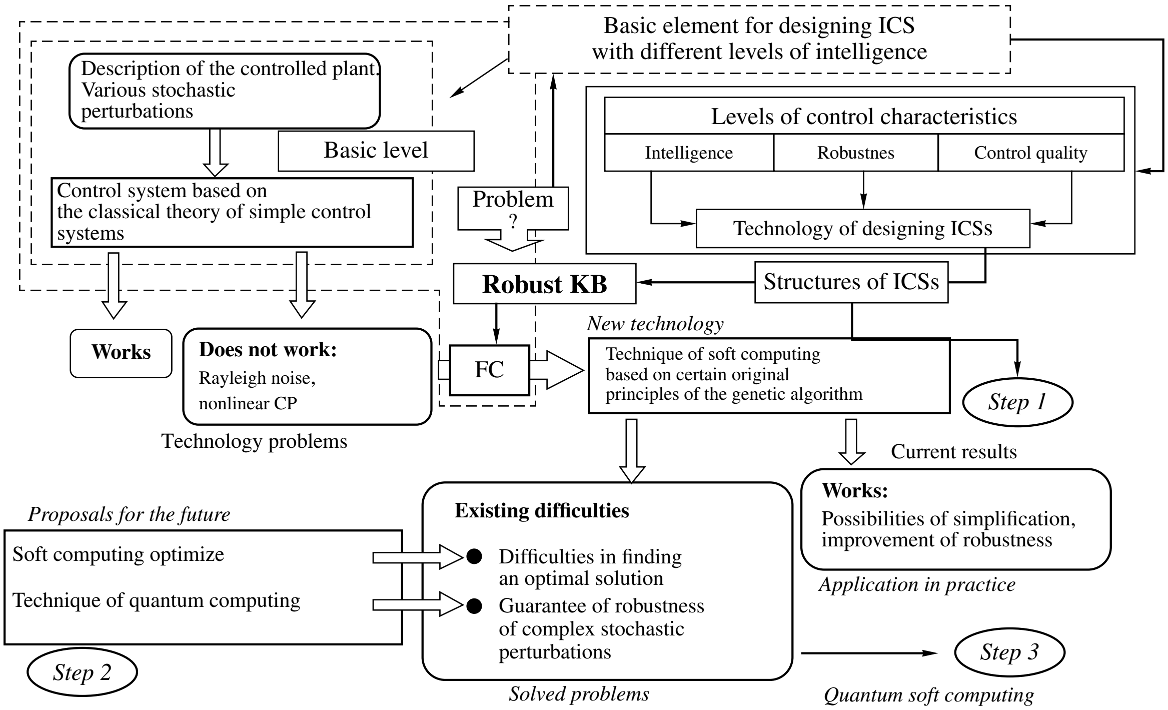


Fig. 3. The process of development and creation of information technology for designing an integrated intelligent control system.

about the optimal control signal (based on the dynamic and thermodynamic behavior of the controlled plant and the PID controller) and a fuzzy neural network approximating a given optimal control signal with the help of a given structure of the neural network. This approach was considered in [1].

The main block in the structure of the intelligent control system (Table 1, position 5) is a system of simulating the optimal control signal (SSOCS) with the help of a genetic algorithm and a control quality index represented in the form of one of the components of the fitness vector function of the genetic algorithm. The output of the global intelligent feedback is a training signal of the optimal control in the form of the following input/output data: $\{E(t_i), K(t_i)\}$, $i = 1,\ldots n$, where $E(t_i) = \{e(t_i), \dot{e}(t_i), \int e(t_i)dt_i\}$ is the vector whose components are the control error, its derivative, and the integral of the error, respectively; $K(t_i) = \{k_p(t_i), k_d(t_i), k_i(t_i)\}$ are optimal (from the point of view of a given fitness function of the genetic algorithm) parameters of the PID controller; and t_i is the time instant.

Using the training signal and the mechanism of supervisor training of the fuzzy neural network based on the error-back-propagation method, we can design the knowledge base of the fuzzy controller represented by a given fuzzy neural network. This stage is denoted as step 1 in Fig. 3 and was described in detail in [1].

The main disadvantage of intelligent control systems with GIF consists in the possibility of reaching the required robustness level on a given class both of parametric and external random perturbations of various probabilistic natures (with different density functions of probability distribution). Simulating the behavior of the controlled plant on the set of chosen typical substantially nonlinear oscillators, the limiting capabilities of the intelligent control system were conducted. As a result, it was established that in the case of instable and substantially nonlinear controlled plants, as well as under the action of Rayleigh stochastic noise on them, it is provided that a certain robustness level is reached for particular classes of random perturbations. However, we cannot manage to design a robust knowledge base using only stage 1 of the design of the knowledge base of the intelligent control system (Fig. 3) [3, 18].

The analysis of results of simulation of the automatic control system based on the first stage of the developed technique of designing knowledge bases has shown that the main drawback of this stage is the nonoptimal choice of the structure of the fuzzy neural network approximating the training signal. As a rule, in the system for designing knowledge bases of intelligent control systems of this type, the design of the corresponding structure of the fuzzy neural network is the duty of an experienced human operator. In this case, the training signal is divided into input and output components, each of which, in turn, consists of one or more signals. In the general form, each of the investigated signals is described by a selective (representative) trajectory of a certain stochastic process. Note that it is kept in mind that, at each time instant, there is a dependence between the input and output signals. For exam-

Table 1. The evolution of the process of designing the structures of knowledge-based ICS and interrelation with classical control theory

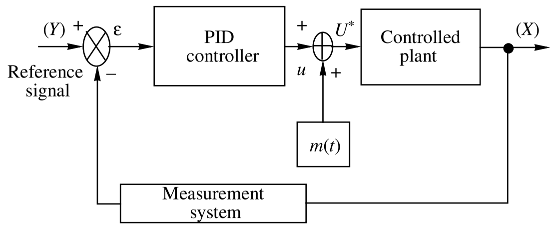
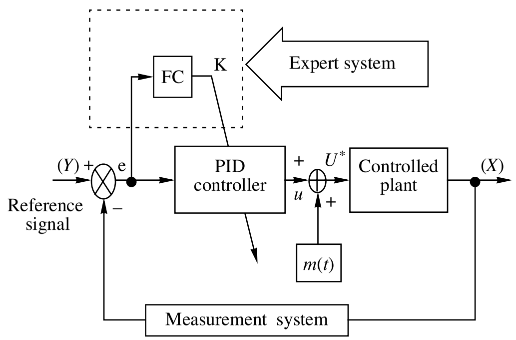
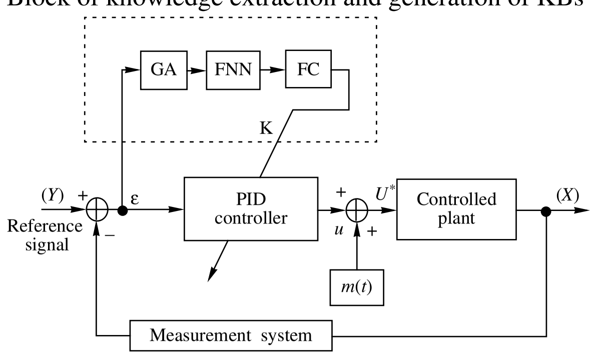
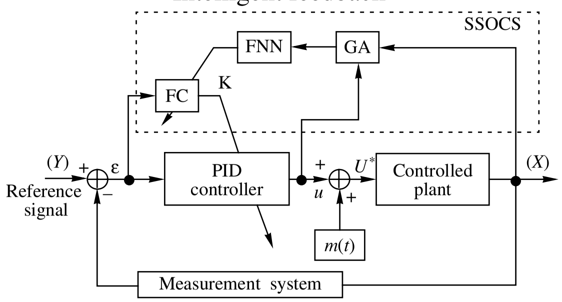
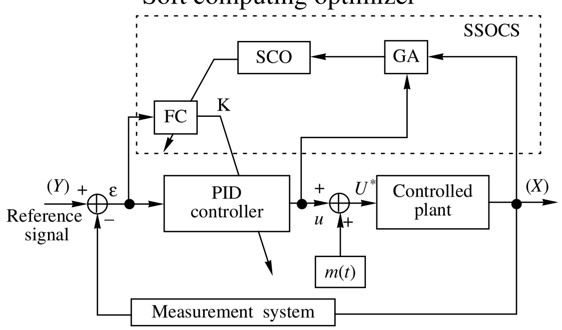
Structures of control systems and evolution of development		Control quality levels	Advantages	Limit capabilities
Position 1	Base element of the ACS  	Stability Controllability Control precision	Simplicity of simulation and physical implementation (min complexity) Simplicity in HW implementation Under minimum complexity of CP provides minimum stability and controllability Guarantees the necessary conditions of control quality, but not sufficient	Under a change of external conditions or the complexity of the CP, does not provide sufficient conditions Stability and controllability (the absence of the required robustness level). Rigid (nonadaptive) structure Does not possesses an ability to learn and be self-organized
Knowledge-based intelligent control systems				
Position 2	Base element of the ICS  	Stability Controllability Control precision Partial adaptation	Simplicity and efficiency of control of complex CPs Can be easily designed and implemented High reliability in exploitation Is used in designing robust KBs	Choice of membership function depends of the qualification level of the expert Has limited capabilities in practical implementations because of constraints on the description of fuzzy relations "input–output" Problem of complexity of designing a KB of the FC since there is no algorithm for constructive generation of KBs Requires large amount of time for constructing logical rules of fuzzy inference
Position 3	Block of knowledge extraction and generation of KBs  	Stability Controllability Control precision Adaptation	Allows one to correct partially the drawbacks of the basic level of the ICS and to achieve the required adaptation level under fixed conditions of functioning of the CP	Does not possess sufficient robustness and stability. Uses information about control error and does not use information about dynamic behavior of the FC and CP

Table 1. (Contd.)

	Structures of control systems and evolution of development	Control quality levels	Advantages	Limit capabilities
Position 4	Intelligent feedback  	Stability Controllability Control precision Adaptation Learning Partial self-organization	Intelligent feedback allows one to acquire objective knowledge and to construct the KB of FC Allows one to encompass a new level of quality control (partial self-organization)	FNN guarantees the required accuracy of approximation of the training signal from the output of the GA Under a sharp change of the external conditions, improves the sensitivity of the CP (reduces robustness)
Position 5	Soft computing optimizer  	Stability Controllability Control precision Adaptation Learning Self-organization of a given level	Retains the advantages of the previous levels of the ICS and provides a background for the technology of designing ICSs. Allows one to optimize the KB Guarantees the attainability of the required control quality based on the designed KB Is an open system, which allows one to introduce additional control objective functionals Allows one to design DBs for the subsequent stage of designing based on quantum computing	Because of limit capabilities of the search algorithm, as a GA, can guarantee the control quality only on a fixed space for searching solutions Process of designing KBs is performed by the method of combinatorial search on the decision tree

ple, when the control signal is approximated, the control error and its derivative (control error rate) may be the input components and either the required value of the control action or certain adjusted parameters of the automatic control system (e.g., the gains of the PID controller) may be the output components. The task of the expert in determining the structure of the fuzzy neural network is reduced to the choice of the model of fuzzy inference and, mainly, to a linguistic description of the given training signal. A linguistic variable that describes the signal by the term-set corresponding to this linguistic variable corresponds to each component of the training signal. The cardinality of the term-set and the characteristics of its elements (the class and parameters of the membership function) are unknown. The "completeness" of the linguistic description of the signal can be given at the level of the interrelation of the term-sets belonging to linguistic variables. This problem is also solved by a human in systems for designing intelligent control problems based on conventional soft computing (the second generation of intelligent control systems). However, as was stated above, under complex control situations, it is difficult even for an experienced expert to solve this problem manually (i.e., to choose an optimal structure of the fuzzy neural network for a given training signal).

Another important problem is to determine the required relation between the accuracy of description (approximation) of the training signal and the required robustness level of the whole structure of the fuzzy neural network. Both specified problems are solved at the second stage of the technology of designing the knowledge base for an intelligent control system by the software facilities of the tool called a soft computing optimizer (see Section 3) [3, 18, 20, 21].

2.2. Structural Analysis of Intelligent Control Systems with the Help of a Soft Computing Optimizer

With the help of random search and natural selection (based on the structure of the genetic algorithm developed by the authors), different variants of robust knowledge bases were simulated. The formed robust knowledge bases allow one to control complex controlled plants in conditions of uncertainty of information about external perturbations acting on the controlled plant and the changes of reference signals (control goals). The robustness of control laws is reached by introducing vector fitness functions of the genetic algorithm, which contain as a component the physical principle of minimum production of the generalized entropy both in the controlled plant and in the intelligent controller [3, 8]. This approach allows one to fulfill the principle of designing an optimal intelligent control system with a maximum level of reliability and controllability for a complex controlled plant under the conditions of uncertainty of the source information; reduce to a required minimum the number of sensors for collection and transmission of information both in the control loop and in the measurement system without loss of accuracy and control quality [22].

The robustness of intelligent control systems obtained based on this approach requires minimum source information both about the behavior of the controlled plant and about the external perturbations [20, 21]. The system for simulation and design of the structures of intelligent control systems was developed based on the soft computing optimizer of the "GA–OKB–Fuzzy PID controller" type (Table 1, position 5).

Analysis of the structures of the existing automatic control systems has allowed us to choose as a basic automatic system the conventional automatic control system in the form of a PID controller. This minimum complex structure joins the maximum number of control quality indices, i.e., stability, control accuracy, and controllability, guaranteeing a certain (minimum) robustness level. Using the physical control law, which relates these criteria, it is possible to design intelligent control systems that meet the requirements of control quality with a sufficient robust level.

Thus, by introduction and interaction of a global negative feedback and a global intelligent feedback, the *principle of saving the lower control level is implemented* in accordance with the hierarchy (priority) of levels of control quality (Fig. 1). This detects a bottleneck in the structure of the intelligent control system, which is the process of forming and designing the knowledge base of the fuzzy controller. To solve this problem, a technique for designing the knowledge base (step 2) was developed for the unified substantiated structure of the intelligent control system (Fig. 3) [3, 20, 21].

As follows from Table 1 (position 5), the advantages of this structural level of the intelligent control system consist in the fact that the global intelligent feedback allows one to design the knowledge base of the fuzzy controller based on objective knowledge acquisition from analysis of the dynamic behavior of the controlled plant and the fuzzy controller itself. Note that because of using the corresponding fitness function of the genetic algorithm (like entropy production rate as a physical optimality criterion, etc.), there arises an opportunity to optimize the structure of the knowledge base itself. The global intelligent feedback helps to encompass new levels of control quality and elements of self-organization simultaneously. The introduction of the level of quality control such that learning allows us to improve the robustness of control and its stability and, together with adaptation, to reduce the requirements for the amount of source information about the external condition of operation of the controlled plant. In addition, as a result of application of learning processes, it is possible to reduce the requirements for required energy expenditure (useful work) both in the controlled plant and in the structure of the conventional PID controller.

Table 2. The types and the role of the fitness function of the GA in the SCO

Type of GA	Criteria	Fitness function (FF)	Role of the FF
GA_1: Optimization of linguistic variables	Maximum joint information entropy and minimum information about signals separately	$H^j_{X_i} = -p^j_{X_i}\log(p^j_{X_i}) = -p(x_i \mid x_i = \mu^j_{X_i})\log[p(x_i \mid x_i = \mu^j_{X_i})] = -\frac{1}{N}\sum_{t=1}^{N}\mu^j_{X_i}(x_i(t))\log[\mu^j_{X_i}(x_i(t))]$	Elimination of redundancy of the TS Choice of an optimal cardinality of term-sets of linguistic variables of the components of the TS
		$H^{(j,l)}_{X_i \mid X_k} = H\left(x_j\Big\vert_{x_i = \mu^j_{X_i},\, x_k = \mu^l_{X_k}}\right) = -\frac{1}{N}\sum_{t=1}^{N}[\mu^j_{X_i}(x_i(t)) * \mu^l_{X_k}(x_k(t))],$ $\log[\mu^j_{X_i}(x_i(t) * \mu^l_{X_k}(x_k(t)))],$ where * is the chosen operation of fuzzy AND	
GA_2: Optimization of rule base	Minimum approximation error	$E = \sum_p E^p,$ where $E^p = 1/2(F(x_1^p, x_2^p, \ldots, x_n^p) - d^p)^2$	Choice of optimal parameters of the right sides of rules
GA_3: Adjustment of the KB	Minimum approximation error or maximum joint information entropy	$E = \sum_p E^p$	Fine adjustment of the parameters of membership functions
		$H^j_{X_i}$	

The introduction of global intelligent feedback allows one to extract valuable information from the open system "CP + conventional controller." To increase the robustness level, it is necessary to develop the corresponding tools that support the formation of the knowledge base of the fuzzy controller. Consider the structure of the soft computing optimizer for forming and designing robust structures of intelligent control systems.

3. THE STRUCTURE OF THE SOFT COMPUTING OPTIMIZER

The soft computing optimizer is a new, efficient software tool for designing knowledge bases of robust intelligent control systems based on soft computing with the use of new optimization criteria (in the form of new fitness functions of genetic algorithms). As these criteria, we take the thermodynamic and information–entropy criteria [2] represented in Table 2.

The structure of the soft computing optimizer [18, 21] for designing robust intelligent control systems is presented in Fig. 4. The soft computing optimizer consists of interrelated genetic algorithms (GA_1, GA_2, GA_3), which optimize particular components of the knowledge base.

The input of the soft computing optimizer is a training signal, which can be obtained either at the stage of stochastic simulation of the behavior of the controlled plant (with the use of its mathematical model) or experimentally, i.e., directly from the measurement of the parameters of the physical model of the controlled plant. Figure 4 also presents the successive implementation of the stages of designing the soft computing optimizer. Let us specify the steps of the optimization algorithm.

Step 1. *Choice of the model of fuzzy inference.* The user specifies the particular type of model of fuzzy inference (Sugeno, Mamdani, etc.) and the number of input and output variables.

Step 2. *Creation of linguistic variables.* With the help of genetic GA_1, an optimal number of membership functions is determined for each input linguistic variable, and an optimal form for the representation of its membership functions (triangular, Gaussian, etc.) is chosen.

Step 3. *Design of the rule base.* At this stage, a special algorithm for selection of the most robust rules is used in accordance with the following two criteria:

(1) "total" criterion: choose only the rules that satisfy the following condition:

$$R^l_{total\_fs} \geq TL,$$

where *TL* (*threshold level*) is a given (manually or chosen automatically) level of rule activation, and

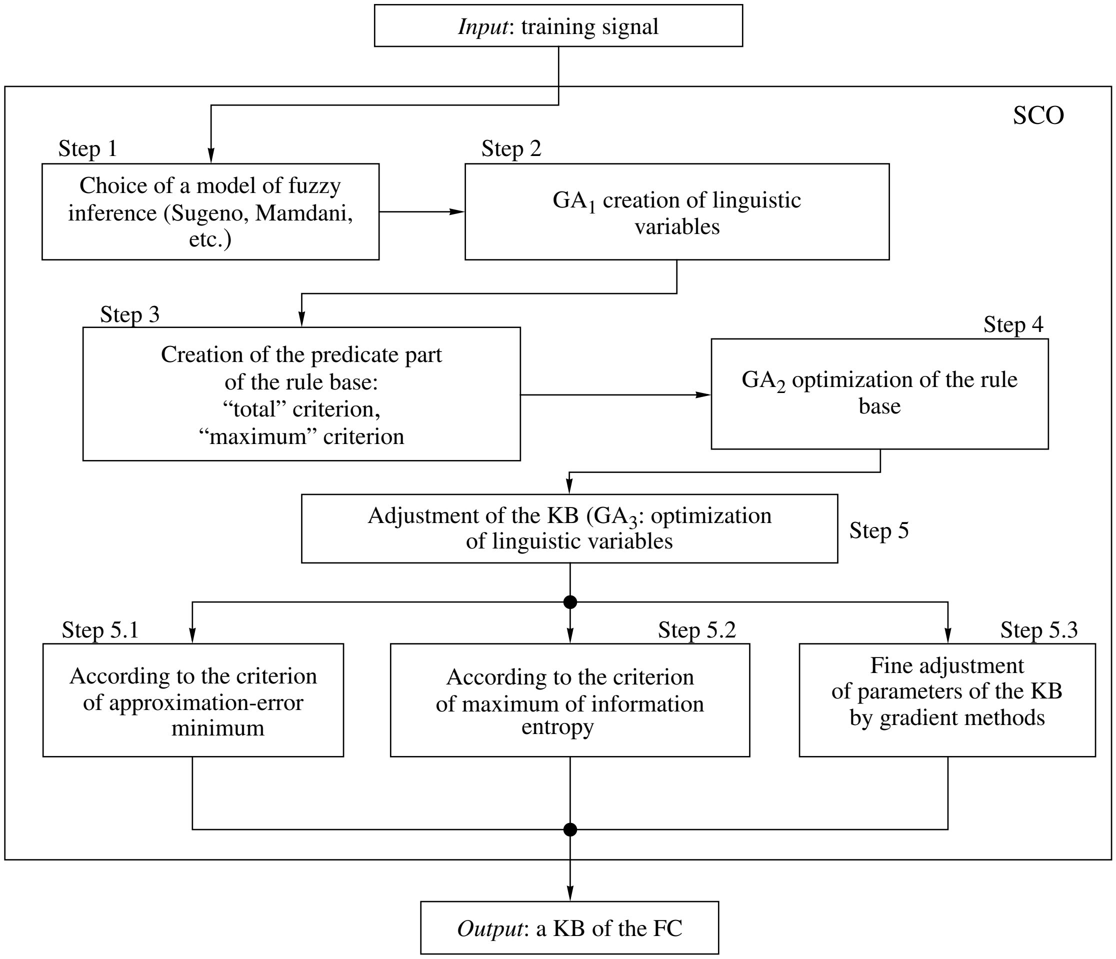


Fig. 4. The algorithm of interaction of operations in the soft computing optimizer based on soft computing.

$$R^l_{total\_fs} = \sum_{k=1}^{N} R^l_{fs}(t_k), \text{ and}$$

$$R^l_{fs}(t_k) = \Pi[\mu^l_{j1}((x_1(t_k)), \mu^l_{j2}x_1(t_k)), \ldots, \mu^l_{jn}(x_n)(t_k))],$$

where t_k are time instants, $k = 1, \ldots, N$, and N is equal to the number of points in the control signal; $\mu^l_{jk}(x_k)$, $k = 1, \ldots, n$ are membership functions of input variables, l is the index of the rule in the knowledge base; and symbol "Π" means the operation of fuzzy conjunction (in particular, it may be interpreted as a product);

(2) "maximum" criterion: choose only the rules that satisfy the condition

$$\max_t R^l_{fs}(t) \geq TL.$$

Step 4. *Optimization of base rules.* With the help of GA_2, the right sides of rules of the knowledge base defined at step 3 are optimized. At this stage, a solution that is close to the global optimum is found (minimum error of approximation of the training signal). With the help of the next step, this solution can be improved locally.

Step 5. *Adjustment of the base of rules.* With the help of GA_3, the left and right sides of the rules of the knowledge base are optimized; i.e., optimal parameters of the membership functions of the input/output variables are chosen (from the viewpoint of a given fitness function of the genetic algorithm). In this optimization process, three different fitness functions chosen by the user (steps 5.1 and 5.2 in Fig. 4) are used. In addition, there is also the opportunity to adjust the knowledge base with the help of conventional error-back-propagation method (step 5.3 in Fig. 4).

Verification (testing) of the designed knowledge base. Constructed at stages 4, 5.1, 5.2, and 5.3 knowledge bases of the intelligent control system are tested from the viewpoint of robustness and control quality. For further use, the functionally best knowledge base is chosen, which is tested in the functioning mode in real time.

Examples of simulation of knowledge bases on the basis of efficient application of the soft computing optimizer are considered in Section 5.

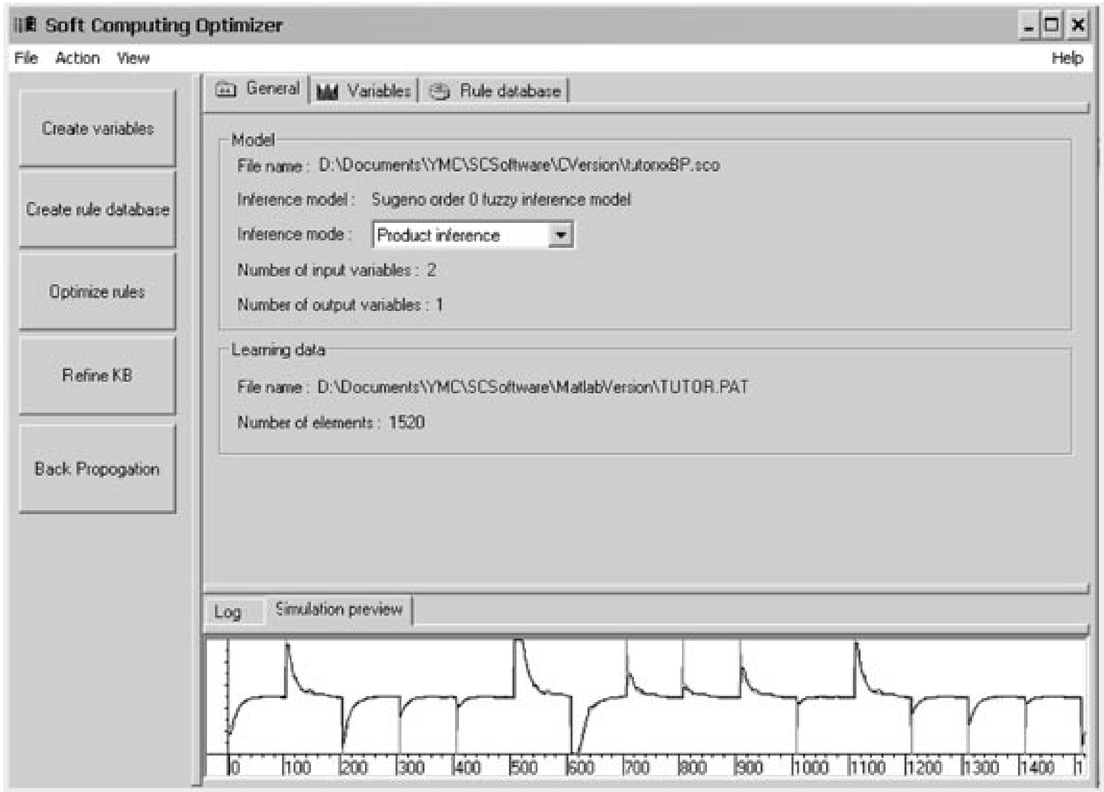


Fig. 5. The main menu of the soft computing optimizer.

4. SOFTWARE IMPLEMENTATION OF THE SOFT COMPUTING OPTIMIZER

The soft computing optimizer was implemented as a software system [3, 18, 21]. As a programming language, C++ (Microsoft Visual Studio.net) was chosen. The algorithmic part devoted to the implementation of the main stages of optimization algorithms was implemented as a platform-independent tool. The graphical interface presented in Fig. 5 was developed for operating systems of the Win32 family and was tested on personal computers with different versions of the Windows operating system.

The main menu of the optimizer was divided into several sections (Fig. 5) devoted to execution of the main functions and visualization of the results of algorithm operation.

In the *left section* of the main menu, a group of buttons is located. These buttons run different optimizing components, such as

creation of linguistic variables (Create variables) with the help of GA_1;

algorithm of generation of the predicate part of fuzzy rules (Create rule base);

GA_2 for optimization of the consequence part of fuzzy rules (Optimize rules);

GA_3, which represent the algorithm of readjustment of the parameters of linguistic variables for a more accurate approximation of the training signal by the obtained rules (Refine KB). The error-back-propagation algorithm is also included (Back propagation), which guarantees a given accuracy of the approximation of the training signal of the designed knowledge base.

In the *central section* of the main menu of the optimizer, the basic information about the designed fuzzy system is located, such as the type, address of the main file of the knowledge base, the number of input and output variables, as well as generic information about the training signal. Here, you can also find the editor of linguistic variables and the editor of rules.

Figure 6 presents the *editor of linguistic variables.* The membership functions of fuzzy variables can be edited both manually, by dragging the corresponding values, and by manual input of parameters.

Figure 7 presents the *editor of the base of fuzzy rules.* The fuzzy rules are structurally represented in the form of a fuzzy neural network. The number of neurons of the first layer corresponds to the number of input signals, while the number of neurons of the second layer corresponds to the total number of membership functions involved in the linguistic variables describing the corresponding input signals. The number of neurons of the third layer is given by the set of fuzzy rules involved in a given knowledge base. To choose a particular rule, it is necessary to choose the corresponding neuron of

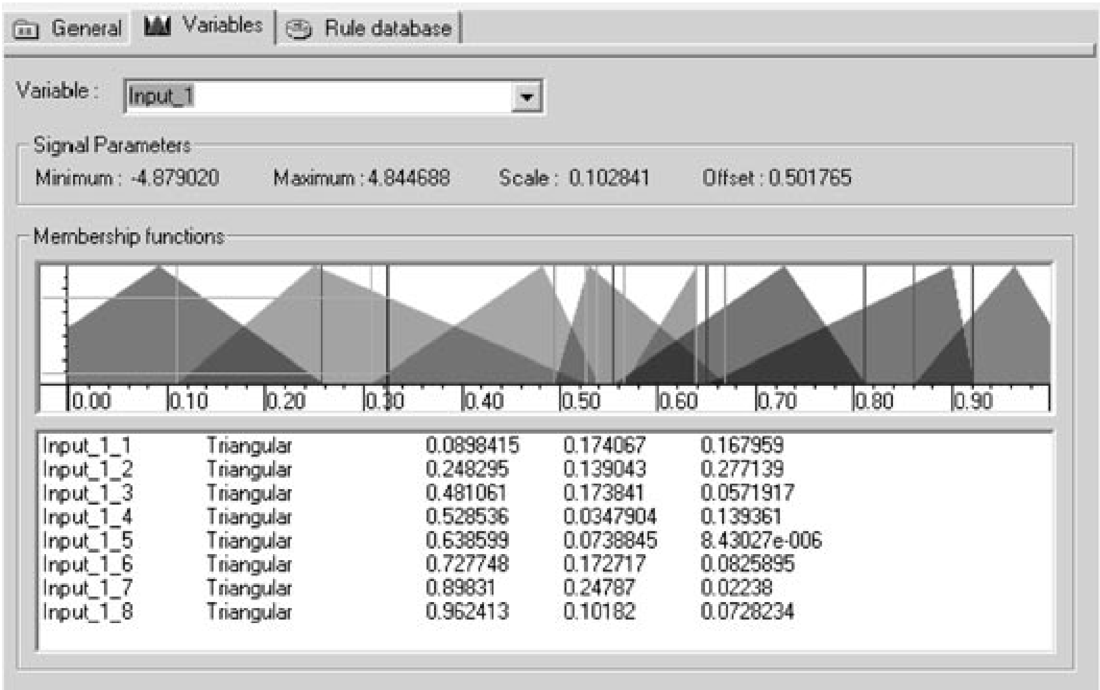


Fig. 6. The editor of linguistic variables.

the third layer. The chosen rule can be further changed and appended.

In the bottom part of the main menu of the optimizer, the window for the output of system messages is located, in which the parameters of algorithms and all actions made by the user are copied. The constantly updated result of fuzzy inference is output together with the approximating training signal. Any actions aimed at a change of parameters of the designed knowledge base results in updating the approximation results. Thus, the user can visually control the effect of modification of parameters of the knowledge base on the result of the approximation.

In the design of this system, it was initially planned to use it together with Matlab, which allows one to flexibly compute the values of the fitness functions of genetic algorithms. Note that, together with the training signal, it is possible to apply the results of numerical integration of models of the controlled plant executed in the Simulink environment controlled by a fuzzy controller with the synthesized soft computing optimizer. An approach that allows one to compute the fitness function in Matlab with the subsequent transfer of the results to the genetic algorithm of the optimizer was developed. For this purpose, the corresponding library of units of the Simulink environment was designed. This library supports the loading of the knowledge base and fuzzy inference (in the simulation mode), as well as the communication with the optimizer (in the optimization mode). The unit of fuzzy inference for Simulink was written in C++, in the form of the corresponding *s*-function of Simulink. To simulate fuzzy inference (without using Simulink models), the corresponding mex-file was prepared, which allows one to obtain the results of fuzzy inference with the help of the command line and executed scripts of Matlab. The program is compatible with Matlab 6.1 and subsequent versions.

Since the main chain in the technology for designing intelligent control systems is the stage of designing the corresponding knowledge base [1], the design of robust knowledge bases under the types of unpredicted control situations specified above allows one to establish in a general form the correspondence between the conditions of functioning of the controlled plant and the required robustness level of the intelligent control system. Consider the results of simulation of robust structures of intelligent control systems with efficient application of the soft computing optimizer.

Remark 5. In Section 4, we described a methodology for designing robust knowledge bases and the corresponding software tools in the form of a soft computing optimizer based on soft computing, which allows one to solve the problem posed within the framework of processes of learning and adaptation. In what follows, we consider particular examples of application of the soft computing optimizer in the problems of testing and evaluating the levels of structural robustness of the designed intelligent control system based on the joint technique of stochastic and fuzzy simulation. As simulation objects, we chose benchmarks that allow us to demonstrate clearly the efficiency and advantage of the developed tools for designing the soft computing opti-

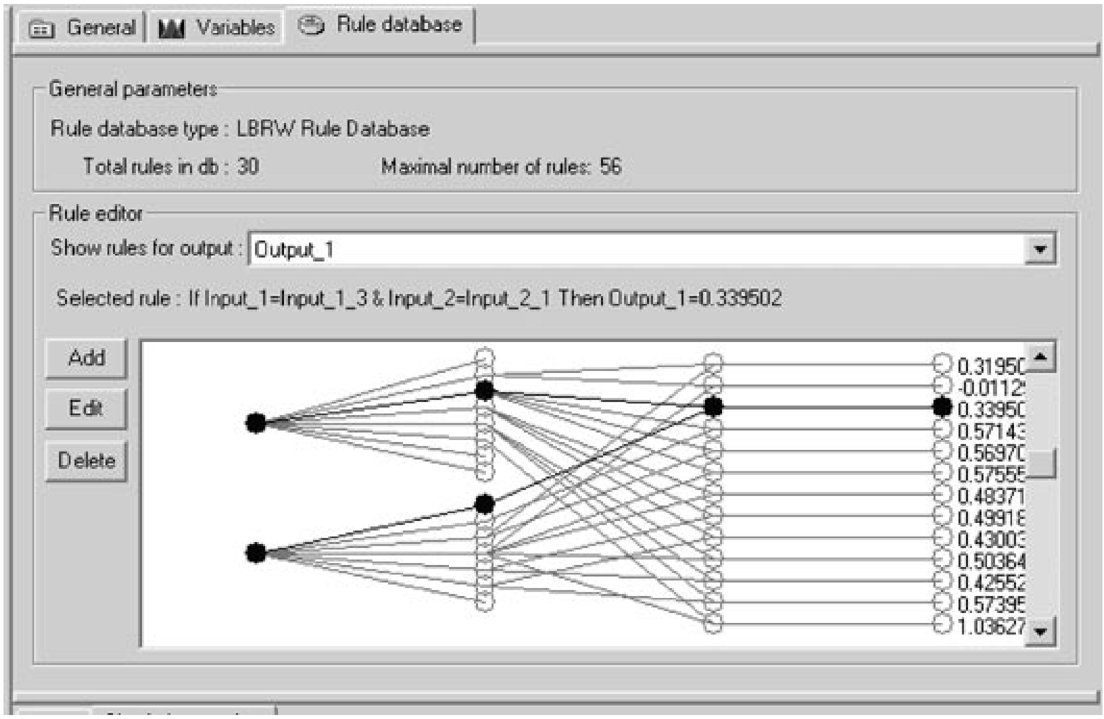


Fig. 7. The editor of the base of fuzzy rules.

mizer. The employed models of the controlled plant possess both local and global dynamic instabilities, high sensitivity to variation of the initial conditions, parameters of the structure of the controlled object, and random parametric, internal, and external perturbations. We present the results of simulation and practical recommendations for using them in the problems of designing robust intelligent control systems. The methodology of stochastic simulation is described in short in the Appendix.

5. A SYSTEM OF STOCHASTIC FUZZY SIMULATION OF ROBUST INTELLIGENT CONTROL SYSTEMS

Fuzzy simulation of robust knowledge bases with the soft computing optimizer is based on the process of extraction of valuable information by simulation and investigation of individual (statistically represented) informative trajectories describing the behavior of the controlled plant and a conventional PID controller under the effect of stochastic processes. Within the scope of correlation theory, stochastic processes, which are different in their statistical nature (i.e., having different density functions of probability distribution), can be indistinguishable in their correlation properties. The density function of probability distribution is the complete statistical characteristics of stochastic processes. Therefore, the output process of the forming filter simulating the external environment must be represented by the informatively significant selective trajectory of the stochastic process that allows one to investigate individual parameters of dynamic fuzzy systems. Selective trajectories should meet these requirements if their density function of the probability distribution is known. Stochastic processes with a required density function of probability distribution are simulated by the method of nonlinear forming filters.

In this section, we use the methodology of designing the structures of intelligent control systems functioning in the external environment under the presence of stochastic processes having the same autocorrelation function and different distribution functions of the probability density. The method of nonlinear forming filters for describing stochastic processes with a required density function for the probability distribution based on the Fokker–Planck–Kolmogorov equations is described in the Appendix. This approach allows us to develop a generalized methodology for investigating the robustness of intelligent control systems based on stochastic fuzzy simulation.

Figure 8 presents the generalized structure of the system of stochastic fuzzy simulation, which was applied for evaluating the robustness and limiting capabilities of the structures of intelligent control systems with specifying the main factors that affect the sensitivity and reliability of control. The efficiency of application of the soft computing optimizer is demonstrated by particular typical examples of models of controlled plants, the so-called benchmarks.

In particular, the investigated models of physical controlled plants and their functioning environment are

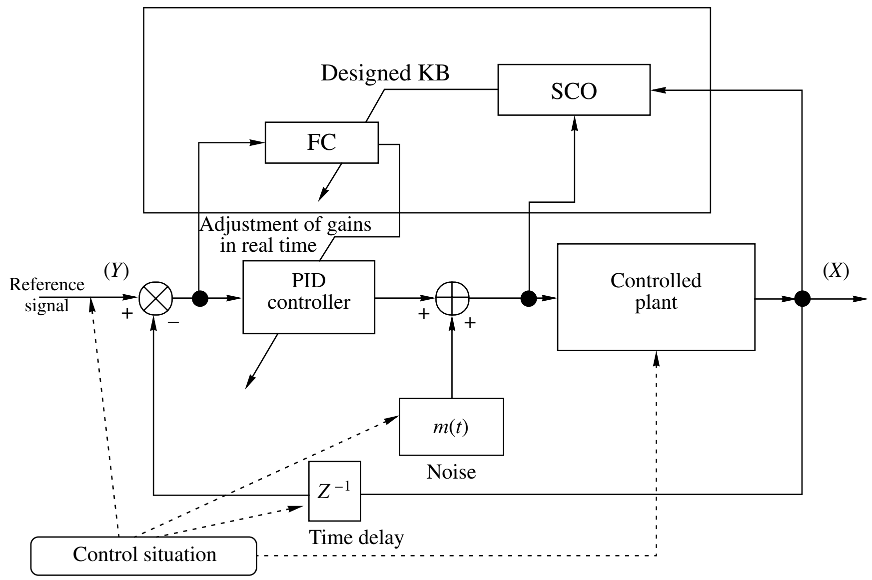


Fig. 8. The block diagram of stochastic fuzzy simulation with unpredicted control situations.

characterized by the following specific features typical of real dynamic controlled plants:

they have local and global dynamic instability with respect to the generalized coordinates;

they have essentially nonlinear cross constraints (stochastic nonlinearities) in the generalized dynamic coordinates, which mutually affect (antagonistically) the dynamic, stability, and controllability of the controlled plant;

they operate under unpredicted control situations.

As unpredicted control situations, we consider four control models under the conditions of uncertainty of the source information: (1) with statistical information about the external and parametric random perturbations variable in time (selective trajectories of stochastic processes with density functions of probability distribution depending on time); (2) with uncertainty of information about the variation of parameters of the structure of the controlled plant; (3) under the presence of random delay time in the loops of control and measurement systems; and (4) when the control (reference signal) goals are changed.

The developed model of the intelligent control system and controlled plant was simulated in the Matlab/Simulink system presented in Fig. 9. As typical random noise, three types of stochastic processes with the corresponding density functions of probability distribution were simulated.

Figure 10 presents the form of the density functions of probability distribution and the simulation results of the output stochastic processes from the corresponding forming filters. Varying the structure of the forming filters, the parameters in the models of the controlled plant, the delay time in the channel for measuring the control error, and the form of the reference signal (control goal), we can simulate unpredicted control situations and evaluate the sensitivity and the robustness level of the designed intelligent control system.

In this section, we present the results of simulating the robust control laws for intelligent fuzzy PID controllers by complex essentially nonlinear dynamic controlled plants. To demonstrate the capabilities of simulation of the processes of intelligent control of a dynamic controlled plant and the conditions of functioning, the results of simulation of the following three typical controlled plants (benchmarks) are considered: (1) a nonlinear oscillator with essential dissipation and local dynamic instability; (2) an inverted pendulum mounted on a moving cart and with global dynamic instability; and (3) an essentially nonlinear oscillator with local and global dynamic instability in cross constraints of the generalized coordinates of the controlled plant.

These oscillators are of independent interest for problems in robotics and mechanics (e.g., a stroboscopic manipulator robot with complex behavior dynamics and considerable dissipation) and allow one to compare our results with the results obtained by methods based on a fuzzy neural network [1].

Remark 6. In view of the large amount of the simulation results and the limited admissible size of the paper, we consider the third version of an oscillator containing all the qualitative specific features of the two types of oscillators listed above.

Example 2. *A swing.* Figure 11 shows a physical swing. The motion equations of the pendulum are represented as

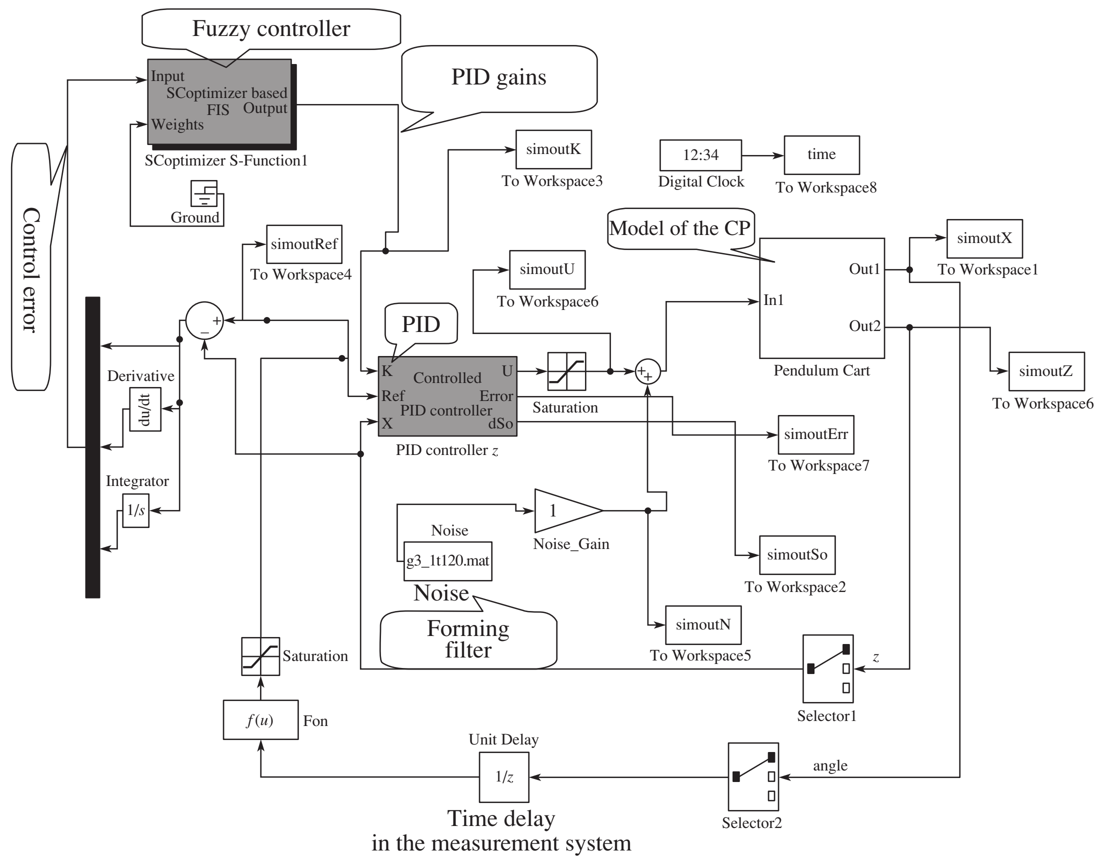


Fig. 9. A Matlab/Simulink Model of the control system.

$$\begin{cases} \ddot{\theta} + 2\frac{\dot{l}}{l}\dot{\theta} + \frac{g}{l}\sin\theta = k'_p e_\theta + k'_d \dot{e}_\theta + k'_i \int e_\theta dt + \xi_1(t) \\ \ddot{l} + 2k\dot{l} - l\dot{\theta}^2 - g\cos\theta \\ = \frac{1}{m}(k_p e_l + k_d \dot{e}_l + k_i \int e_l dt + \xi_2(t)), \end{cases} \qquad (5.1)$$

where $\xi_1(t)$ and $\xi_2(t)$ are the corresponding stochastic actions described by various density functions of the probability distribution.

The thermodynamic equations of the entropy production rate in the controlled plant and the PID controller have the form

$$\underbrace{\frac{dS_\theta}{dt} = 2\frac{\dot{l}}{l}\dot{\theta}\theta; \quad \frac{dS_l}{dt} = 2k_i\dot{l};}_{\text{Controlled plant}}$$
$$\underbrace{\frac{dS_{\text{PID}(\theta)}}{dt} = k'_d \dot{e}_\theta^2; \quad \frac{dS_{\text{PID}(l)}}{dt} = k_d \dot{e}_l^2}_{\text{PID controller}} \qquad (5.2)$$

and are considered together with motion equations of the controlled plant (5.1).

The motion of the system described by Eqs. (5.1) represents a globally instable (with respect to the axis l) and locally instable (with respect to the axis θ) dynamic system (Fig. 12). Note that, in model (5.1), there are cross nonlinear constraints that affect the local instability with respect to the generalized coordinate θ. Thus, (5.1) involves local and global instability with respect to the generalized coordinates of the controlled plant and is a generalization of the previous models. Here and in what follows, in Figs. 13–23, we use the following notation: X: angle ($\theta = x$) is an angle; Y: Length ($l = y$) is a length; Time (S) is the time; SCO for a soft computing optimizer; and Refsignal for a reference signal.

Consider the following *problem of feedback control*: in the presence of Rayleigh stochastic noise (see Fig. 10, position 2) acting on the controlled plant along the axis θ (the maximum amplitude of noise is ten), and under Gauss stochastic noise along the axis l (the maximum amplitude of noise is four), steer the pendulum from the initial position to a given position (control goal) and hold the motion of the controlled plant in this state $\theta_{\text{ref}} = 0.4$ and $l_{\text{ref}} = 3.5$.

Consider the control problem under the following values of parameters: $m = 1$ and $k = 1$ and the initial conditions $[x_0 = 2.5, y_0 = 25\}$ and $[\dot{x}_0 = 0, \dot{y}_0 = 0.01]$. The structure of the intelligent control system is a fuzzy

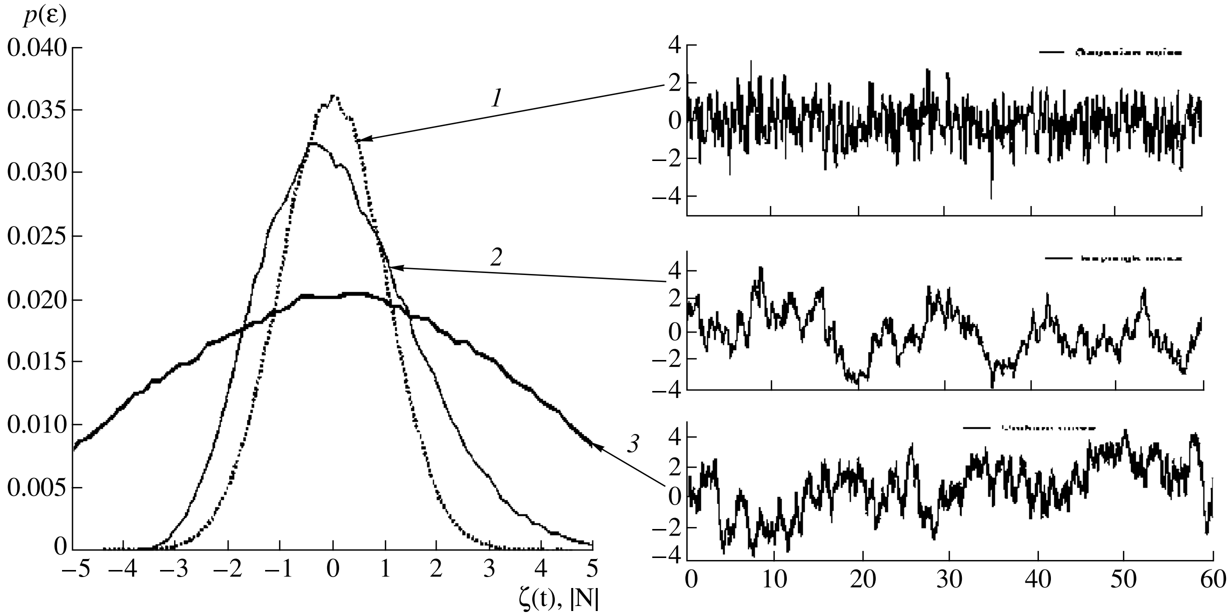


Fig. 10. The form of the density function of the probability distribution and the results of simulation of output stochastic processes from the corresponding forming filters: (*1*) Gaussian; (*2*) Rayleigh; (*3*) uniformly distributed.

controller for two PID controllers along the axes θ and *l*. In this case, we consider the problem of *coordinated control* for the gains of two PID controllers, which is of independent interest for control theory and systems [2, 3, 8].

Figures 13–17 show the results of simulation of the system motion in the three cases of control: with the help of two classical PID controllers (with gains $K = \{6, 6, 6\}$); based on conventional soft computing (with the help of the structure of a fuzzy neural network chosen manually; and the method for designing knowledge bases with the help of the error-back-propagation method; and with application of tools of an soft computing optimizer developed in [3, 18, 21]. Therefore, the intelligent control system designed based on the soft computing optimizer is more efficient than the intelligent control system obtained with the help of conventional soft computing using a fuzzy neural network, and more efficient than conventional PID controllers. From the point of view of the processes of optimization of the structures of automatic control systems according to the control quality criteria, such as minimum of control error; minimum entropy production in the controlled plant and in the automatic control system (minimum heat loss, loss of useful work and energy), the developed structure of the intelligent control system is optimal and has a minimum complexity.

Investigation of robustness of the intelligent control system. Consider the robustness property of the designed knowledge bases for the three control cases specified above. Let us formulate a control problem with new conditions (unpredicted control situation), which are different from the initial control problem for which an optimal training signal was chosen, and compare the results of simulation for the three control cases.

Control problem with new conditions:

new initial position of the controlled object [–0.52, 2.5] [0.01, 0];

new reference signals: $\theta_{ref} = 0.78$; $l_{ref} = 5$;

other noises acting the controlled plant;

Gaussian noise along the axis θ (the maximum amplitude of the noise is 1.5);

Rayleigh noise along the axis *l* (the maximum amplitude of noise is equal to one).

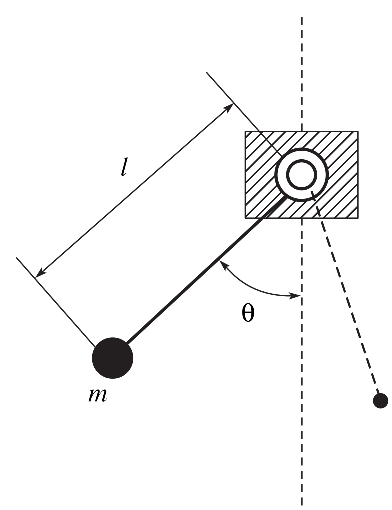


Fig. 11. A physical swing.

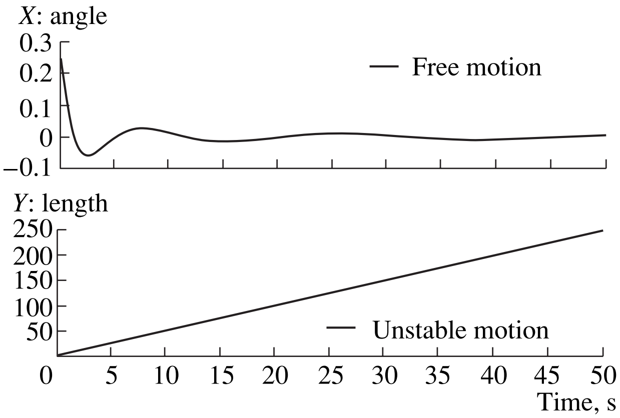


Fig. 12. A swing: free motion of the system. The coordinate *Y* (length) shows globally unstable motion.

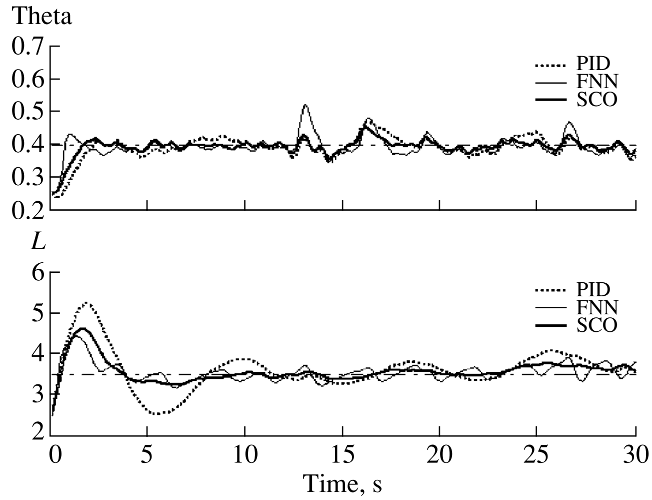


Fig. 13. A swing. The motion of the system under the stochastic action with three control types (PID, FNN, and SCO).

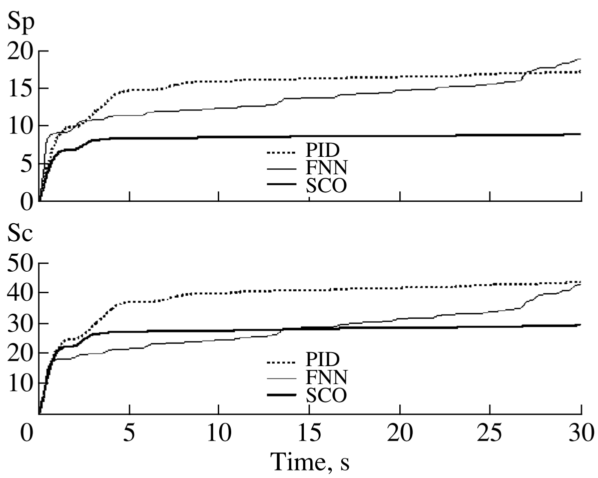


Fig. 14. A physical swing. Entropy production in the controlled plant and in the control system (PID, FNN, and SCO).

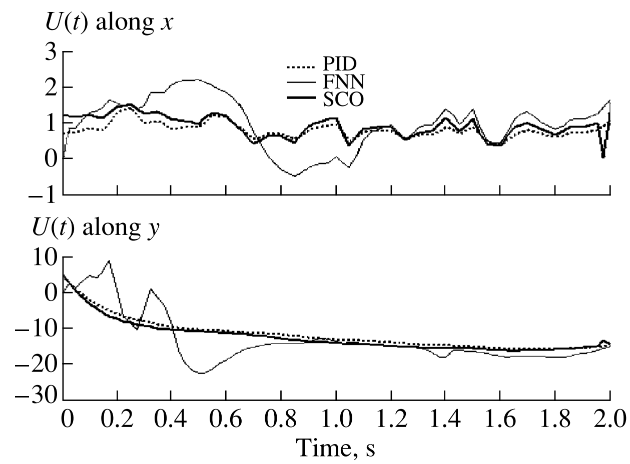


Fig. 15. A physical swing. The control force along the coordinate axes $\theta(x)$ and $l(y)$.

Figures 18–20 show the results of simulation of the system motion in the three control cases under the new conditions.

In Figs. 21–23, the control force and the gains of the fuzzy PID controller based on the conventional method of soft computing presented by a fuzzy neural network are zero. This means that the knowledge base of the fuzzy controller designed with the help of a fuzzy neural network is not robust; i.e., for the new initial conditions, there are no activated rules in the knowledge base. By the simulation results, the designed knowledge base based on a fuzzy neural network for the fuzzy controller in the intelligent control system cannot cope with the control situation. Therefore, the knowledge base of the intelligent control system designed with the help of conventional soft computing based on a fuzzy neural network is not robust. On the contrary, the knowledge base of the intelligent control system obtained with application of the soft computing optimizer is robust and efficient from the point of view of a given control quality criterion.

6. EXAMPLES OF PRACTICAL APPLICATION OF THE SOFT COMPUTING OPTIMIZER IN ACTUAL CONTROLLED OBJECTS

The tools of the soft computing optimizer based on soft computing were employed in designing robust intelligent control systems of industrial controlled plants were experimentally tested on actual controlled objects, such as an inverted physical pendulum without a mathematical model, semi-active car suspension [23], navigation control for a robot–cyclist [24], control of a combustion engine [25], etc.

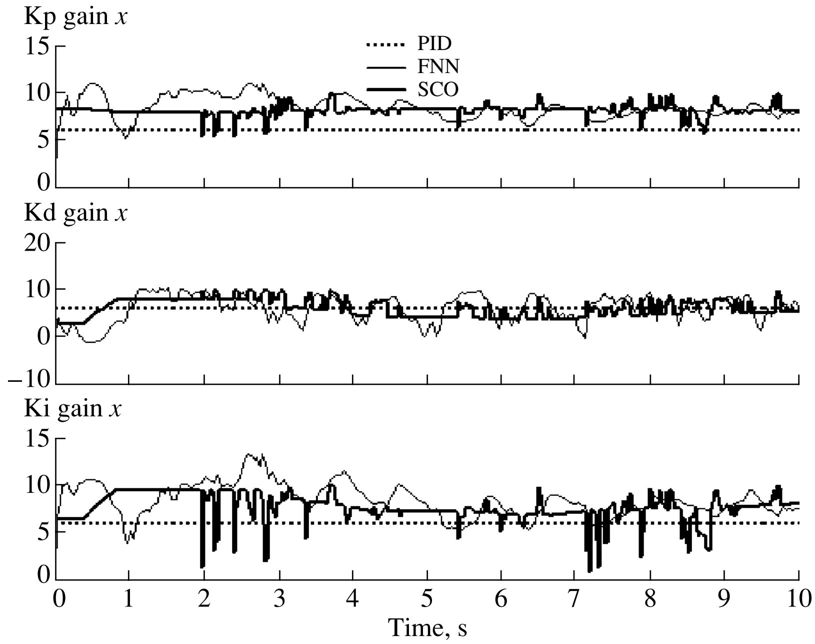


Fig. 16. Control laws force along the coordinate axes θ (PID, FNN, and SCO).

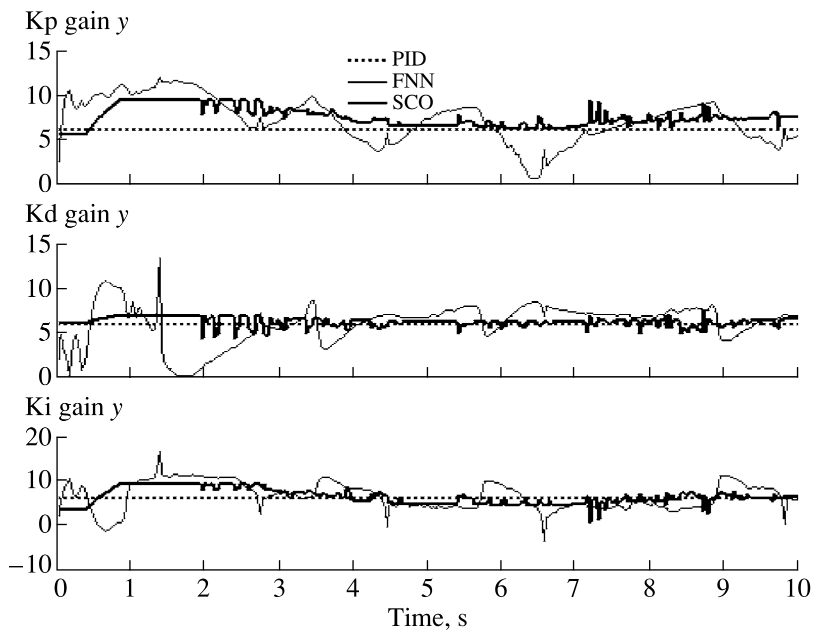


Fig. 17. Control laws force along the coordinate axes *l* (PID, FNN, and SCO).

The conducted tests have shown a high efficiency of the operation of the soft computing optimizer both on the controlled plant with a model and with the use of experimental data obtained with a physical model of the controlled plant. The results of simulation and industrial exploitation have demonstrated that:

the designed knowledge base of the fuzzy controller, which controls the motion of the controlled plant, is robust;

from the viewpoint of the control quality criteria such as the minimum control error, the minimum entropy production in the controlled plant and control system (i.e., the minimum heat loss and loss of useful work and energy), as well as with due account of the minimum of control force the developed structure of the intelligent control system, is more efficient than the conventional PID controllers and fuzzy controllers

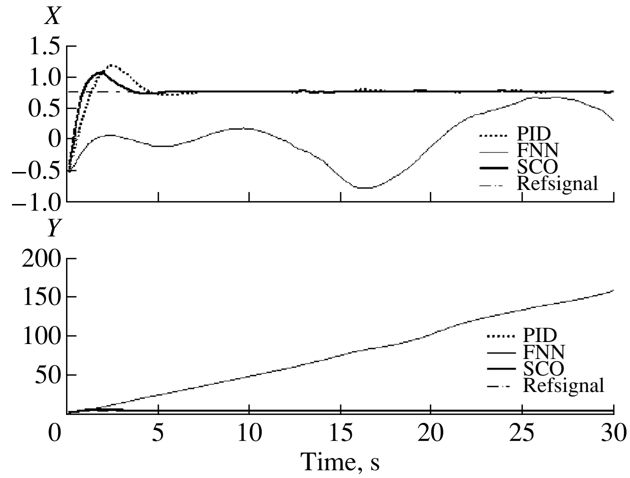


Fig. 18. A physical swing. The motion of the system under the stochastic action with three control types (PID, FNN, and SCO). A new control situation.

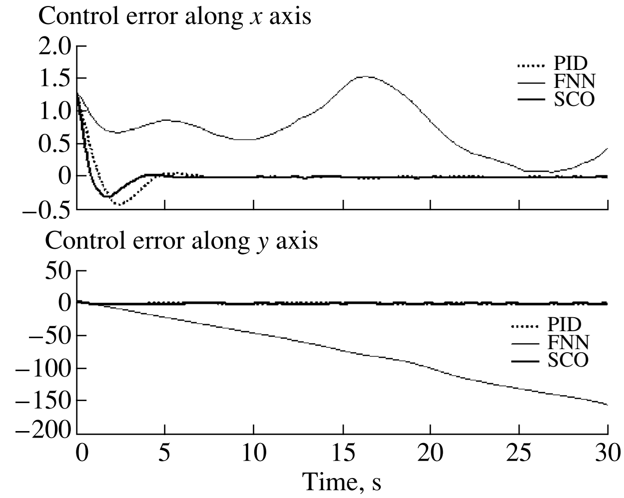


Fig. 19. A physical swing. A control error. A new control situation.

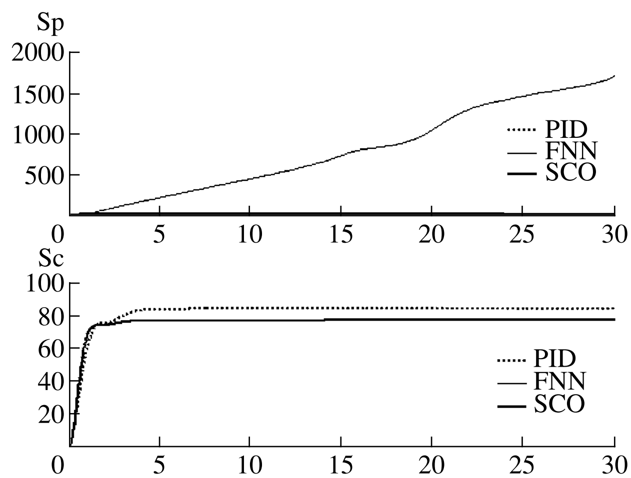


Fig. 20. A physical swing. Entropy production in the controlled plant and in the control system. A new control situation.

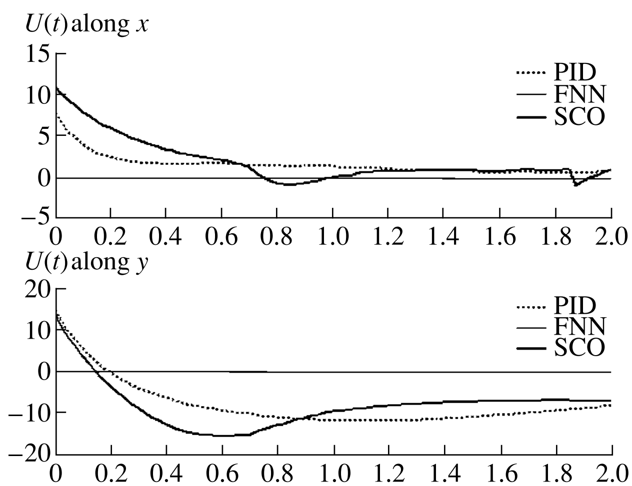


Fig. 21. A physical swing. The control force along the coordinate axes $\theta(x)$ and $l(y)$. A new control situation.

designed based on the conventional tools of soft computing of the fuzzy neural network type;

the developed methods has its limitations in achievement of the required robustness level, which makes us introduce new methods of simulation and computing (quantum computing and quantum fuzzy inference) to the tools of the soft computing optimizer [7].

Based on the proposed tools of the soft computing optimizer, the topical problems of forming knowledge bases for designing robust fuzzy controllers were considered, e.g., the problem of coordinated control of gains of two PID controllers, which are of independent interest for control theory and systems. The employed tools of the soft computing optimizer allow one to implement simultaneously the process of designing robust knowledge bases based on algorithms of learning and adaptation, implementing the first stage of information technology of designing robust intelligent control systems.

7. CONSTRAINTS AND PROSPECTS OF DEVELOPMENT OF SOFTWARE TOOLS OF THE SOFT COMPUTING OPTIMIZER

As was mentioned, using the integration with Matlab, the soft computing optimizer gives the opportunity to introduce additional control quality criteria not changing the source code of software units of the system. In view of the advantages listed above, the soft computing optimizer provides a background for the first stage of technology of designing intelligent control systems [3, 20, 21] (Fig. 3).

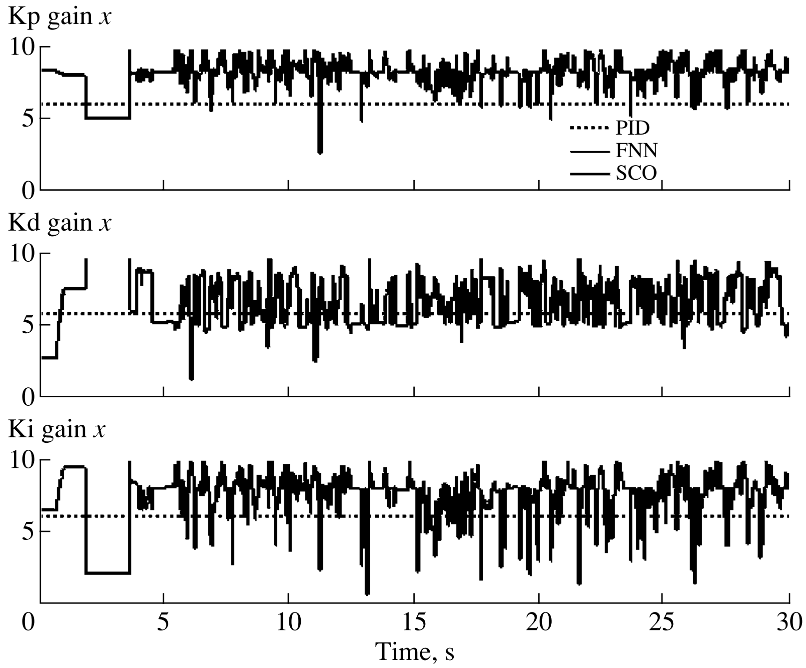


Fig. 22. Control laws force along the coordinate axes $\theta(x)$. A new control situation.

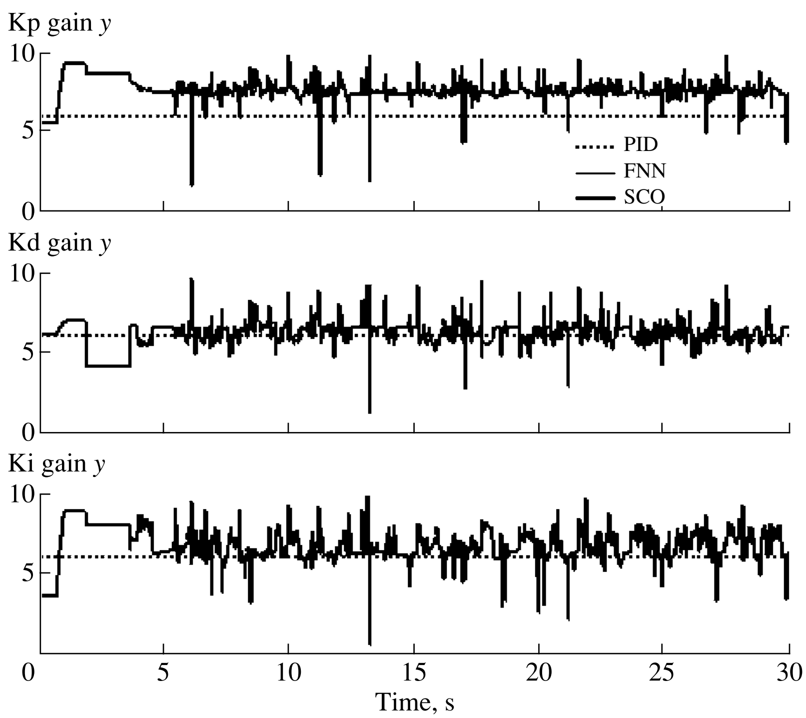


Fig. 23. Control laws force along the coordinate axes l. A new control situation.

Remark 7. The large capabilities of the tools of the soft computing optimizer in designing robust knowledge bases of intelligent control systems for a wide class of control situations have been investigated and demonstrated. However, the proposed method also has limitations in achievement of the required robustness level.

Figures 24 and 25 present the results of simulating the "cart-pole" and "swing" systems in unpredicted control situations. For the "cart-pole" system, the new

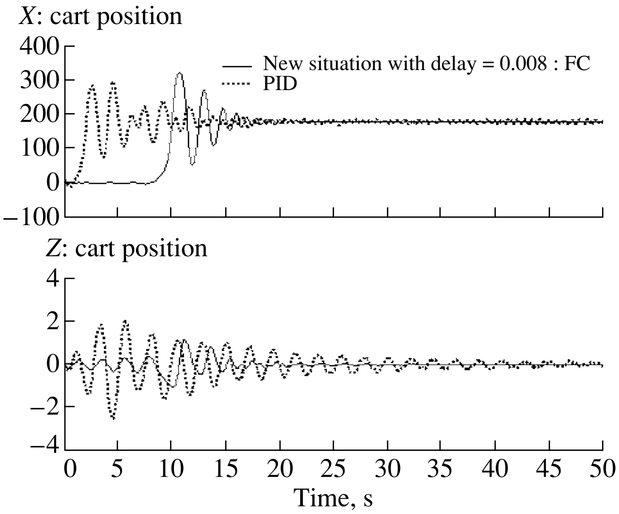


Fig. 24. Unstable dynamic behavior of the CP in a new unpredicted control situation (the time delay is enlarged to 0.008 s).

delay time in the measurement channel was 0.008 s (under the delay time 0.001 and 0.002 s the system is stable and robust) and resulted in loss of control for the fuzzy and conventional PID controllers.

For the "swing" system, the unpredicted situation for the initial parameters of the system $m = 0.5$, $k = 0.4$, $c = 2$; and $[\theta_0 = 0.25, l_0 = 0.5]$ $[\dot{\theta}_0 = 0, \dot{l}_0 = 0.01]$ had the following characteristics: Gaussian noise along the axis x, and the time delay in the measurement channel was 0.075 s. The Rayleigh noise along the axis y and the time delay in the measurement channel were 0.04 s, and the reference signals along the axis x and axis y are equal to zero and two, respectively. Even without a limitation on the control force, the conventional PID controller with averaged optimal parameters cannot cope with the unpredicted control situation.

Remark 8. In Figs. 24 and 25, we use the following notation: X is the angle of pendulum deflection; Z is the cart position; S_p is the entropy production in the controlled plant; S_c is the entropy production in the controller; and K_p, K_D, and K_I are the gains of the PID controller. These and other simulation results lead to the necessity to develop and introduce new methods and computing (quantum computing and quantum fuzzy inference [7, 13] to the tools of soft computing optimizer.

The constraints arise from the physical nature of the algorithm of random search in the structure of genetic algorithm. The proposed soft computing optimizer is able to work on a single space of solutions (because of limit capabilities of the genetic algorithm). For global optimization on the set of spaces of solutions, it is required to pass to a new type of computing that allows one to join the sets of spaces of solutions into a single

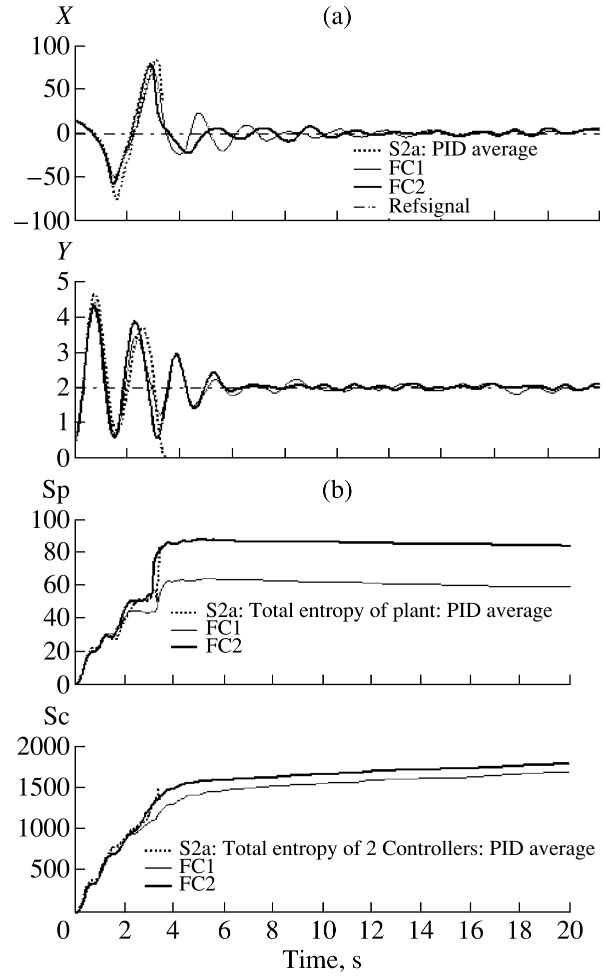


Fig. 25. The dynamic behavior of the CP in an unpredicted control situation (the description in the text): (a) loss of controllability of the PID controller; (b) entropy characteristics of the CP and controllers.

set with the help of the quantum superposition operator [4, 7]. This type of computing is *quantum computing.*

In this case, the quantum optimizer that applies methods of quantum computing uses particular knowledge bases designed based on the soft computing optimizer as the source data. This means that the soft computing optimizer provides a background for implementing the second stage of technique using quantum computing. For this purpose, an interface that can be inserted by a program with a unit of quantum computing is incorporated in the architecture of the soft computing optimizer (Fig. 26).

Thus, the promising information technology of designing the structures of robust intelligent control systems is two-level. The first level is based on the soft computing optimizer, and the second level is based on quantum computing.

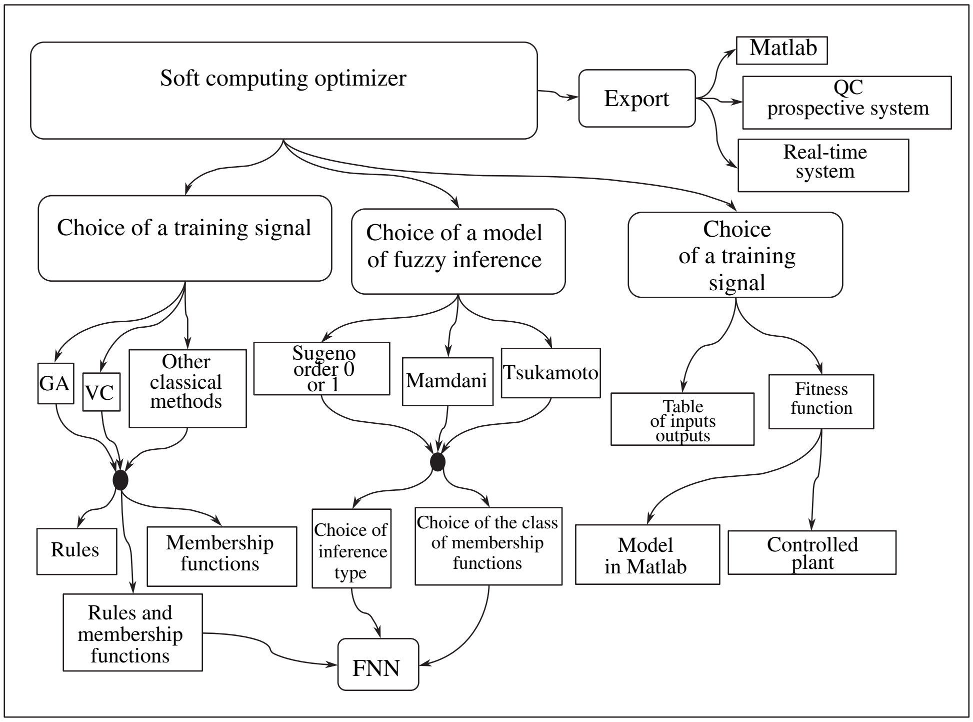


Fig. 26. The block diagram of the CSO.

CONCLUSIONS

The methods for development and the technology for designing intelligent control systems based on the soft computing optimizer presented in this paper allow one to implement the principle of designing an optimal intelligent control system with a maximum reliability and controllability level of a complex controlled plant under conditions of uncertainty in the source data, and in the presence of stochastic noises of various physical and statistical characters. The knowledge bases formed with the help of a soft computing optimizer produce robust control laws for the gains of conventional PID controllers for a wide range of external perturbations and are maximally insensitive to random variations of the structure of the controlled plant.

The robustness of control laws is achieved by introducing a vector fitness function for the genetic algorithm, whose one component describes the physical principle of minimum production of generalized entropy both in the controlled plant and the control system, and the other components describe conventional control objective functionals such as minimum control error, etc. The approach based on the soft computing optimizer for designing robust intelligent control systems allows one to design an optimal intelligent control system with a maximum reliability and controllability level for the set of dynamic systems under the presence of uncertainty in the source data [8]; to reduce the number of sensors both in the control channel and in the measurement system without loss of accuracy and control quality [22].

The robust intelligent control system obtained based on this approach requires minimum source data on both the behavior of the controlled plant and the external perturbations [3, 20].

APPENDIX

The system for simulating stochastic processes with a required density function of probability distribution by the method of nonlinear forming filters. In this appendix, we describe the methodology of designing the structures of forming filters of stochastic processes that have the same autocorrelation function and different functions of the probability distribution density. The results of statistical analysis of actual stochastic processes have shown that the typical autocorrelation functions describing these processes are

$$R(\tau) = B(0)\exp\{-\alpha|\tau|\}; \qquad \text{(A.1)}$$

$$R(\tau) = B(0)\exp\{-\alpha|\tau|\}\cos\beta\tau; \qquad \text{(A.2)}$$

$$R(\tau) = B(0)\exp\{-\alpha|\tau|\}\left[\cos\beta\tau + \frac{\alpha}{\beta}\sin(\beta|\tau|)\right], \qquad \text{(A.3)}$$

where α and β are the values of coefficients determined from the experimental data. The presented autocorrelation functions and their parameters are used in the practice of stochastic simulation of stochastic processes based on forming filters.

In the framework of correlation theory, stochastic processes that are different in their nature (i.e., having different density functions of probability distribution) may be indiscernible in their correlation properties. The density function of probability distribution is a complete statistical characteristic of stochastic processes. Consider the methodology of designing the structures of forming filters of stochastic processes by the example of an autocorrelation function (A.1) with various types of density functions of probability distribution.

Let us take a stationary stochastic process $X(t)$ defined on the interval $[x_l, x_r]$ whose boundaries may be both bounded and unbounded. Without loss of generality, we assume that $X(t)$ has a zero mean value. Then, we have $x_l < 0$ and $x_r > 0$. Knowing the density function of probability distribution $p(x)$ and the spectral density $\Phi_{XX}(\omega)$ (as the Fourier transform of the autocorrelation function $R_{XX}(\tau)$ of the stochastic process $X(t)$), we can simulate the stochastic process $X(t)$ with the help of a forming filter, whose structure and parameters are determined in terms of the form and parameters of the autocorrelation function and density function of the probability distribution [26–28].

Assume that the spectral density of the stochastic process has the form

$$\Phi_{XX}(\omega) = \frac{\alpha\sigma^2}{\pi(\omega^2 + \alpha^2)}, \quad \alpha > 0, \tag{A.4}$$

where σ^2 is the mean square deviation of $X(t)$. If $X(t)$ is a Markovian diffusion process, then it can be considered as a solution to the following stochastic equation (in the Ito sense):

$$dX = -\alpha X dt + D(X)dB(t), \tag{A.5}$$

where $B(t)$ is a unit Wiener process, the coefficients $-\alpha X$ and $D(X)$ are known as the shift and diffusion coefficients of the stochastic process $X(t)$, respectively. We multiply the left and right sides of (A.5) by $X(t - \tau)$ and average over the ensemble of random trajectories. As a result, we obtain

$$\frac{dR(\tau)}{d\tau} = -\alpha R(\tau), \tag{A.6}$$

where $R(\tau)$ is the autocorrelation function of the stochastic process $X(t)$; i.e., $R(\tau) = E[X(t - \tau)X(t)]$. Equation (A.6) has the following solution

$$R(\tau) = A\exp(-\alpha|\tau|), \tag{A.7}$$

where A is the corresponding normalizing factor.

Taking $A = \sigma^2$, Eqs. (A.4) and (A.7) can be related by the Fourier transform.

Thus, Eq. (A.5) reproduces the stochastic process $X(t)$ with the required spectral density (A.4). Note that the form of the diffusion coefficient $D(X)$ does not affect the form of the spectral density.

Let us define the form of the diffusion coefficient $D(X)$ so that the random process $X(t)$ has the required density function of probability distribution $p(x)$. It is known that the density function of probability distribution for a given class of dynamic systems can be determined by solving the Fokker-Planck–Kolmogorov equation [26, 28], which can be obtained in the stationary case from (A.5) as follows:

$$\frac{d}{dx}G = -\frac{d}{dx}\left\{\alpha x p(x) + \frac{1}{2}\frac{d}{dx}[D^2(x)p(x)]\right\} = 0, \tag{A.8}$$

where G is known as the probability flow. Since the stochastic process $X(t)$ is defined on the interval $[x_l, x_r]$, the probability plow G must satisfy two boundary conditions for $x = x_l$ and $x = x_r$.

In this one-dimensional case, the flow G exists and is stationary; i.e., the density of the probability flow is $\frac{d}{dx}G = 0$. In accordance with this condition, Eq. (A.8) takes the form

$$\alpha x p(x) + \frac{1}{2}\frac{d}{dx}[D^2(x)p(x)] = 0. \tag{A.9}$$

The integration of Eq. (A.9) leads to the result

$$D^2(x)p(x) = -2\alpha\int_{x_l}^{x_r} up(u)du + C, \tag{A.10}$$

where C is the integration constant.

To determine C, we consider two cases. In the first case, if either $x_l = -\infty$ or $x_r = \infty$, or both cases are true, then $p(x) = 0$ on these boundary conditions, and Eq. (A.10) implies that $C = 0$. In the second case, if x_l and x_r are finite, then the shift coefficient $-\alpha x_l$ for the right boundary condition is negative, while, for the left boundary condition, it is positive.

This means that the averaged probability flows for these two boundary conditions have different directions. However, the existence of a stationary probability distribution density gives an additional condition that states that, for these two boundary conditions, the diffusion coefficient is $D^2(x_l) = D^2(x_r) = 0$. This condition is valid only if $C = 0$. As a result, we have

$$D^2(x) = -\frac{2\alpha}{p(x)}\int_{x_l}^{x_r} up(u)du. \tag{A.11}$$

The function $D^2(x)$ computed from Eq. (A.11) is nonnegative since $p(x) \geq 0$ and the mean value of $X(t)$ is zero.

Thus, the stochastic process $X(t)$ is reproduced as a solution to Eq. (A.5) with the diffusion coefficient $D(x)$ determined from (A.11) with the required density function of probability distribution $p(x)$ and spectral density (A.4).

Table 3. The structure of forming filters for typical density functions of probability distribution $p(x)$

Correlation function	Probability distribution function	Structure of the forming filter
$R_y(\tau) = \sigma^2 e^{-\alpha\|\tau\|}$	Gaussian	$\dot{y} + \alpha y = \sigma^2 \xi(t)$
$R_y(\tau) = \sigma^2 e^{-\alpha\|\tau\|}$	Uniform	$\dot{y} + \frac{\alpha}{2} y = \frac{\sigma^2}{\sqrt{2\pi}} \sqrt{\alpha(\Delta^2 - y^2)}\xi(t)$
$R_y(\tau) = \sigma^2 e^{-\alpha\|\tau\|}$	Rayleigh	$\dot{y} + \alpha y \pm \frac{2\alpha}{\gamma} = \frac{\sigma^2}{\sqrt{2\pi}} \sqrt{\frac{2\alpha}{\gamma}\left(y + \frac{2}{\gamma}\right)}\xi(t)$
$R_y(\tau) = \sigma^2 e^{-\alpha\|\tau\|}$	Pierson	$\dot{y} + \alpha y + \frac{\alpha}{a_1 + 2b_2}(b_2 x + b_1)$ $= \frac{\sigma_2}{\sqrt{2\pi}} \sqrt{\frac{2\alpha}{a_1 + 2b_2}(b_2 y^2 + b_1 y + b_0)}\xi(t)$

Table 4. The structure of forming filters of stochastic processes with autocorrelation function (A.3) and typical density functions of probability distribution

Correlation function	Density function of probability distribution	Structure of the forming filter
$R(\tau)$ $= \sigma^2 e^{-\alpha\|\tau\|}\left[\cos\omega\tau + \frac{\alpha}{\omega}\sin\omega\|\tau\|\right]$	2D Gaussian $p(y_1, y_2) = \frac{1}{2\pi\sigma_1\sigma_2} e^{-\frac{1}{2}\left(\left(\frac{y_1 - \mu_1}{\sigma_1}\right)^2 + \left(\frac{y_2 - \mu_2}{\sigma_2}\right)^2\right)}$	$\ddot{y} + 2\alpha\dot{y} + (\alpha^2 + \omega^2)y$ $= \sqrt{2\alpha\sigma^2(\alpha^2 + \omega^2)}\xi(t)$
	2D Uniform $p(y_1, y_2) = \frac{1}{4\Delta_1\Delta_2}$ $-\Delta_1 < y_1 < \Delta_1$ $-\Delta_2 < y_2 < \Delta_2$	$\dot{y}_1 = \frac{1}{2}a_{11}y_1 + a_{12}y_2 + \sqrt{\left(-\frac{a_{11}}{2\pi}(\Delta_1 - y_1^2)\right)}\xi_1(t)$ $\dot{y}_2 = \frac{1}{2}a_{22}y_2 + a_{21}y_1 + \sqrt{\left(-\frac{a_{22}}{2\pi}(\Delta_2 - y_2^2)\right)}\xi_2(t)$
	2D Hyperbolic $p(y_1, y_2) = \rho(\lambda) = C_1(\lambda + b)^{-\delta}$ $b > 0; \quad \delta > 1$ $\lambda = \frac{1}{2}y_1^2 - \frac{a_{12}}{2a_{21}}y_2^2$	$\dot{y}_1 = a_{11}y_1 + a_{12}y_2 - \frac{2a_{11}^2}{(\delta - 1)^2}$ $\times\left[\frac{1}{2}y_1^2 - \frac{a_{12}}{2a_{21}}y_2^2 + b\right]y_1$ $- \frac{2a_{11}}{\sqrt{2\pi}(\delta - 1)}\left[\frac{1}{2}y_1^2 - \frac{a_{12}}{2a_{21}}y_2^2 + b\right]\xi_1(t)$ $\dot{y}_2 = a_{21}y_1 + a_{22}y_2 + \frac{2a_{22}^2 a_{12}^3}{a_{21}^3(\delta - 1)^2}$ $\times\left[\frac{1}{2}y_1^2 - \frac{a_{12}}{2a_{21}}y_2^2 + b\right]y_2$ $+ \frac{2a_{22}a_{12}}{\sqrt{2\pi}a_{21}(\delta - 1)}\left[\frac{1}{2}y_1^2 - \frac{a_{12}}{2a_{21}}y_2^2 + b\right]\xi_2(t)$

The stochastic differential equation (A.5) in the Ito form can be transformed to the corresponding Stratonovich form

$$\dot{X} = -\alpha X - \frac{1}{4}\frac{dD^2(X)}{dX} + \frac{D(X)}{\sqrt{2\pi}}\xi(t), \quad (A.12)$$

where $\xi(t)$ is the Gaussian white noise with unit spectral density. Equation (A.12) is more practical in simulation of the selective trajectories of stochastic processes. Consider certain illustrative examples that are of independent interest for the theory and practice of stochastic simulation of stochastic processes [26–28].

$X(t)$ Suppose that $X(t)$ is a stationary stochastic process with a uniform density function of probability distribution (Fig. 10, position 3).

$$p(x) = \frac{1}{2\Delta}, \quad -\Delta \le x \le \Delta. \quad (A.13)$$

Substituting (A.13) into (A.11), we obtain

$$D^2(x) = \alpha(\Delta^2 - x^2). \quad (A.14)$$

In this case, the Ito stochastic differential equation has the form

$$dX = -\alpha X dt + \sqrt{\alpha(\Delta^2 - X^2)}dB(t). \quad (A.15)$$

It is worth noting that the family of stochastic processes can be obtained from the following generalized form of Eq. (A.15)

$$dX = -\alpha X dt + \sqrt{\alpha\beta(\Delta^2 - X^2)}dB(t). \quad (A.16)$$

The equations have different forms, but the same spectral density (A.4).

Example 4. Admit that $X(t)$ has a Rayleigh density function of probability distribution

$$p(x) = \gamma^2 x\exp(-\gamma x), \quad \gamma > 0, \quad 0 \le x \le \infty. \quad (A.17)$$

Let us transform $X(t)$ to the following form $Y(t) = X(t) - 2/\gamma$ with the probability distribution density:

$$p(y) = \gamma(\gamma y + 2)\exp(-\gamma y + 2), -2/\gamma \le y \le \infty. \quad (A.18)$$

Equation (A.11) implies that

$$D^2(y) = \frac{2\alpha}{\gamma}\left(y + \frac{2}{\gamma}\right). \quad (A.19)$$

The Ito stochastic differential equation for $Y(t)$ has the form

$$dY = -\alpha Y dt + \sqrt{\left[\frac{2\alpha}{\gamma}\left(Y + \frac{2}{\gamma}\right)\right]}dB(t) \quad (A.20)$$

vand the corresponding Stratonovich equation for $X(t)$ is

$$\dot{X} = -\alpha X + \frac{3\alpha}{2\gamma} + \sqrt{\left(\frac{\alpha}{\pi\gamma}X\right)}\xi(t). \quad (A.21)$$

Note that the spectral density for $X(t)$ contains a delta-function of the form $(4/\gamma^2)\delta(\omega)$ with the mean value $2/\gamma$ different from zero.

Example 5. Consider a family of density functions of the probability distribution satisfying the equation

$$\frac{d}{dx}p(x) = J(x)p(x). \quad (A.22)$$

Equation (A.22) can be integrated as

$$p(x) = C_1\exp(\int J(x)dx), \quad (A.23)$$

where C_1 is a normalizing constant. Then, we have

$$D^2(x) = -2\alpha\exp[-J(x)]\int x\exp[J(x)]dx. \quad (A.24)$$

Note the following special cases. Admit that

$$J(x) = -\gamma x^2 - \delta x^4, \quad -\infty < x < \infty, \quad (A.25)$$

where γ is an arbitrary constant if $\delta > 0$. Substituting (A.25) into (A.11), we obtain

$$D^2(x) = \frac{\alpha}{2}\sqrt{\pi/\delta}\exp\left[\delta\left(x^2 + \frac{\gamma}{2\delta}\right)^2\right]erfc\left[\sqrt{\delta}\left(x^2 + \frac{\gamma}{2\delta}\right)\right], \quad (A.26)$$

where erfc(y) is a special error function defined as

$$\operatorname{erfc}(y) = \frac{2}{\sqrt{\pi}}\int_y^\infty e^{-t^2}dt. \quad (A.27)$$

The case $\gamma < 0$ and $\delta > 0$ corresponds to a bimodal distribution, and the case $\gamma > 0$ and $\delta = 0$ corresponds to a Gaussian distribution. The Pierson family of probability distributions is represented in the form

$$J(x) = \frac{a_1 x + a_0}{b_2 x^2 + b_1 x + b_0}, \quad (A.28)$$

and, in the special case for $a_0 + b_1 = 0$, we have

$$D^2(x) = -\frac{2\alpha}{a_1 + b_2}(b_2 x^2 + b_1 x + b_0). \quad (A.29)$$

Thus, the structure of forming filters with autocorrelation function (A.1) and different density functions of the probability distribution can be described by typical structures of forming filters represented in Table 3. By a similar method, the structures of forming filters for stochastic processes with autocorrelation functions (A.2) and (A.3) are determined.

Table 4 presents the structures of forming filters for autocorrelation function (A.3) for the typical density functions of the probability distribution in the two-dimensional case.

Figure 10 presents examples of application of the methodology for stochastic simulation of stochastic processes [26–28] with the required density function of the probability distribution. Other methods for simulating stochastic processes and guaranteed estimates of stochastic stability of schemes of numerical integration were described in [29–33] and were taken into account in the simulation of the considered stochastic nonlinear models of the controlled plant.

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