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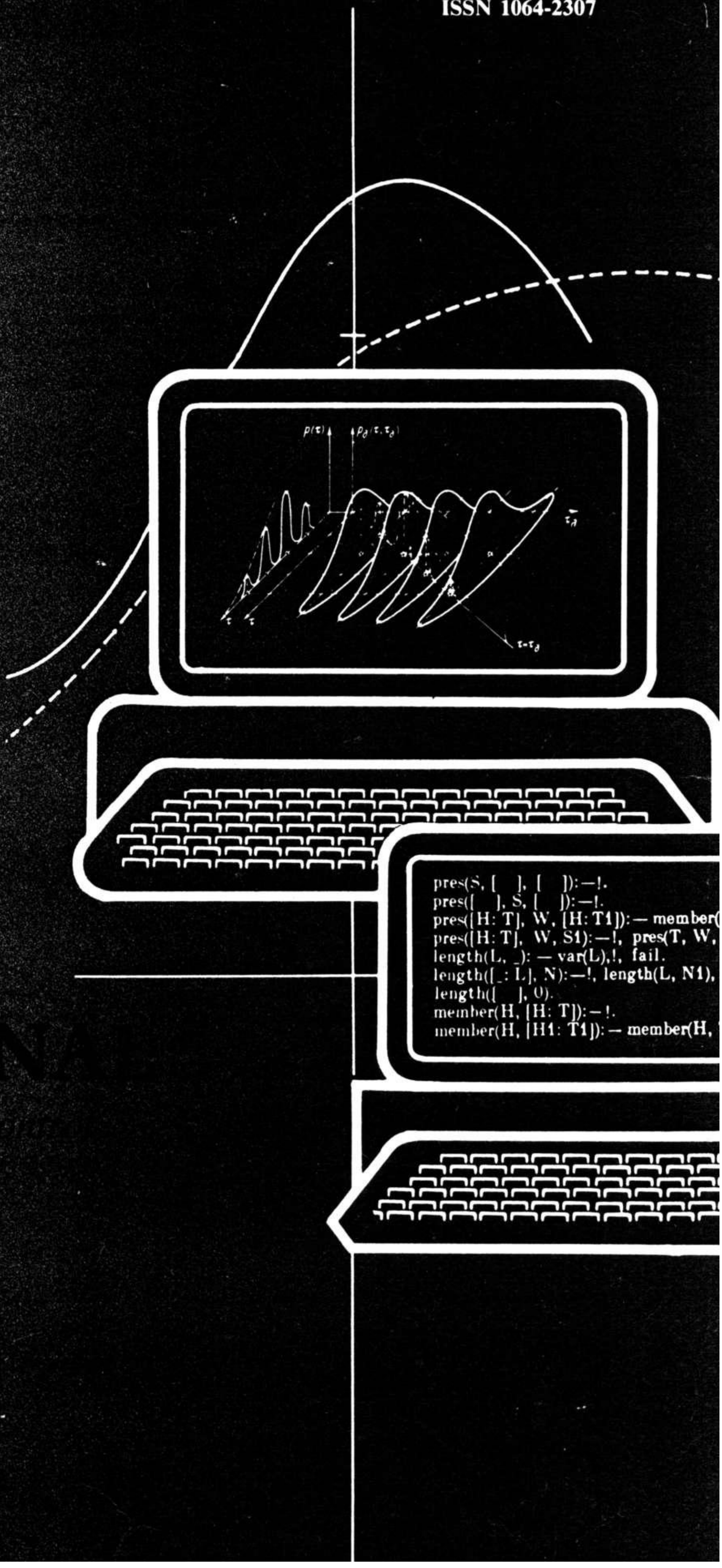

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Fuzzy Models of Intelligent Industrial Controllers and Control Systems. III. Design Procedure*

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The problems of designing industrial controllers and control systems with various degrees of intelligence are discussed. The primitive nature of existing hardware and software support of knowledge-based control processes and methods of designing intelligent control systems is noted. The need to develop a special procedure for designing such control systems is emphasized. The principles of a design procedure for multilevel intelligent automatic control systems are proposed. The features of the design of control systems that are intelligent "in the large" and "in the small" are analyzed. Numerous examples of designed systems are presented.

Key words: Fuzzy control systems; intelligent automatic control systems; fuzzy neural networks; fuzzy expert systems; FZUP-systems; PID-controller.

INTRODUCTION

Traditional design methods have long included qualitative characteristics to describe models of control processes in order to improve estimates of the adequacy of model formalizations and to improve the performance of controllers and automatic control systems (ACSs) when there is information uncertainty regarding the dynamic behavior of complex controlled systems or the environment. When the qualitative characteristics of the dynamic behavior of weakly-structured control systems are introduced into the design processes, it is necessary to employ nonclassical optimization criteria [1]. Qualitative attributes commonly include such concepts as insensitivity, sensitivity, stability, adaptation, etc. [1-3]. By taking into account and testing such qualitative attributes in the design of controllers and ACSs it is possible to reduce the need to generate and analyze nonclassical optimization criteria considerably [1-3]. Extremal searches based on nonclassical optimization criteria make it necessary to investigate analogs of logical dynamical models of control processes [1, 3, 4] followed by linguistic approximations of such processes [5, 6].

Analysis of the results of simulation and practical applications of qualitative attributes in a linguistic approximation of specific fuzzy controllers and ACS designs has confirmed the effectiveness of the new intelligent technology for fabricating flexible mobile control systems for complex (weakly structured) industrial systems [3, 5-26]. The synthesis of a wide variety of design methods and the use of commercially developed prototypes of fuzzy controllers and ACSs [5, 18, 23-29] have shown that the design procedure and the hardware and software support for such intelligent systems remain in their initial development stage [30].

In the development of engineering methods of designing problem-oriented knowledge-based control systems (generally, fuzzy expert systems [31, 32] designed as intelligent "in the large" [5]) it has been determined that, given the application conditions, such design processes require additional research and special theoretical substantiation. One example is the attempt to formulate a philosophical reexamination of the relationship between fuzzy logic and the Japanese interpretation of the metaphysics of "irrational" logic as well as an interpretation of traditional Tai-chi symbols and design principles [25].

The subject of this paper, which is a continuation of [5], is the problems of developing a special procedure and the principles of organizing the design of knowledge-based fuzzy control systems. Examples of systems that illustrate certain features of the procedure proposed here are presented.

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1. A Procedure for Designing Intelligent ACSs

The primary object of research in industrial intelligent control systems includes: problems relating to the development of multilevel architectures of knowledge-based control systems [33–35] and the corresponding classification of problem-oriented problems in industrial automation [36], and the rational construction of knowledge bases and effective analytic models of knowledge-based control processes [37] in accordance with the principles of organizing intelligent control systems and levels of intelligence in ACSs formulated in [5]. A special procedure for designing such systems is required to solve these problems.

The proposed procedure is based on methods for choosing means of imparting intelligence to achieve the required dynamic behavior of the ACS in cases where traditional methods of improving the dynamics of system behavior cannot be used to solve this problem. In such cases, knowledge-based tools are employed. The intelligent tools selected are employed to overcome the uncertainty of information on the environment or the controlled system (its behavior). It should be emphasized that the problem of improving the dynamic characteristics of a system can be solved by various techniques in the search for the required behavioral form: either by improving control quality through the use of traditional methods (choosing a more complex ACS model on the execution level) that employ simple tools on the intelligence level or, alternately, by developing effective intelligent tools that improve the characteristics of a simple model on the execution level. In the first case, the model of the execution level becomes more complex because of the hardware implementation of the functions controlling the qualitative attributes describing the control process. In the second case, a simpler model of the execution level may be chosen by increasing the intelligence level of the ACS and by programming changes in the qualitative attributes describing the knowledge-based control process [30, 39]. Thus, the problem of identifying control functions realized on the lowest sublevel of the execution level [5] must be solved at the initial design stage.

Consequently, the design procedure for multilevel intelligent ACSs can be based on two methods: a method of generating (calculating) models of the execution level (by identifying adequate control functions), and a method of matching (or coordinating) the execution and intelligence sublevels. In this case, it may be useful to have a method of identifying initial simple models (followed by corresponding expansion) for choosing adequate intelligence sublevels [39].

The method of coordinating (matching) execution and intelligence sublevels is illustrated in Fig. 1. The execution levels are shown on the left in Fig. 1, and the intelligence levels for constructing ACS models are shown on the right. It is obvious from Fig. 1 that the degree of correlation can be determined by different techniques. Each of the versions chosen will determine the complexity of the hardware and software employed, while the final version for choosing the ACS model will be based on simulation of the system under design.

This approach to constructing a procedure for designing intelligent ACSs also includes: an estimate of the effect of incorporating the intelligence level on the functional capabilities of the control processes, a classification of knowledge-based ACSs as well as those based on the complexity of the controls executed, a determination of the role of the knowledge base (with an estimate of its completeness) in the distribution of functions among the execution and the intelligence levels, calculation of ACS structures on an execution level of minimum complexity for a given level of intelligence (analysis) and vice versa (a synthesis problem), and a solution of the problem of system integration and decomposition of knowledge-based ACS structures (on both the execution and the intelligence levels).

Methods of simulating fuzzy models of industrial fuzzy neural network ACSs [40–44] to extract expert information from the fuzzy behavior of a control system for developing corresponding knowledge bases and constructing membership functions of the fuzzy "input-output" relations play a special role in this procedure. Consequently, two phases of constructing fuzzy models of intelligent ACSs are examined in this case. The first phase—simulation—makes it possible to establish fuzzy "input-output" relations by organization of the learning and adaptation processes on the fuzzy neural networks (FNNs) and to formulate the structure of the knowledge base of an ACS with fuzzy inference mechanisms. Such a phase is commonly referred to as the learning phase [25]. In addition to running fuzzy identification algorithms [46, 47] and nonlinear fuzzy regression models [48], this stage involves correct formalization of a description of the control process of the test fuzzy object. The second phase involves the design and realization of the fuzzy models of the controllers and ACSs for which the structured knowledge is used in the control processes [5, 6].

Note 1. There are certain additional features when employing fuzzy neural networks in the first stage of the design of fuzzy controllers and ACSs within the framework of this procedure. A variety of learning methods based on fuzzy neural networks are employed at this stage [41–44, 49]. In particular, a fuzzy associative memory (FAM) neural network model [44, 49] has been used effectively in simulation for adaptive formulation for "if . . . , then . . ." production rules. The formation of fuzzy production rules based on FNNs as a means of extracting the representing knowledge represents one of

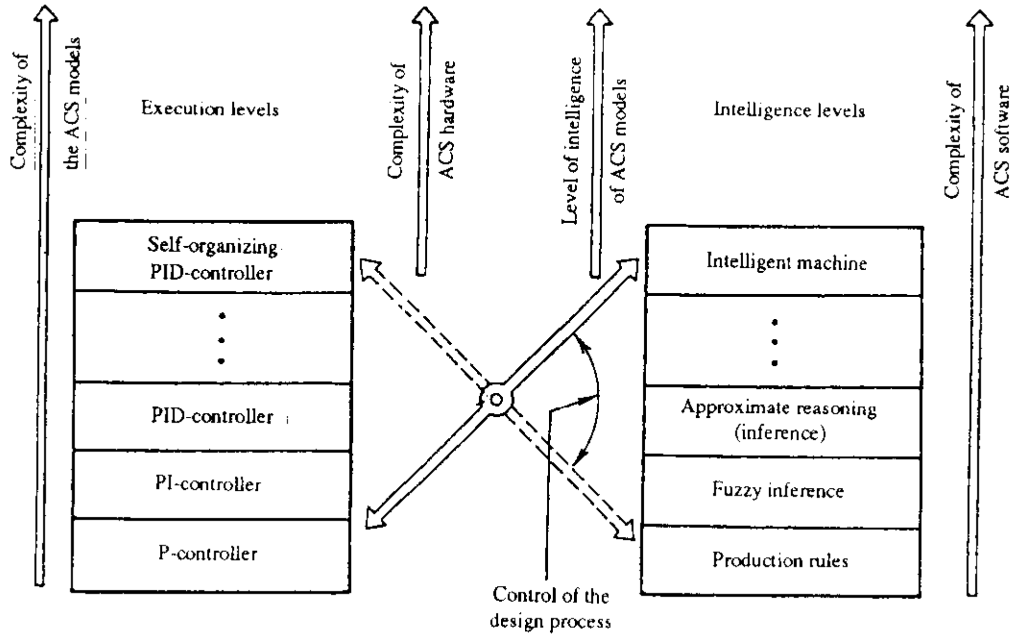

Fig. 1. A procedure for designing ACS structures (on the execution and intelligence levels).

the many algorithms for supplementing knowledge bases of fuzzy intelligent controllers and ACSs [49–54]. In particular, these methods play a special role in identification problems [49], in developing procedures for estimating the sensitivity and comprehensiveness of knowledge bases [40–43], and in estimating the effects of external factors and information ambiguity on the structure of these control processes. For example, estimates of the sensitivity and robustness of the knowledge base of fuzzy controllers can be obtained by FNN simulation when a subset of random production rules or otherwise "sabotage" fuzzy inference rules with a moderated truth level of the reasoning process are incorporated in the FAM. The results of simulation show [51, 55] that when the first design phase is employed, robustness of the dynamic behavior of a fuzzy controller is retained with as much as a 50% reduction in the truth level of the fuzzy inference.

The effective use of FNN methods in problems of controlling complex robotic systems is discussed in [40–44, 55–58].

Definition [39]. The procedure for designing multilevel intelligent ACSs based on successive (and possibly, multiple) application of formation (calculation) and matching (coordination) methods employing simulation estimates is referred to as a FZUP-system design procedure (or an FZUP-procedure).

Hardware and software support of design procedures based on fuzzy processes, fuzzy memory, and fuzzy flip-flops are widely used in the systems for designing fuzzy controllers and ACSs [5, 59–69]. The development of microelectronic technology and of a procedure for organizing computational processes [70] has made it possible to develop a fundamentally new type of fuzzy processor [71] by means of quantum-mechanical Josephson junctions. Such an approach enables the inference speed as well as storage space for production rules to be increased considerably. An example of a hard-wired FNN is the FAM [72] design for realizing control processes based on the hybrid application of neural and fuzzy technologies to design processes [73–75].

The development of intelligent system design has required corresponding software [76]. Software packages have been developed for the design and support of fuzzy controllers and ACSs with different problem orientations [5, 77].

Expert systems (ESs) used as a special intelligent tool for adjusting computer-aided design systems within the framework of the design procedure shown in Fig. 1 can be classified as among the software tools available for supporting the design of intelligent controllers and ACSs. An investigation of the general principles of constructing intelligent machines [76] and their relation to control processes [78, 79] together with the subsequent development of cognitive processes for designing control systems operating under conditions of uncertainty of various physical (information) types has made it necessary to improve control quality by using knowledge bases of active expert systems that in this case are component parts of models of the control system under design [80–82].

An analysis of the qualitative features of the dynamic behavior of control systems as well as the ultimate capabilities of information control processes [3, 4], in conjunction with model identification, learning, and adaptation methods, reveal the extensive diversity in developing a procedure for the design of ACSs based on variously structured knowledge and the structural hierarchy of the ACSs themselves [83–96].

An additional analysis of applied methods of investigating and simulating knowledge-based systems has confirmed [79, 97, 98] the value of combining traditional methods from automatic control theory with the methods of intelligent system and cognitive process theory. In this case, it is convenient to analyze and synthesize the intelligent control systems themselves by traditional control theory methods (for example, for estimating the robustness, sensitivity, and stability of the dynamic behavior of intelligent ACSs to changes in production rules in the knowledge base [88–93, 99–103]). Estimates from a qualitative analysis of the dynamic behavior of intelligent ACSs in combination with neural network simulation in turn comprise the basis for developing a knowledge base for choosing corresponding control laws in an expert system for control systems [79, 104] and for determining the degree to which models accurately represent the actual system in the identification of control processes [95, 96].

Note 2. The joint use of neural network simulation methods and the development of intelligent ACSs based on cognitive processes has led to a new class of ACSs that are intelligent "in the large": cognitive controllers and control systems [79, 105–108]. In the special case (when only a single FNN fuzzy neural network based on an FAM is used) such controllers become fuzzy controllers and ACSs [107, 109]. Further progress in the development and application of very large system integration (VLSI) circuits to fuzzy processors based on fuzzy flip-flops will lead to improvements in hardware and software support for such cognitive controllers and will lead to the development of specialized hardware [110]. The use of such cognitive controllers that are intelligent "in the large" will make possible a significant improvement in the mobility of autonomous robots.

2. Examples of the Use of Active Expert Systems in the Simulation of Intelligent Controllers

As an illustration, let us compare a simulation of the dynamic behavior of a simple control system whose control loop includes a traditional proportional integrating and distributing (PID) controller and a controller with an active expert system. According to the design procedure presented in Fig. 1, such a situation corresponds to the case of a lower execution level and upper control coordination level.

Example 1. A linear system with a delay and a transfer function of the type $\Phi(s) = \dfrac{0.63\exp(-s)}{(33.5s+1)}$ will be used as a model of a control system describing the actual process of loading coal into a blast furnace [111]. The purpose of the analysis was to determine the response of the given control system to typical dynamic inputs for various control laws and criteria. In the first case, a PID-controller was used. Optimal selection of the PID-controller parameters was accomplished by using a mean square $e^2(t)$ criterion of the type $Q(n) = \min \sum_{i=1}^{m} e^2(i)\,T$, by the method described in [111] as the choice of the control law $u(n) = u(n-1) + k_i e(m) + k_j \Delta e(n)$. Parameters k_i and k_j were determined on the basis of minimization of a cost functional of the type

$$P[k_i(n) + \Delta_1,\ k_j(n) + \Delta_2] = P[k_i(n+1),\ k_j(n+1)] = \min\left[e^2(n+1) + \sum_{i=1}^{m} Q(i)\right],$$

where P is the cost functional, Δ_1 is the increment of k_i, and Δ_2 is the increment of k_j.

A typical block diagram of the simulation of the dynamic behavior of a controlled system (CS) based on active expert systems is shown in Fig. 2a [112]. The database of this ES contains information on the experimental measurement data relating to the actual characteristics of the dynamic behavior of the test control system (such as the duration of the transient, the delay, the magnitude of the overcontrol, the overcontrol time, the amplitude of the transient, etc.) as well as the types of criteria and control laws, limiting values characterizing the stability of the CO (from the knowledge inference unit in Fig. 2a), the results of simulation, etc. Such active expert systems for control processes are classified as second-generation deep knowledge representation expert systems [88, 89, 104], whose structure and functions have been described in [113]. The inference mechanism (in the inference rule selection unit in Fig. 2a) employs three modifications of decision (production) rules: (1) the present control algorithm, which satisfies the required control criterion, is used or certain parameters of the

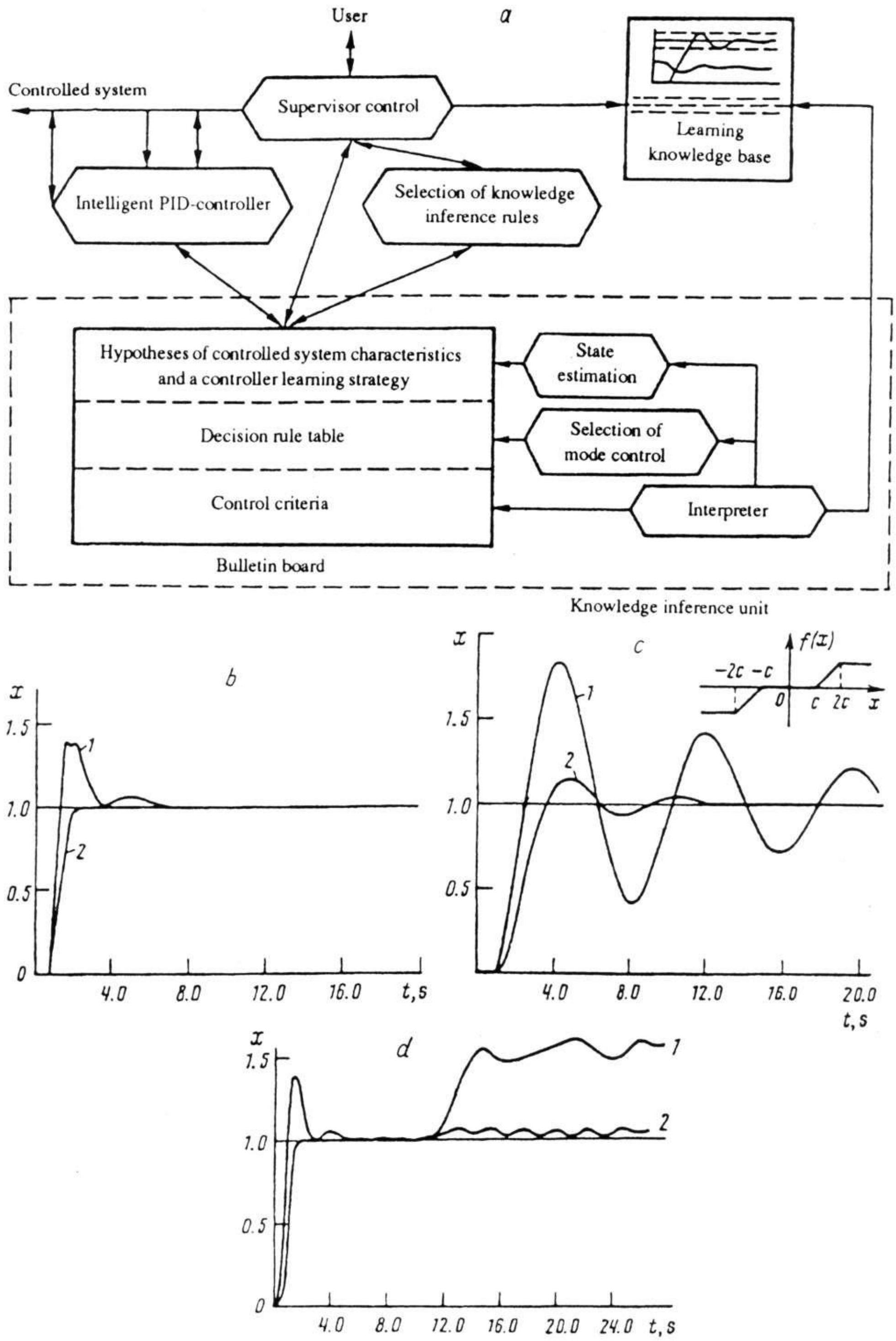

Fig. 2. Simulation of the dynamic behavior of a controlled system (1 is a PID-controller; 2 is an intelligent controller with an expert system): a) block diagram of the expert system for simulating real-time control; b) the transients of a linear controlled object under delay with stepped input; c) the transients of a nonlinear controlled system; d) the transients of a linear controlled system with random inputs.

control algorithm require modification; (2) a new control algorithm is chosen; (3) two or more control algorithms are allowed. Such an assumption is based on the hypothesis that a broad range of errors or error rates exists on different segments of the phase portrait that will lead to a system of alternating structure that uses different control laws on the given segments of the phase portrait [114]. These inference rules and control algorithms take the following form:

$$
\begin{aligned}
&\text{R1: if } (e_i > e_0), \text{ then } u_i = u_0;\\
&\text{R2: if } (e_1 < e_i \le e_0), \text{ then } u_i = k_i u_0;\\
&\text{R3: if } (-e_1 < e_i < -e_2), \text{ then } u_i = k_5 e_i(n) + k_6 \Delta e_i(n);\\
&\text{R4: if } (e_i < -e_1), \text{ then } u_i = k_i u_0;\\
&\text{R5: if } (e_2 < e_i \le e_1) \text{ and } |\dot{e}_i| \le G_1, \text{ then } u_i = k_3 e_i(n) + k_4 \sum_{i=1}^{l} e_i(n);\\
&\text{R6: if } (e_2 < e_i \le e) \text{ and } |\dot{e}_i| > G_1, \text{ then } u_i = k_2 e_i(n);\\
&\text{R7: if } (e_3 < e_i \le e_2) \text{ and } |\dot{e}_i| \le G_2, \text{ then } u_i = k_5 e_i(n) + k_6 \Delta e_i(n);\\
&\text{R8: if } (e_3 < e_i \le e_2) \text{ and } (G_2 < |\dot{e}_i| \le G_3), \text{ then } u_i = k_5 e_i(n) + k_6 \Delta e_i(n);\\
&\text{R9: if } (e_3 < e_i \le e_2) \text{ and } |\dot{e}_i| > G_3, \text{ then } u_i = k_5 e_i(n) + k_6 \Delta e_i(n);\\
&\text{R10: if } (|e_i| \le e_3) \text{ and } (e_i \cdot \dot{e}_i > 0 \text{ and } |\dot{e}_i| < G), \text{ then } u_i(n) = u_i(n-1) + k_7 e_i(n) +\\
&\qquad + k_8 \Delta e_i(n);\\
&\text{R11: if } (|e_i| \le e_3) \text{ and } (e_i \cdot \dot{e}_i > 0 \text{ and } |\dot{e}_i| > G), \text{ then } u_i(n) = u_i(n-1) + k_7 e_i(n) +\\
&\qquad + k_8 \Delta e_i(n);\\
&\text{R12: if } (|e_i| \le e_3) \text{ and } (e_i \cdot \dot{e}_i > 0 \text{ and } e_i \cdot \dot{e}_{i-1} > 0), \text{ then } u_i(n) = u_i(n-1) + k_7 e_i(n) +\\
&\qquad + k_8 \Delta e_i(n);\\
&\text{R13: if } (|e_i| \le e_3) \text{ and } (e_i \cdot \dot{e}_i > 0 \text{ and } e_i \cdot \dot{e}_{i-1} < 0), \text{ then } u_i(n) = u_i(n-1) + k_7 e_i(n) +\\
&\qquad + k_8 \Delta_i(n);
\end{aligned}
\tag{2.1}
$$

where $e_0 > e_1 > e_2 > e_3$.

The coefficient e_0-e_3, and G-G_3 in Eqs. (2.1) are positive constants (these constants are represented on the basis of prior information and may vary during the simulation). The first group of production rules R1-R9 from Eqs. (2.1) takes into account the broad range of the error of $e_i(n)$ and uses a traditional control algorithm for P-, and PI-controllers. The second group of rules R10-R13 takes into account the dynamics of the control system as well as the differential characteristics $\Delta u_i(n)$ of the control process (low level overcontrol, stability of dynamic processes, etc. and checking of the logic conditions in the "if. . ." statement) by applying a control algorithm for a PID-controller. Controller models that use such expert systems in the control lop have come to be called expert intelligent control systems (EICSs). Results of the simulation of the response of a control system to a stepped input are shown in Fig. 2b; the response of the control system to a stepped input when there is a significant nonlinearity in the control system with a dead zone is given in Fig. 2c, and the results of a simulation for the case of adaptive white noise of uniform intensity and a normal probability distribution are given in Fig. 2d. It is obvious from Fig. 2b that the response of a control system employing an EICS-controller reduces to an ideal characteristic with a minimum overcontrol level and time compared to an optimized PID-controller. It likewise follows from the results of a simulation that a control system with an EICS-controller is less sensitive to very nonlinear elements (such as a dead zone) compared to a control system employing a PID-controller (see Fig. 2c) and is robust with a noisy control input (see Fig. 2d). This example provides a clearer representation of the role of a knowledge base and logic inference in intelligent controllers designed in accordance with these principles. A number of other analogous examples can be found in [80,-84, 86-94, 101-104, 112, 114].

Let us consider in greater detail the qualitative estimation of the sensitivity and robustness of intelligent PID-controllers to changes in the larger control laws as well as the degree of complexity of the control system model descriptions.

Example 2. Let us assume that a logic PID-controller has a control law of the form

$$
u(n) = \begin{cases} K \cdot e + u_0(n-1), \text{ if } d|e|/dt \ge 0, \\ u_0(n) = u_0(n-1) + kKe_m(n) = kK \sum_{i=1}^{m} e_i(m), \text{ if } d|e|/dt < 0, \end{cases}
\tag{2.2}
$$

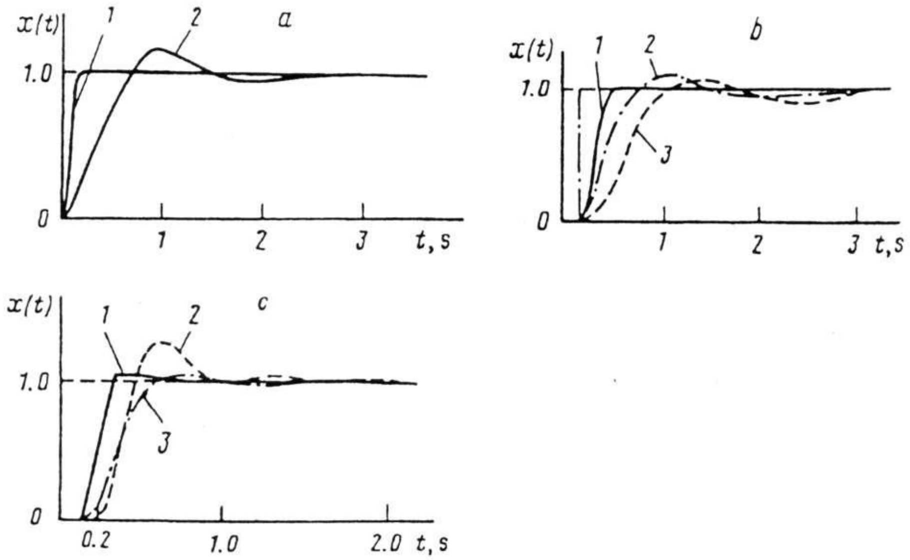

Fig. 3. Results of the simulation of transients: a) transient in a control system for intelligent (1) and logic (2) PID-controllers with a control system function of the type $\Phi = \exp(-0.05s)/(1.5s + 1)^2$; b) transient of a control system for intelligent (1), logic (2), and traditional (3) PID-controllers with a control system transfer function of the type $\Phi = \exp(-1.5s)/(0.5s + 1) \times (0.4s + 1)$; c) transients for an intelligent PID-controller when there is a change in the form of the control system transfer function: 1: $\Phi = \exp(-0.15s)/(1.6s + 1)$; 2: $\Phi = \exp(-0.2s)/(0.4s + 1)(0.45s + 1)$; 3: $\Phi = \exp(-0.15s)/(0.4s + 1)$.

where K is a given coefficient of variation, while k is the variable gain. The logical selection of the control law in Eq. (2.2) will be made depending on the sign of the change in the control error. The control law for an intelligent PID-controller is formulated in a manner analogous to Example 1 on the coordination level and is described by ES production rules of the type [115]:

$$\text{if } d|e|/dt \ge 0, \text{ then } u(n) = Ke + u_I(n-1), \quad \Delta u_I(n) = \frac{1}{T_I}\int e(n)dt, \tag{2.3}$$

$$\begin{aligned}&\text{if } d|e|/dt < 0 \text{ and } d|\dot{e}|/dt > 0, \text{ then } u(n) = T_d \cdot de/dt + u_I(n),\\ &\text{if } d|e|/dt < 0 \text{ and } d|\dot{e}|/dt \le 0, \text{ then } u(n) = u_I(n) = \Delta u_I + \Delta u_I(n-1) =\end{aligned} \tag{2.4}$$

$$= \sum_{j=1}^{n} \Delta u_{Ij} = \frac{1}{T_I}\sum_{j=1}^{n} \int e_j dt. \tag{2.5}$$

The control law in this case is chosen based on a supplementary logic constraint in the form of a test of the sign of the change in control error. Relations (2.3)–(2.5) are descriptions of the P-, I-, and D-controllers and comprise a multimode PID-controller in the logic sum [115].

Results are given of the simulation of transients for a given control system by using logic (2.2), intelligent (2.3)–(2.5), and traditional PID-controllers in the control loop for a unit step input signal in Fig. 3. In this case, the following parameter values are used in Fig. 3a: $K = 100$, $k = K^{-1} = 0.01$ for the logic PID-controller and $K = 750$, $T_d = 27$, $T_I - 0.05$, $T = 0$ for the intelligent PID-controller. The values $K = 6.4$, $k = 1/6.4$ are used for the logic PID-controller in Fig. 3b, while $K = 11.4$, $T_d = 1.525$, $T_I = 0.15$, $T = 0$ are used for the intelligent PID-controller. A comparison of the results of the simulation reveals that the quality of the transients of the control system using the intelligent PID-controller is superior to that of a logic PID-controller (see Fig. 3a); the intelligent PID-controller has a greater degree of coarseness and adaptation with changes in the transfer function of the control system compared to the traditional or logic PID-controller (Fig. 3b and c).

It follows from Examples 1 and 2 that it is necessary to introduce a two-level design approach to improve the effectiveness and extend the operating range of traditional controller models: the control algorithm is generated on the upper (coordination) level and the selected control algorithm is implemented on the lower (execution) level. Consequently, we arrive at the procedure for designing controllers with different levels of intelligence shown in Fig. 1.

The further reduction in the accuracy requirements in descriptions of the dynamic behavior of control systems through linguistic approximation has led to a new principle for designing knowledge bases of active expert systems in terms of the theory of fuzzy sets [79, 104, 116–121]. This has resulted in the development of a fairly large number of second-generation fuzzy expert system models [113, 121, 122], widely used in a variety of problem-oriented domains: robotics [5, 119, 123], fuzzy control systems and fuzzy controllers for atomic control systems [124], man-machine systems [125], hierarchical supervisory control systems for complex dynamic facilities (such as rotating kilns for annealing and drying, industrial coolers and chillers [126], etc., [5]), in auxiliary control devices commonly used to replace organs in the event of loss of function of the entire body (such as artificial lung ventilation [127]), to regulate the average blood pressure in artificial circulation systems and as artificial kidneys for treating cancerous tumors [128, 129], and for controlling heartbeat and average blood pressure for cardiovascular operations [130] in conjunction with narcotics as well as antiseptics for relaxing cardiac muscles [130–132].

According to the FZUP design procedure, the application of expert systems in conjunction with fuzzy neural networks in a control loop is classified as a learning stage for the purpose of supplementing or testing the correctness of the knowledge base and likewise for generating control algorithms. Experience in using expert systems in fuzzy controllers and ACSs has revealed [133–147] additional features in developing the design stages of intelligent controllers and ACSs based on fuzzy expert systems, which have been partially reflected in models of fuzzy computer-aided design systems [148–150]. We will discuss one such feature of practical importance in designing fuzzy controllers and ACSs. The models of control systems have a variable structure and a wide range of structural parameters (nonstationary nonlinear systems), while many control systems are used in emergencies (for deactivating facilities at nuclear power plants, for firefighting, and for protecting structures subjected to intense vibrations) or for developing pathophysiological processes (such as acute respiratory difficulties, etc). Thus, it is necessary to develop intelligent ACSs for controlling control system under extreme conditions. The development of fuzzy controllers with active expert systems also includes the problem of the reliability of similar intelligent ACSs with faults and failures in the control processes and unreliable elements in the system and ACS structures [133]. Such intelligent ACSs for control systems of variable structure are designed for extreme conditions on the basis of this procedure and of the principles of constructing hierarchical structures (FZUP-systems) that are intelligent "in the large" [5, 39]. In this case, the control loop of such control systems include two fuzzy controllers, one of which controls the system operating under conditions of variable parameters that do not modify the structure of the control system. The second, which is based on an active expert system with deep knowledge representation, is designed to control the system under extreme conditions. Examples of such models have been described in [127, 133]. In this case, the first fuzzy controller is classified as intelligent "in the small," and the second, as intelligent "in the large." Such an approach is of special interest for developing mobile systems with vertical climbing robots designed to counter emergency situations, e.g.,to fight fires, to clean up after explosions, etc. [152]. An example of a fuzzy expert system for assessing the size and dynamics of fire development can be found in [153].

Here we will consider as an example the features of the use of knowledge bases of expert systems to improve the dynamic characteristics of traditional controller models, i.e., those that are intelligent "in the small."

Example 3. In existing technologies for developing fuzzy logic controllers [154–162], special attention is devoted to defining the qualitative characteristics of the dynamic behavior of the control system using a knowledge base in the form of production rules, compared to a traditional PID-controller. The considerable advantages of using fuzzy controllers in this case have been pointed out, where the model of the control system is essentially nonlinear; the descriptions of the relations have a high degree of uncertainty (weakly structured models), and the model can be reduced to a limited number of production rules etc. [5]. In developing design processes it is interesting to compare the qualitative characteristics of control systems for three cases when an intelligent controller, a fuzzy controller, or an optimal PID-controller is used in the control loop. Let us assume that the control system is described by a transfer function of the type $\Phi(s) = 1/(1 + T_1 s)(1 + T_2 s)$. Let us consider three cases where a traditional PID-controller with a quality criterion $\min \int_0^t |e(t)|\, dt$ and a PID-controller with an expert system are used. The results of a simulation [138] demonstrating the effectiveness of the intelligent PID-controller are presented in Fig. 4.

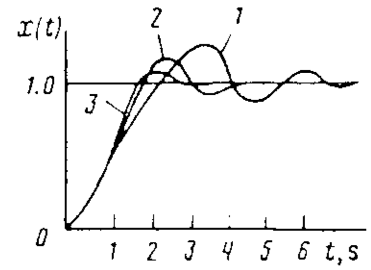

Fig. 4. The results of a simulation of an oscillatory system with different controllers: 1) PID-controller; 2) optimal PID-controller; 3) intelligent PID-controller.

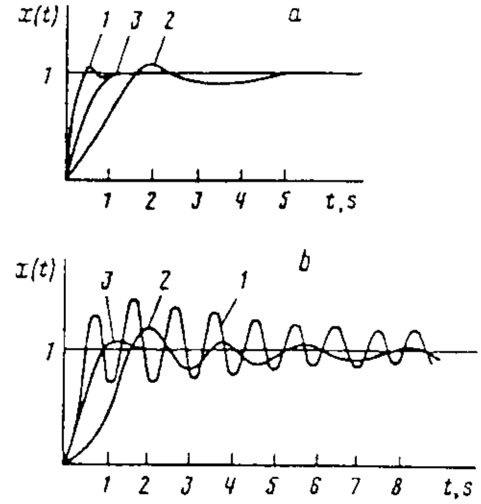

Fig. 5. The results of a simulation for a linear system with a delay for different types of controllers used: 1) PID-controller; 2) fuzzy PID-controller; 3) intelligent PID-controller; a) $\tau = 0.5$ s; b) $\tau = 1.0$ s.

Example 4. Let us now consider a linear control system with a delay of the form $\Phi(s) = \exp(-\tau s)/(1 + 5s)$. As in Example 3, we will specify three cases when a PID-controller, a fuzzy PI-controller, and the intelligent controller from Example 1 are used in the control loop. Results of the simulation [139] of the dynamic response of the control system to a step input for different delays are presented in Fig. 5. It can be seen from Fig. 5a and b that the effectiveness of the intelligent controller increases as the delay increases compared to the fuzzy and traditional PID-controllers. Additional simulation examples can be found in [135].

The results of simulation given in Examples 1–4 demonstrate that intelligent controllers have advanced functional capabilities and a greater degree of adaptation and robustness [5, 99, 100]. This procedure is a component part of computer-aided design systems for designing fuzzy intelligent controllers and ACSs.

4. The Procedural Features of the Development of Models of Logic Controllers That Are Intelligent "in the Small" (Fuzzy Controllers)

We will discuss certain qualitative features of the procedure for designing fuzzy controllers, using the results of specific examples. Rigorous mathematical constructions and methods of analyzing fuzzy controllers are presented in subsequent sections of this series of papers.

The possibility for using a linguistic approximation of a control system in control algorithms has a considerable advantage over traditional controllers when the model of the control system itself is essentially nonlinear or the system operates in a chaotic environment. The conditions for the existence of nonlinearities in the control system and the process of overcoming difficulties of analysis by means of fuzzy controller models have been demonstrated in many papers [163]. We will give a simple illustrative example where a fuzzy controller is used effectively (compared to a traditional PID-controller) in the case of a chaotically organized environment.

Example 5. Consider a model of a fuzzy controller for an automatic airport door system (Fig. 6a) presented in the paper "Basic Study of an Automatic Door System Using Fuzzy Inference" at the Sino-Japanese Symposium on Fuzzy Sets and Systems (15–18 October 1990) [164]. The door opening-closing procedure (where the doors are the system being controlled) is executed in a chaotic environment in the form of irregular moving traffic (the arrival and departure of visitors). The following parameters are measured when the passenger stream crosses section 9 containing the sensors: the speed of each individual in the traffic stream, the present position of the door, the time required to reach and pass through the doors, anthropometric data on the individual (height, weight, etc.), and the present distance between moving visitors. The sampling

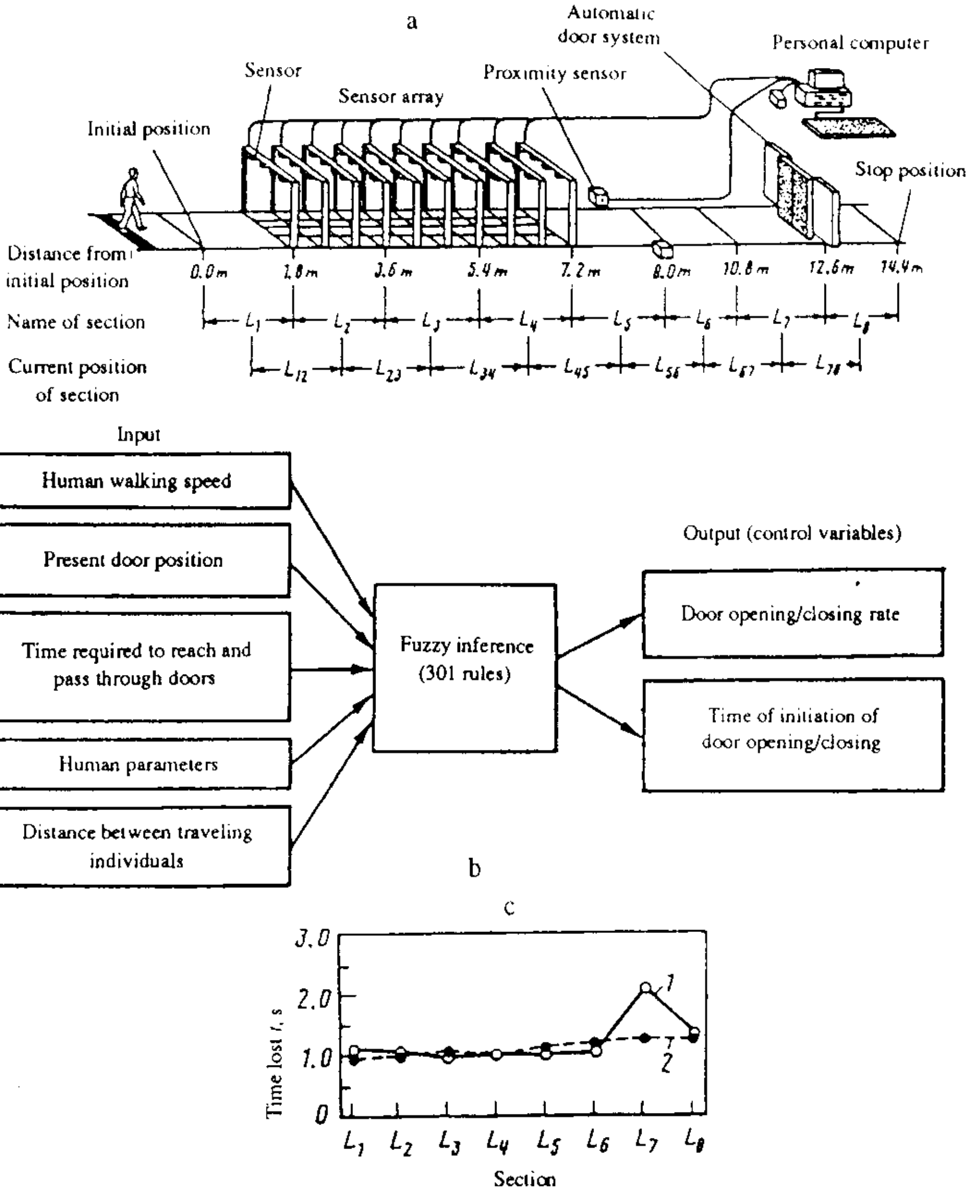

Fig. 6. A fuzzy system for controlling automatic door opening and closing: a) overall system configuration; b) structure of the fuzzy inference unit; c) experimental data from measurements of the time lost in walking across each section L_i ($i = 1, 2, \ldots, 8$): *1*) traditional method of automatic door control; *2*) fuzzy logic based control.

time is 50 μs. These data constitute the input signals for the fuzzy inference unit (see Fig. 6b) containing 301 production rules in its knowledge base. The output parameters from this unit include the control variables for the door opening/closing speed and initiation. The figure of merit of ACS operation is the time a visitor has to wait for the door to open. Results of an experimental test of the fuzzy controller compared to a traditional sensor control method are given in Fig. 6c. The excellent performance of the fuzzy controller under experimental conditions, when a visitor walks quickly or runs across the sections and the control system successfully performs its function, should be noted. The time a visitor has to wait for the door to open is reduced on the average by 87% when the fuzzy controller is used. An effective (alternative) approach based on fuzzy controllers can therefore be offered in place of the traditional stochastic control method in a chaotic environment.

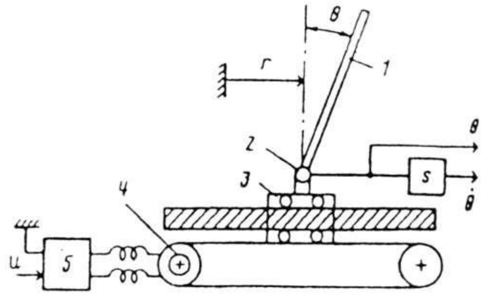

Fig. 7. Experimental configuration for testing the stability of an inverted pendulum: *1*) pendulum; *2*) potentiometer; *3*) moving frame; *4*) motor; *5*) power amplifier.

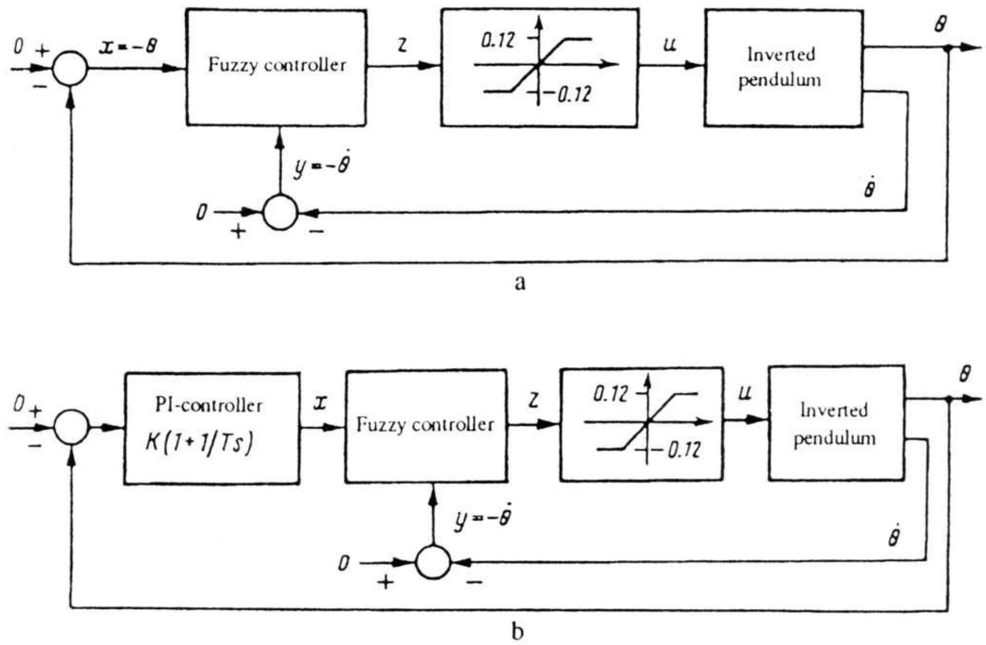

Fig. 8. Block diagrams for controlling the stability of an inverted pendulum: a) with fuzzy controller; b) combined control design (PI-controller and fuzzy controller).

We will consider one additional feature of the design of fuzzy controllers by solving the well-known problem of the stability of an inverted pendulum [165–172], which is of independent interest for intelligent human-operator control systems [173].

Example 6. A model of the inverted pendulum is shown in Fig. 7. It is required to hold the unstable pendulum in a stable position by means of a control force that moves the frame in a horizontal position. It is well known in practice that an inverted pendulum can easily be held in a stable position in the palm by hand movements. This fact led to the idea of employing a fuzzy controller employing a total of seven production rules to solve this problem [165]. An analogous approach was used to solve the problem of the stability of an inverted double pendulum [172]. The equation of motion of an inverted pendulum under a control force u is well known from analytical mechanics and takes the form

$$(M + m)\ddot{r} + ml\cos\theta\ddot{\theta} = -D\dot{r} + ml\dot{\theta}^2\sin\theta - Gu, \qquad (4.1)$$

$$ml\cos\theta\ddot{r} + (\sigma + ml^2)\ddot{\theta} = -c\dot{\theta} + mlg\sin\theta,$$

where we take $M = 0.393$ kg, $m = 0.074$ kg, $D = 2.847$ kg/s, $G = 56.29$ N/V, $g = 9.8$ m/s^2, $l = 0.358$ m, $\sigma = 0.0095$ kgm^2, $c = 0.00218$ kgm^2/s.

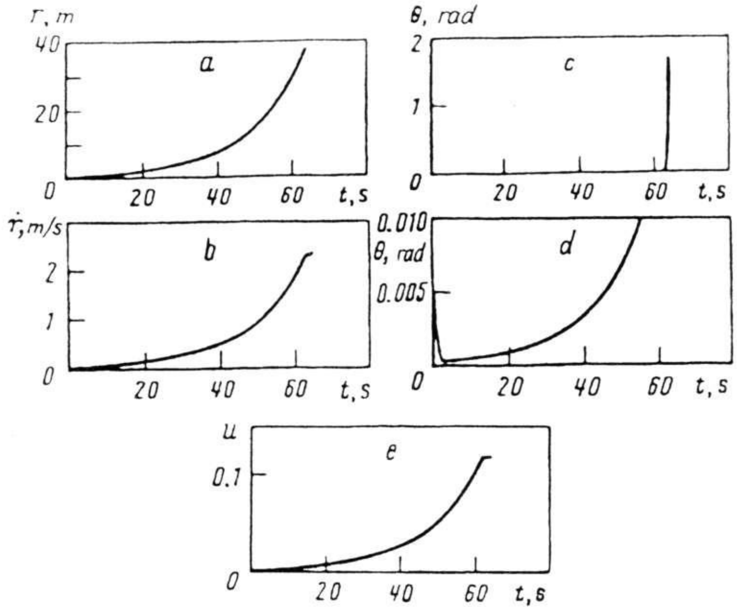

Fig. 9. Results of a simulation of the stability of an inverted pendulum as shown in Fig. 8a: a) position of the moving frame; b) speed of the frame; c) angle of the inverted pendulum; d) magnified image of Fig. 9c; e) change in control signal.

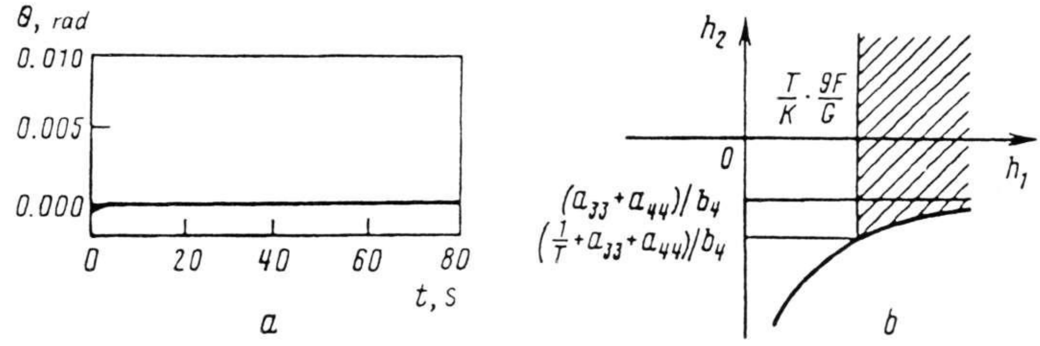

Fig. 10. Results of a simulation of the stability of an inverted pendulum in accordance with Fig. 8b: a) angle of the position of the inverted pendulum; b) regions of stability in parameter space of the fuzzy controller and a PI-controller.

In model (4.1) we will apply a constraint on the amplitude of the permissible control force u in the form $|u| \leq 0.12$ V, unlike existing approaches.

A block diagram of the control system for stabilizing an inverted pendulum using a fuzzy controller and a control constraint is shown in Fig. 8a.

Results of a simulation [170] of the dynamic behavior of an inverted pendulum under the initial condition $\theta(0) = 0.01$ rad are presented in Fig. 9. It is clear from Fig. 9c and d that the angle of deviation from the position of equilibrium increases with time and the pendulum loses its stable state. A block diagram of a combined control system using a PI-controller in conjunction with a fuzzy controller is given in Fig. 8b. Results of a simulation of the dynamic behavior of an inverted pendulum with the control configuration shown in Fig. 8d are presented in Fig. 10a. It is evident from Fig. 10a that by incorporating the PI-controller in the structure of the fuzzy control system it is possible to maintain the inverted pendulum in a stable position relative to the unstable equilibrium position. In this case, the parameters of the PI-controller took the form [170] $K = 5$, $T = 2.5$. Analysis of the conditions of stability of the inverted pendulum can be obtained from linearized system (4.1) of the form ($v = [r, \theta, \dot{r}, \dot{\theta}]^T$) $\dot{v} = Av + bu$, where

$$A = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & a_{32} & a_{33} & a_{34} \\ 0 & a_{42} & a_{43} & a_{44} \end{bmatrix}, \quad b = \begin{bmatrix} 0 \\ 0 \\ b_3 \\ b_4 \end{bmatrix}, \quad \begin{array}{l} a_{32} = -m^2 l^2 g \cdot \beta^{-1}; \; a_{33} = -D(\sigma + ml^2)\beta^{-1}; \\ a_{34} = cml\beta^{-1}; \; a_{42} = (M + m)mlg\beta^{-1}; \\ a_{43} = Dml\beta^{-1}; \; a_{44} = -(M + m)c\beta^{-1}; \\ b_4 = mlG\beta^{-1}; \; b_3 = -(\sigma + ml^2)G\beta^{-1}; \\ \beta = \sigma(M + m) + Mml^2. \end{array}$$

The problem of estimating the stability of a linearized system with a fuzzy controller (described by the linear gain in the feedback loop $H = [0h_1 0h_2]$) reduces to the analysis of a polynomial of the form

$$s\,[s^3 + (Q_{11} + Q_{12}h_2)s^2 + (Q_{21} + Q_{22}h_1)s + Q_{31}] = 0, \tag{4.2}$$

where $Q_{11} = -a_{33} - a_{44}$; $Q_{12} = b_4$; $Q_{21} = a_{33}a_{44} - a_{42} - a_{34}a_{43}$; $Q_{22} = b_4$; $Q_{31} = -a_{43}a_{32} + a_{33}a_{42}$. It follows from Eq. (4.2) that the necessary condition of stability is a negative value of the free term Q_{31} of the form

$$Q_{31} = \frac{Dm^3 l^3 g - D(\sigma + ml^2)(M + m)mlg}{\beta^2} < 0, \quad D \neq 0,$$

which denotes the presence of narrow boundaries on the region of stability of the fuzzy controller in this case. For the configuration shown in Fig. 8b the analogous polynomial will have the form [170]

$$s^2 \left[s^3 + (Q_{11} + Q_{12}h_2)s^2 + (Q_{21} + kb_4h_1)s + Q_{31} + \frac{Kb_4h_1}{T} \right] = 0, \tag{4.3}$$

which will include, in addition to the parameters of the fuzzy controller, the parameters of the PI-controller. Such a configuration has wider limits of stability compared to Fig. 8a. The limits of stability of the combined system in the parameter domain (h_2, h_1) for polynomial (4.3) are shown in Fig. 10b.

The idea of the combined use of PI- and P-controllers was also employed in [171] depending on the form of feedback employed. Thus, it is recommended that a PI-controller be used for negative feedback and that a P-controller be used for positive feedback.

A similar result on the combined use of a fuzzy controller and linear feedback was achieved in [174] in analyzing the stability of an inverted pendulum which is driven to a vertical state from the stable position with constraints on the permissible range of the frame. In this case, the fuzzy controller is used to drive the pendulum from its stable state to the vertical unstable position (the fuzzy controller is an intelligent tool for overcoming the essentially nonlinear nonholonomic relations), while the pendulum is held in a stable vertical position by linear feedback in traditional controller models.

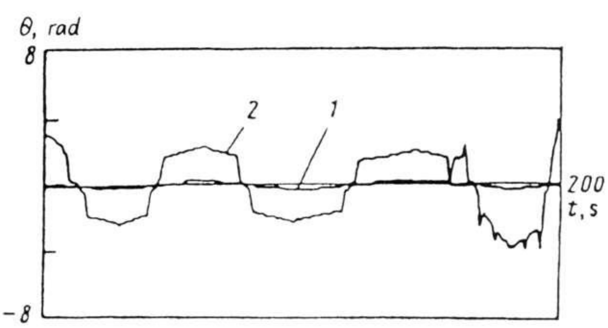

Fig. 11. Results of a simulation of the stability of an inverted pendulum using an adaptive fuzzy controller in the control loop: 1) output signal (angle of deviation of the pendulum); 2) output control signal of the fuzzy adaptive controller.

A more extensive analysis [175–176] has demonstrated the value of a hybrid approach to the use of a fuzzy controller in conjunction with a PID-controller. On the other hand, it is possible to achieve a stable state of the inverted pendulum without employing a PI-controller by increasing the complexity of the fuzzy controller control algorithm by means of adaptation [157] or by neural network learning [169, 172]. Results of a simulation of the stability of an inverted pendulum with an adaptive fuzzy controller are presented in Fig. 11. The example given in Fig. 11 suggests the possibility of solving the problem of the stability of an inverted pendulum by employing intelligent tools in the form of fuzzy logic production rules.

Generally, as suggested in [177], it is also necessary to introduce two levels: a coordination level (upper level) as the intelligent level and a lower level (a fuzzy controller or a PID-controller) as an execution level. Hence, in this case we arrive at the design procedure presented in Fig. 1.

CONCLUSION

This procedure for designing fuzzy models of intelligent controllers and control systems leads to the following conclusions.

The use of fuzzy models of controllers and, particularly, control systems that are "intelligent in the large" can improve considerably the dynamic characteristics of control systems operating under conditions of uncertainty of input information or in a chaotic environment. The design of such control systems is a complex problem to the extent that a variety of methods can be employed to obtain the necessary dynamic characteristics, including increasing the complexity of the model on the execution level or incorporating intelligent tools with more extensive capabilities. The procedure presented in this paper makes it possible to establish the desired relation between the execution and the intelligence levels based on the results of a simulation, depending on the problem orientation of the routine executed, the purposes of the control action, and the operating conditions of the control system.

Simulation, learning, and adaptation by neural networks that make it possible to formulate a special knowledge base on the intelligence level used are the basis of the procedure for designing control systems with different intelligence levels. This makes it possible to formulate the fundamental structural requirements imposed on the corresponding computer-aided design systems based on such units as a simulation unit, a learning and adaptable fuzzy neural network, an approximate reasoning unit (including fuzzy inference), a knowledge base generator, and a fuzzy generator and interpreter.

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