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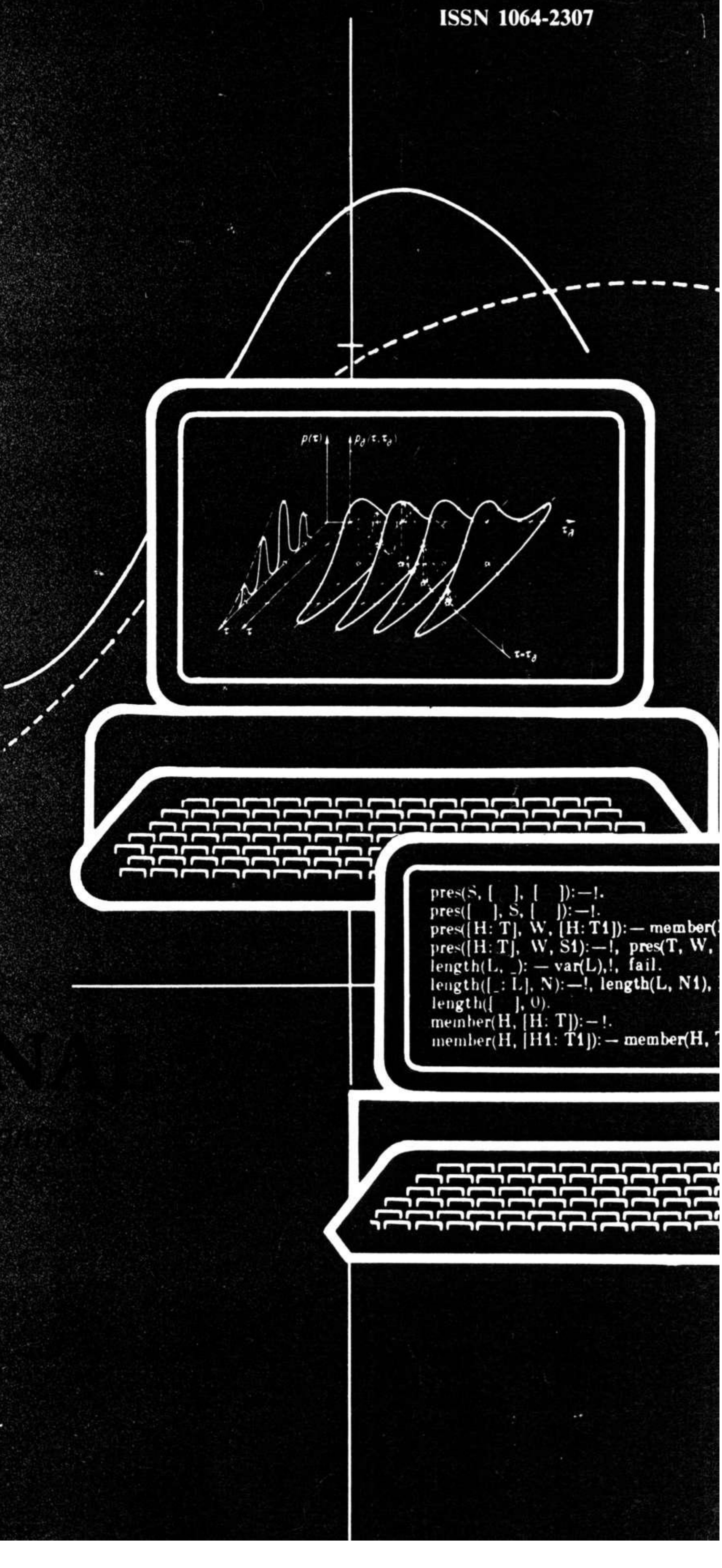

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Fuzzy Models of Intelligent Industrial Controllers and Control Systems. II. Evolution and Principles of Design*

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This paper is a continuation of studies of fuzzy simulators of intelligent industrial automatic control systems the first part of which was published in 1992 [12]. A retrospective analysis of the corresponding simulators is presented. Principles for the organization of structures of intelligent control systems are developed and evaluated at the physical and information levels. Concepts related to the intelligence of control systems are introduced. A detailed analysis and evaluation of these principles for the development of intelligent systems are presented.

Key words: Automatic control systems; intelligent control systems; degree of intelligence; fuzzy controller; Hamilton-Jacobi-Bellman equation.

INTRODUCTION

Once it became possible to design intelligent industrial automatic control systems based on the use of fuzzy simulators of controllers, engineers became increasingly interested in obtaining theoretical and practical results in this area of research. Two of the most important factors that have had an impact on the emergence of this new trend in control theory are: (1) the development of applied methods in the theory of artificial intelligence (and the creation, on the basis of these methods, of a procedure for constructing systems oriented toward knowledge development and utilization), and (2) the development of the theory of fuzzy simulators of dynamic control systems. The active use of fuzzy controllers in industrial development, together with the design of control algorithms for actual objects based on fuzzy logic, has, in the case of a single firm (Matsushita (Japan)), produced sales of 1 billion dollars [1]. In turn, from 1987 to 1990, the leading Japanese firms, taken together, developed 389 types of products that use control systems based on applications of fuzzy logic in 30 problem-oriented fields [2]. In 1989 one of the leading Japanese firms in the production of fuzzy processors and controllers (Omron Tafeitsy Electronics, Tokyo) had sales of commercial simulators of fuzzy processors valued at $ 8,000,000 and anticipates sales of more than $ 700,000,000 for 1994 [3]. The economic effect and technical progress resulting from the introduction of these types of control systems in Japan has stimulated applied research in Western Europe, the United State, China, and elsewhere [4–9]. In particular, by means of the PFC-S5000 fully programmable work stations developed by Apt Instruments (company president, Wei Xu) it is possible to control complex dynamic processes through the use of over 200 simulators of fuzzy controllers, traditional proportional-integral-differential (PID) controllers, nonlinear controllers, and intelligent expert system controllers in the internal structure of the work station. Because they employ expert systems, these types of intelligent work stations select fuzzy controller simulators as a function of the complexity of the control object. Moreover, a fuzzy processor processes (and inferences) production rules at a rate of 5×10^8–5×10^9 rules per second [9]. A CS/1 type specialized work station employs a hierarchical structure consisting of 128 simulators, has 200 inputs, and contains 32,000 logical rules for fuzzy controller simulators. Each of these production rules has a designated degree of truth of logical inference, and the digital processor inferences at a rate of 4×10^6 truth-valued rules per second (or TIPS, "truth-valued inferences per second"). In the judgment of experts [10], in the next three years a total of 11,000,000 DM will be spent in Germany alone to enable research centers, such as those at Dortmund and Aachen (in northern Westphalia), to compete with the international laboratory

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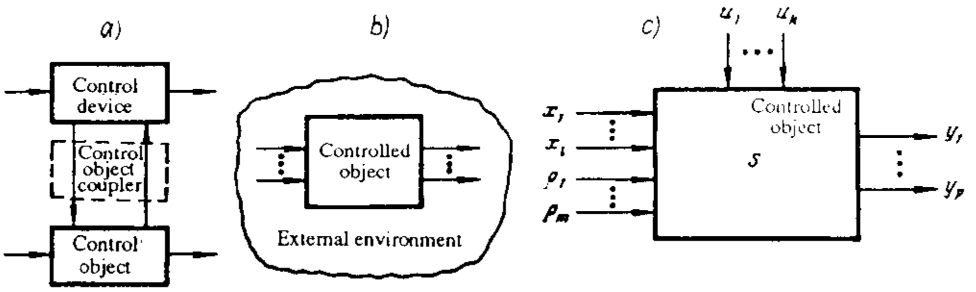

Fig. 1. Structure of the controlled object: $u_1, \ldots, u_k$ are control inputs (control or trigger actions) to which control information is fed (by altering the corresponding input values a desired control of the object may be realized), $x_1, \ldots, x_l$ are external controlled inputs required in order for the object to carry out its functions, $\rho_1, \ldots, \rho_m$ are external uncontrolled inputs of random disturbances, $y_1, \ldots, y_p$ are external outputs required by the object in order for it to carry out objective functions, information from which makes it possible to determine whether the object is capable of reaching a designated control objective, and S is the set of states.

of LIFE (Japan) or the BISC center (USA).

Analysis of the design processes for practical control systems based on the ideology of fuzzy controller simulators together with a trial run in industry have led to the development of a second generation of simulators of fuzzy control systems, one which is "user friendly" for the human operator [1].

Basic information on cost-benefit and scientific management problems in the industrial development of simulators of fuzzy controllers and control systems has been presented previously [1–4, 9, 12, 13]. In [12] actual examples are given of designs and implementations of fuzzy automatic control systems in industry. In the present paper, which is the second part of the survey begun in [12], the evolution of the development of traditional automatic control systems is reviewed,and developmental features of the structures of dynamic intelligent control systems oriented toward knowledge processing and application are discussed.

1. Evolution and Classification of Simulators of Automatic Control Systems

In traditional automatic control theory a generalized simulator of a controlled object presupposes the presence of two components of a controlling system [14]: a control object and a control device. In a number of instances there is an intermediate component, a control object coupler, that contains amplifiers or converters of intelligence and control signals that transform these signals into a form suitable for use in the control device or the control object (Fig. 1a). In the present paper we mean by a controlled object a control object together with a control device the operation of which is described by a unified formal simulator in which the controlled object is represented by a single module linked by its inputs and outputs to an external environment (Fig. 1b). Knowledge of the characteristics of the external environment (the amount of information available to the researcher), the types of interdependence and elements of the interaction of the controlled object and the external environment define the knowledge base of the designer of a model of a controlling system.

Remark 1. The influence of the physical nature of the external environment and the controlled object on the description of the latter as a unified system should not be overlooked. For example, the description of a simulator of a relativistic controlled object as a unified object depends in essential respects on the observer's frame of reference and the physical conditions underlying this frame (e.g., inertial or noninertial, existing in a gravitational or electromagnetic field, etc.). The description of a quantum control object depends basically on the physical method of measuring the state of the object, since the measurement process destroys the state of a controlled object. For this reason, indirect nondestructive quantum measurements, which are also more informative than direct measurements [15, 16], are employed. In this case, the concept of an orbit is replaced by a statistical ensemble, and the dimensions of the state space of the controlled object employed in descriptions of quantum stimulators increases formally. The role of physical control theory has been noted in [17].

In traditional automatic control theory [14] controlled objects are characterized by the following properties: objective purpose, state set, controllability, observability, stability, etc. By means of these properties the relations between a controlled

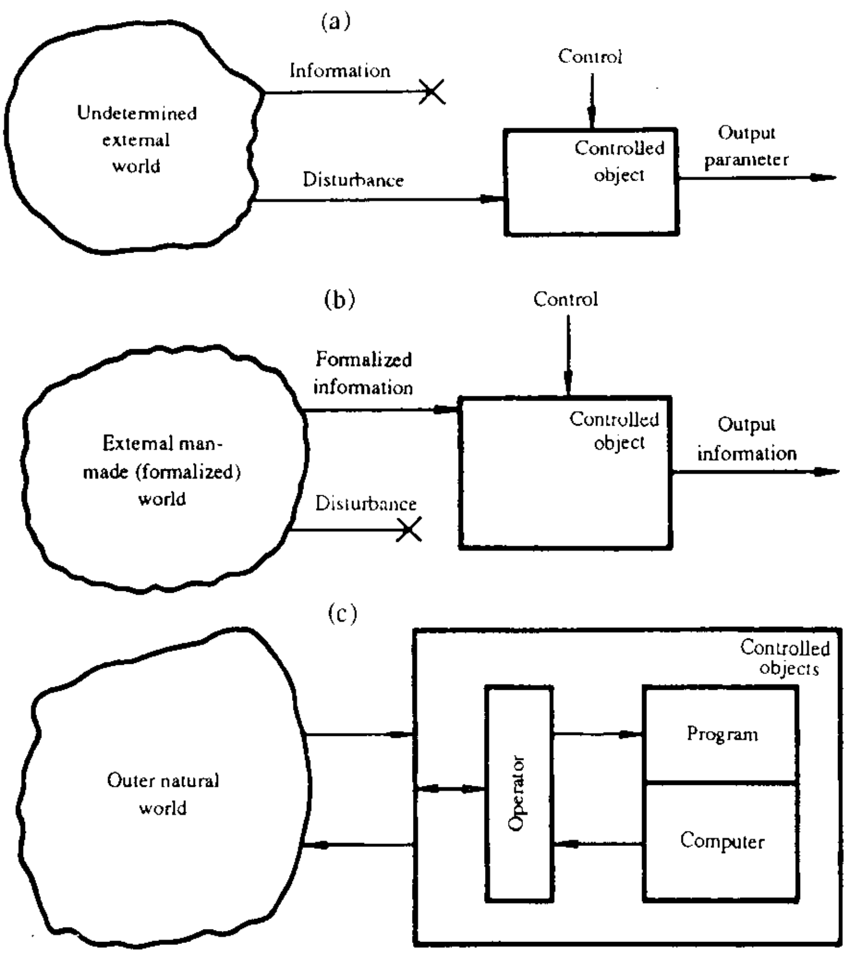

Fig. 2. Controlled objects of Class 1 (a), Class 2 (b), and Class 3 (c).

object and the external environment presented in Fig. 1b may be improved. An improved simulator of a controlled object, together with the necessary notation for the external actions, is shown schematically in Fig. 1c. The sequence of states in which the controlled object is found in the course of operation is taken to be a path through state space. In this case there are two global control problems that may be posed: (1) find a required program control that ensures that the object will travel along a prescribed path; (2) a problem of optimal control that ensures that the object will travel along some optimal path that corresponds to a required (maximum or minimum) value of a prescribed functional (optimality criterion).

Control system simulators have been designed as the constraints on automatic systems in practical applications have increased. Three classes of simulators may be distinguished in terms of the interaction between the controlled object and the external environment: Class 1 — independent systems (informationally closed relative to the external world) that "live" in the external real world and employ neither information nor actions (other than, perhaps, perturbation actions) from this world; Class 2 — systems that are bound to the external man-made world (informationally closed through the external world) and "live" in the external man-made (formalized) world, reprocessing information from this world; and Class 3 — systems that are informationally bound to the external real world and "live" in the external natural world, reprocessing information from this world (Fig. 2).

Remark 2. Systems that belong to the first class are those for which automatic control theory (initially, regulator-type automatic control theory) was itself created as a means of description. Controllers subsequently became the subject of study of automatic control theory. The standard scheme of a controller fits entirely within the overall scheme of a controlled object presented in Fig. 1c. The main difference is that in real-world simulators controlled objects from the first class lack controlled inputs. By means of this type of system, the required values of physical quantities characterizing a particular mode of operation of an object may be maintained (without the intervention of a human operator). A controlled object that consists of a feedback-coupled controller and a control object is known as an automatic regulator-type control system. The main problem in the design of automatic regulator-type control systems is that of stability [14].

The demand for the development of automatic devices of every possible description operating according to the principles of digital data processing became especially acute with the development of transportation and communications networks. These and similar types of systems constitute the basis of the second class of control systems (Fig. 2b). Their overall layout also fits entirely within the layout of controlled objects presented in Fig. 1c. The main difference is that systems belonging to the second class operate in discrete time and reprocess discrete signals arriving at external controlled inputs. Disturbances from the external man-made world do not reach the controlled object, since there are no such disturbances in the man-made world (assuming it is properly organized).

Investigations that attempted to analyze the behavior and synthesize appropriate simulators of control systems belonging to the second class led to the creation and development of the theory of finite automata. On the basis of this theory, a number of different systems were created, beginning with the simplest automata and concluding with discrete-action computers. However, the operation of a computer no longer fits within the general interpretation of the simulator presented in Fig. 1c. To describe the operation of a computer, more complex simulators, based on a composition of simulators of the form shown in Fig. 1c, have been developed.

The appearance of the computer has also influenced the development of control theory. It was discovered quite quickly that the computer constitutes a general-purpose computation machine capable of functioning as something more complex than just a super-high-speed adding machine. A reorientation of applications of computers toward functions of nonnumeric data processing has served as the principal basis for the emergence of an entirely new class of control systems (Fig. 2c).

Computers have a special role to play in systems from the third class. In these systems the computer reprocesses only formalized information that had previously been prepared by a human operator, who, in the general case, would translate noncomputational problems from the external world into computational problems, and the results of computations into actions that are to be performed in the external world. Thus, man-machine systems— the first examples of systems belonging to the third class— made their appearance. The attempt to eliminate subjective attributes connected with the presence of a human operator in the control loop of the system made it necessary to construct systems oriented toward the processing and use of knowledge of the external world, and of real-world problems derived from the external world. The first encouraging results appeared as a result of investigations involving the writing of computer programs that imitate human creative activity, constructed within the framework of a new scientific field that has since been given the title of "artificial intelligence." The development of "intelligent systems" of every possible description soon became the principal domain of application of this field, which, ultimately, made it possible to formulate the notion of intelligent control systems.

2. Design Specifications for Intelligent Control Systems

With the improvement of systems oriented toward the storage, replenishment, processing, and utilization of knowledge, systems began to be designed in which the decision-making process produced results that approached, in terms of quality, the decisions that are reached by a human operator, and, in terms of speed of operation, reached these results in far less time than the response time of a human being (especially in unpredictable and unforeseen situations). It was thought that the activity of such systems could be stimulated by incorporating specialized supplementary modules for generating control actions on the basis of decision-making. Such intelligent systems, connected directly to the object, came to be called "active" systems, in particular, "active expert systems."

Strictly speaking, from the standpoint of the new types of functions which it performs, an active expert system is no longer an expert system. It is an expert system in terms of architecture, however, so long as it contains the following basic modules, which have long been traditional and essential components in virtually any system oriented toward knowledge processing and utilization: a knowledge base with high-level knowledge inference mechanisms, an intelligent solver, an intelligent planner, an explanation system, and a user interface (see Fig. 3). Expert systems may differ in important respects in their architecture and in the functions they carry out, though to one degree or another, the above modules are always present. In active expert systems, the user interface module is naturally replaced by a module for interfacing with a control object.

Among the first systems in this class were intelligent controllers that made use of all the basic functions for working with knowledge that are accepted in expert systems.

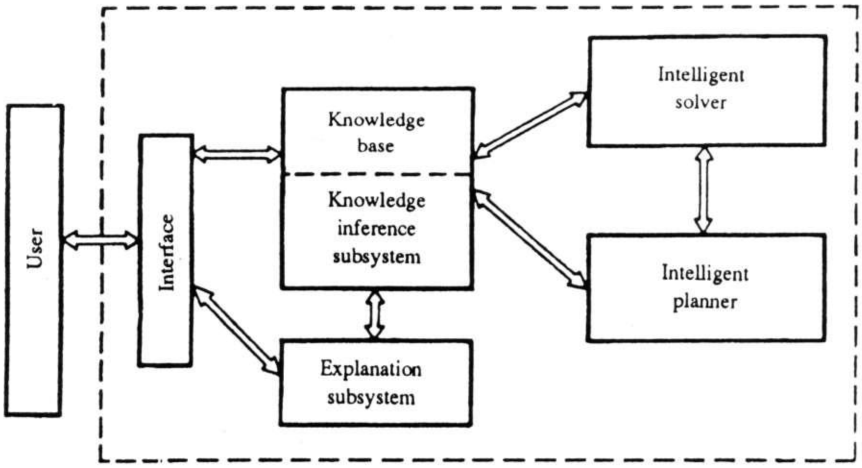

Fig. 3. Standard structure of an expert system.

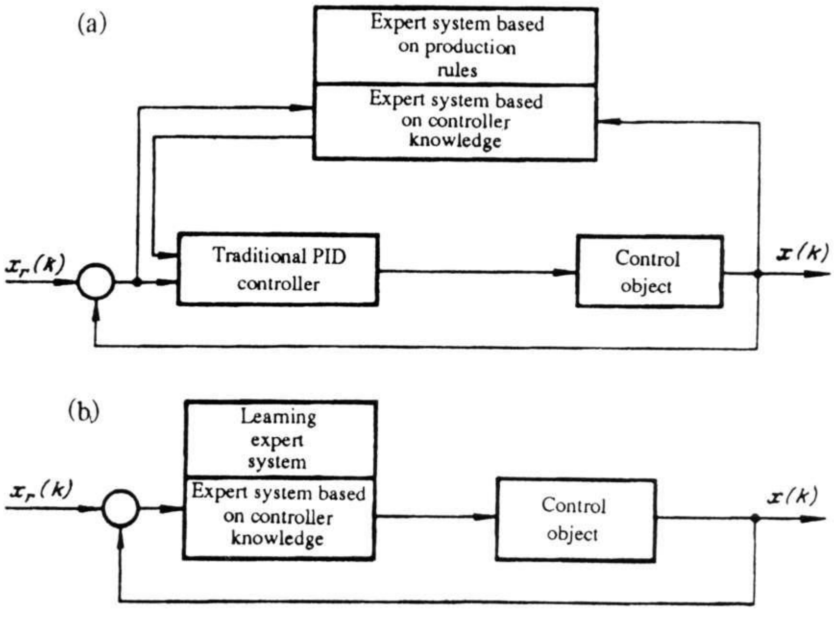

Fig. 4. Standard structures: (a) a controller with parametric adaptation and (b) a self-organizing controller.

As an example, Fig. 4a shows the standard structure of an intelligent controller with parametric adaptation in which accommodation of parameters, a process typical of traditional proportional-integral-differential controllers, is employed. Figure 4b shows an intelligent controller that uses both adaptation and learning. In the most general case, it is a self-organizing controller [18].

The next not unimportant factor that forced researchers to turn their attention to the design of specialized simulators of intelligent control systems was the development of hardware that support the kinds of processes realized in intelligent systems. Hardware-implemented modules capable of performing some of the functions of a system, even its principal functions, began to be developed, initially to speed up data processing procedures, and, subsequently, to simplify the development of intelligent systems that are part of these modules and to reduce the time required to develop such systems. Three basic groups of these types of modules may be identified: specialized processors supporting high-level programming languages (e.g., Lisp, Prolog, Refal, etc.); specialized processors for intelligent databases and knowledge bases (including knowledge inference processors); and specialized intelligent interface processors (image, text, and speech processing) [19]. A separate group consists of hardware-implemented tools for processing fuzzy and linguistic information of every possible description (fuzzy processors) [3, 12, 19, 20]. Intelligent systems that include these types of modules have been called systems with high-level hardware support tools. Of all the different types of intelligent systems, the most common in the field of control are the expert systems that serve as consultants to a human operator responsible for interacting with the real world. With the appearance of expert systems possessing high-level hardware support tools capable of providing intelligent assistance to a manager that would be no worse than that of human specialist experts, the initial period of research into the capabilities of systems in the third class—systems in which man serves as a kind of highly distinctive control link whose labor developers had long been unable to formalize—has been completed. What are known as open systems, i.e., systems capable of improving their behavior over the course of time, thanks to embedded learning algorithms, proved to be particularly well suited for control purposes. The general systems approach to the problem of designing these types of integrated systems led to the formation of a new scientific field—the theory of intelligent machines—at the interface of such scientific disciplines as artificial intelligence, operations research, and automatic control.

The main subject of research in the theory of intelligent machines has been the development of special structures, that simulate, within the framework of a general interpretation of machine architecture, intelligent behavior in the solution of different types of problems. One of the first versions of an intelligent machine with complex architecture was published in [21]. Here, by the structure of an intelligent machine was meant a hierarchical structure of an intelligent control system consisting of three generalized levels, ordered in accordance with a certain basic principle that is considered fundamental in the theory of intelligent machines. The principle, which has the acronym IPDI (Increasing Precision with Decreasing Intelligence), was formulated by Saridis [21] in 1989. It asserts that as the upper levels of a hierarchical structure are reached, the intelligence of the system increases but its precision falls, and vice versa. It is important to note that, here, the "intelligence" of a system means the ability of the system to work with a base of events in order to discover certain specialized areas of knowledge by means of which the statement of some problem could be improved and techniques for solving the problem marked out. Similarly, "imprecision" (or "fuzziness") means uncertainty as to the process of solving the problem. The general form of the architecture corresponding to this basic principle is shown in Fig. 5 [21]. To each level (which may, in turn, be multi-level) there corresponds a specialized subsystem that carries out the functions enumerated below characteristic of this level. For example, at the upper level of the structure there is a knowledge-based manager, a knowledge-based coordinator corresponds to the intermediate level, and a hardware control system, which solves the particular problems after they have been reduced to actual algorithms, corresponds to the lowest level.

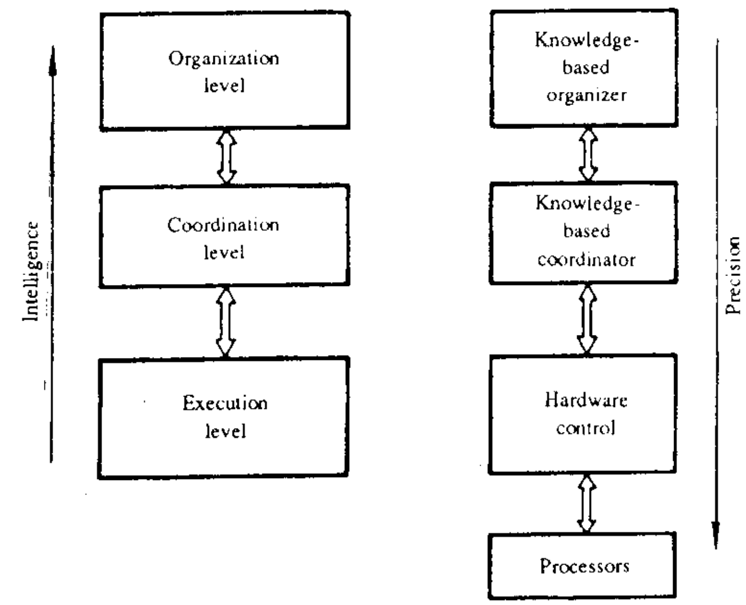

Fig. 5. Implementation of the IPDI principle.

We will now attempt to extend what we mean by the concept of "intelligence" by reference to Saridis's interpretation in order to reach a more well-defined determination of the class of intelligent control systems. We will first discuss briefly their structural organization.

3. The Organizing Principles of Intelligent Control Systems

We will consider a certain class of control systems, corresponding to the following five principles of organization of a control structure.

First principle. The interaction between control systems and the external real world maintained through the use of data communications channels.

Second principle. The formal openness of systems, to increase the intelligence and sophistication of the system's own behavior.

Third principle. Mechanisms exist for predicting changes in the external world and in the system's own behavior in a dynamically varying external world.

Fourth principle. A multilevel hierarchical structure in the control system, constructed in accordance with the following rule: increase intelligence and liberalize constraints on simulator precision as the rank of hierarchy in the system increases (and conversely).

Fifth principle. The preservability of functionality (possibly with some loss of performance, otherwise, with some degradation) when relations are disrupted or when control actions from higher levels of the hierarchy of the control structure are lost.

Remark 3. We will try to interpret these five principles and see what they mean, emphasizing, at the same time, their exceptional importance in terms of evaluating the behavior of intelligent control systems.

The first principle emphasizes the direct link between intelligent control systems and the external world. In their continuous interaction with the external world, intelligent systems receive from it all necessary information in the form of extracted knowledge. The control system itself may, in turn, exert a direct and deliberate influence on the external world through its own behavior. In this sense, a simulator of the knowledge of the external world held by an intelligent system must presuppose the ability to produce changes in the external world and changes in knowledge of the external world as a result of its own actions on it. The principle of interaction between a system and the external world enables us to organize communications channels to extract the knowledge needed to organize appropriate behavior.

Formal openness of systems in accordance with the second principle (which is intended to increase the intelligence and sophistication of the system's own behavior) is supported by the presence of such upper-rank levels in the hierarchical structure as self-adjustment, self-organization, and self-learning. The knowledge system of an intelligent control system consists of two parts: permanent (verified) knowledge, which the system possesses and uses constantly, and tentative (verifiable) knowledge, which the system does not trust and which it experiments with in a learning process. The second type of knowledge is either discarded by the system or turned into knowledge of the first type, depending on the results of the system's analysis of its own behavior in the external world. The second principle, if followed, makes it possible to organize, in the form of a control system, the process of knowledge acquisition and replenishment.

By the third principle, an intelligent control system should not be considered to be fully intelligent if it is not able to predict changes in the external world itself and in its own behavior (in a dynamically varying external world). A system lacking predictive capability (but which functions precisely in a dynamically varying external world) may, as a result, wind up in a critical situation from which it is unable to extricate itself due to time constraints on the functioning of mechanisms of generating the control actions that determine what system behavior is appropriate to the existing situation. As an example, we might consider an independently functioning intelligent robotic system in extremal situations.

By virtue of the fourth principle,methods for constructing simulators of complex control systems may be outlined for those situations in which the fuzziness of knowledge of a simulator of the controlled object or of the behavior of the controlled object may be compensated by increasing the intelligence of already-created systems or of the corresponding control algorithms.

Finally, the fifth principle establishes solely a loss of intelligence, but not a cessation of functioning, if there are failures in the operation of higher levels of the system hierarchy. Preservation of independent operation within the framework of the simpler (automatic) system behavior, typical of lower levels of a control structure, is also of extraordinary importance for independently operating systems in the real external world. The same types of intelligent robots as were mentioned above are one example.

The five principles for the organization of the structure of an intelligent control system define the class of control systems we are investigating. The very concept of the "intelligence of a control system" may now be refined and the concept of the "degree (or level) of intelligence" introduced.

4. General Schematic Structure of an Intelligent Control System. Definition of Degree of Intelligence

We present the basic definitions required to formalize the description of these concepts.

Definition 1. Control systems organized and operating in accordance with all five of the above principles are called control systems that possess the property of "intelligence in the large."

From Definition 1 it follows that systems possessing the property of intelligence in the large must possess a multilevel hierarchical structure with the following levels (in order of decreasing rank): a learning level, a self-organization (self-adjustment) level, an event prediction level, an operation level of event and knowledge bases, a decision-making level, an operations planning level for carrying out a previously reached decision, an adaptation level, and an execution level. Each of these levels has its own functional specification and, in any actual system, may consist of several sublevels. At the lowest, or execution, level, moreover, the traditional simulators of automatic control systems are usually employed. All other levels of higher rank may be considered as forming a superstructure imposed on top of traditional management simulators designed to meet the needs of modern information technology basic to knowledge operations that expand the capabilities of these simulators considerably. A minimal superstructure may contain only a knowledge base consisting of several production rules. In this, the simplest case of all, the decision-making and planning levels may be missing (or functions from these levels may be identical to functions involved in processing several of the rules).

It is easily seen that, by means of Definition 1, links may be established with the basic concepts of traditional control theory by applying methods for constructing intelligent control systems that have been developed in traditional control theory.

Definition 2. Control systems that, in terms of structure, are not organized in accordance with the above five principles, but which make use of knowledge (for example, in the form of rules) in the course of operation as a means of overcoming the uncertainty of input information or a simulator of the controlled object or of its behavior are called control systems that possess the property of "intelligence in the small."

Fuzzy controllers are one example of control systems with the property of intelligence in the small.

Definition 2 corresponds to the generally accepted definition of an intelligent system as a system oriented toward knowledge processing for the purpose of finding the solution of some problem. Definitions 1 and 2 establish limits on the intelligence of control systems. Within these limits, the degree of intelligence of a control system may be determined from the presence or absence of one or another of the levels introduced above. For example, the control system that possesses the highest degree of intelligence is that system capable of learning, altering its structure, and predicting external situations (intelligence in the large). A system that is not capable of learning but is capable of self-organization as a result of analyzing predictable situations, and of all the other properties, right up to the property of intelligence in the small, is said to possess a lower degree of intelligence.

From this analysis of the above principles, the basic stages in the development and refinement of simulators of control systems possessing different levels of intelligence may be represented in general form, by analogy with [22], by means of the block diagram in Fig. 6.

Remark 4. The introduction of the concept of levels of intelligence for a control system is related directly to traditional questions in the development of scales of estimating the functional capabilities of control systems. The levels of intelligence considered here form a nonuniform, partially ordered sequence (see Fig. 6) on the scale of estimates of the functional capabilities of automatic control systems that depend upon the control objectives, the complexity, and the uncertainty of the control object. It then becomes meaningful to ask whether a procedure can be developed for designing automatic control systems possessing varying degrees (levels) of intelligence. In such an approach to the design of intelligent automatic control systems as a function of the particular complex object control problem, the following subproblems are solved: determine the required general level of intelligence of a planned automatic control system appropriate to the level of complexity and degree of uncertainty of the dynamic behavior of the controlled object; optimally redistribute the control subproblems in the hierarchical structure of the automatic control system among execution, coordination, and organization levels; for these subproblems, select appropriate simulators and means of describing and implementing the individual control subproblems.

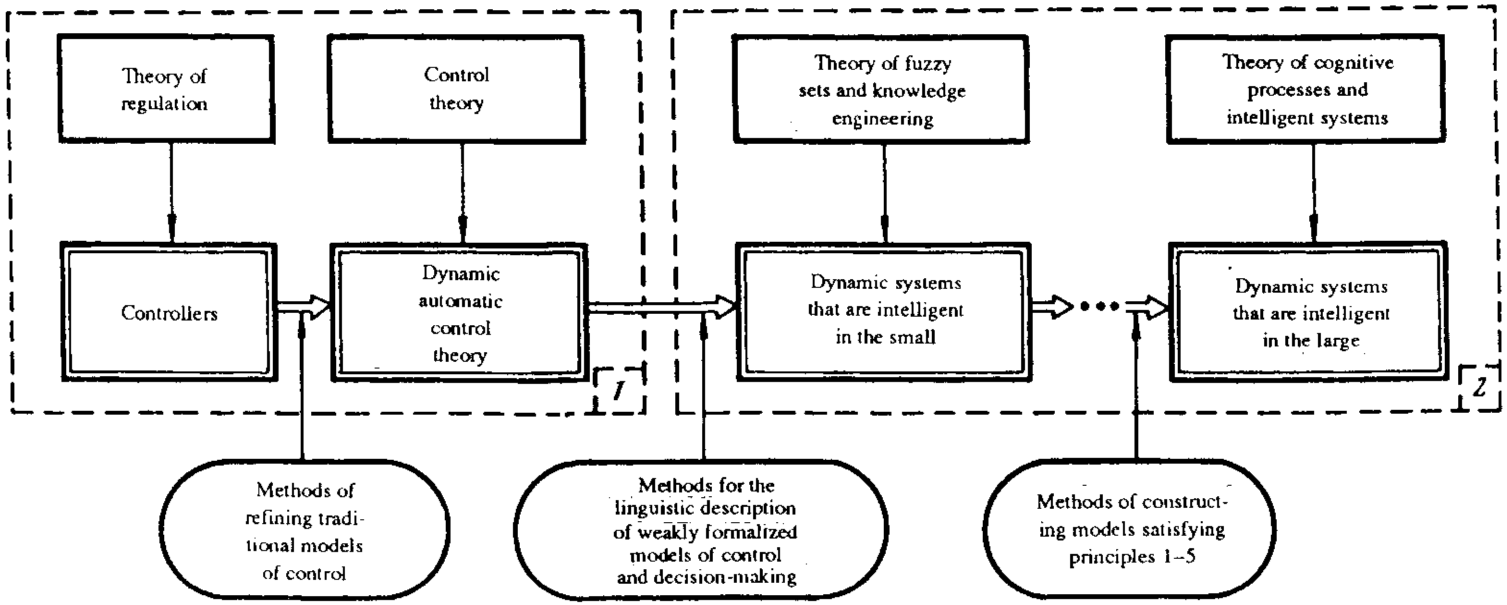

Fig. 6. Stages in the refinement of traditional simulators of automatic control systems: 1) methods from automatic control theory; 2) methods from the development of knowledge-based control systems.

etc. These questions are related to the organization of design processes in CAD systems of intelligent automatic control systems and will be discussed in the third part of this study.

The above principles were formulated on the basis of a logical and empirical analysis of experience gained from operating complex control systems that incorporate a human operator in the control loop and make use of his or her knowledge in the decision-making processes. Such an approach requires an additional evaluation of the necessity and comprehensiveness of the principles together with application of objective methods for constructing dynamic systems that do not contradict any well-known general physical laws, for example, the second law of thermodynamics. Therefore, let us discuss certain aspects of these principles for organizing structures of intelligent control systems from the standpoint of the information and thermodynamic analysis of the evolution of the dynamic behavior of a controlled object that plays an important role in control theory [17, 23, 24]. A detailed thermodynamic analysis of the evolution of dynamic systems demonstrates [23, 25] that estimates of the well-formedness, dynamic stability, physical realizability, and development (degradation) of a controlled object are related directly to the estimated entropy production and entropy exchange with the external environment. Using a specific example, we will consider the interdependence between these estimates and principles 1–5. Note that an informational analysis of principle 4 has been presented in [21, 23, 26–28].

5. A Physical Approach to Evaluating the Necessity and Comprehensiveness of the Organizing Principles of Intelligent Control Systems

An estimation of the operational stability of intelligent automatic control systems is an important constituent element of the design process and enables the ultimate capabilities of knowledge-based systems to be assessed. The thermodynamic-information method of [23] is one of several general approaches to estimating the stability of these types of automatic control systems. Using this method an integral estimate of the range of dangerous instability of an automatic control system [24] as a function of the structural parameters of the dynamic system and the magnitude and rate of the information exchange process may be found [25]. The necessary definitions of the concepts used in the thermodynamic analysis of automatic control systems are presented in [23, 29].

Let us apply the concept of a "simple thermodynamic system" [30] and a definition of entropy expressed in terms of the structure of Hamiltonian systems [31]. In this case, from the standpoint of thermodynamics, a system is characterized by sets of simple nongeometric-type variables (energy, temperature, or entropy) and geometric-type variables (phase variables, such as position, velocity, etc.). For a dynamic Hamiltonian system with n degrees of freedom the Lagrangian $L = K - U$ exists, where K is the kinetic and U the potential energy. The equation of motion of such a system follows from a Lagrange equation of the second kind. The total energy $E = K + U$ becomes the Lyapunov function V in the theory of stability of automatic control systems [14]. In this case, for a dynamic system isolated from the external environment, a strict relation of the following form [23, 29] holds between the entropy production and the Lyapunov function V:

$$\sigma = \frac{d_i S}{dt} = -\frac{1}{T}\frac{dV}{dt}, \tag{5.1}$$

where S is the entropy of the closed (isolated) system and T is a normalizing factor. From (5.1) there follows a relationship between the stability of the motion of a dynamic system and the second law of thermodynamics. In this case the motion of the dynamic system generates a production of entropy (a form of information), while a variation of this form of information generates a new motion (moreover, the Lyapunov stability conditions, $dV/dt < 0$, and the second law of thermodynamics $\sigma > 0$ must be satisfied). From (5.1) it follows that violation of the thermodynamic criterion of physical realizability leads unavoidably to a loss of stability of the dynamic system, whereas a change in the conditions of positional stability can occur only at the expense of the corresponding structures [25] (cooperative effects of synergetic control processes).

Thus, Principles 1 and 2 for organizing intelligent control systems and a thermodynamic analysis of isolated automatic control systems in the form of criterion (5.1) underscore the necessity for the property of structural openness and exchange of information with the external environment in order to maintain stable operation of a knowledge-based automatic control system. The absence from the structure of an automatic control system of processes for exchanging information with the external environment leads to a build-up of entropy (degradation) in the system and violation of the stability condition (5.1).

Dynamic systems with controlled entropy exchange in the simplest case [25] are described by an equation of motion of the form

$$\dot{x} = \varphi_k(x_1, \ldots, x_n, S); \quad S = S_{pr} - S_{ex}, \tag{5.2}$$

an equation describing entropy production,

$$S_{pr} = \psi(x, \dot{x}, S), \tag{5.3}$$

and an equation that describes the rate of entropy exchange:

$$\dot{S}_{ex} = F(x, \dot{x}, S). \tag{5.4}$$

The Lyapunov function V for the system of equations (5.2)–(5.4) has the form

$$V = \frac{1}{2}\left(\sum_{i=1}^{n} x_i^2 + S^2\right). \tag{5.5}$$

It should be noted that we are considering the general case of the motion of a dynamic system with entropy S incorporated into its internal structure as a parameter that specifies the form of motion, while S_{pr} is the entropy produced by an isolated system and S_{ex} is the entropy of the exchange between the dynamic system and the external environment (as a physical analog of the process of extracting knowledge from the external environment). By [25, 32], the coupling condition for entropy production, the rate of information exchange, and the Lyapunov function (5.5) for the dynamic system (5.2)–(5.4) has the following form, assuming, moreover, that the system is open in the thermodynamic sense:

$$\frac{dV}{dt} = \sum_{i=1}^{n} \varphi_i x_i + (S_{pr} - S_{ex})(\psi - F). \tag{5.6}$$

Note that a special case of system (5.2)–(5.4) was considered in [30], and that a generalization to quantum systems was discussed in [32, 33].

Equation (5.6) describes the condition for the stability of a dynamic system with controlled entropy (information) exchange by means of which the progressive evolution of evolving dynamic systems may be realized [25]. Such an approach plays an important role in the qualitative analysis of multilinked intelligent automatic control systems possessing a hierarchical structure (for example, evolving systems or degrading ("pathological") man-machine or robotic bio-engineering systems with a high level of responsibility). From (5.6) there at once follows a physical interpretation of the necessity and sufficiency of Principles 1–5 of the structure of control systems that are intelligent in the large. Thus, Principles 1–3 attest to the necessity of the property of openness for system (5.6) and of the exchange of information with the external environment; a breakdown in interdependence in the system (5.2)–(5.4) may be compensated through a redistribution of the rate or magnitude of information exchange (Principle 5) in the remaining links of the hierarchical structure (Principle 4) without, in general, violating the stability condition (5.6).

These principles for constructing intelligent control systems, together with their physical interpretation, enable us to define the concept of a fuzzy regulator (controller).

Definition 3. A fuzzy regulator (controller) is a hierarchical, two-level control system that is intelligent in the small, at whose lower (execution) level may be found a traditional PID controller, and at whose upper (coordination; see Fig. 5) level, a knowledge base (with fuzzy inference module in the form of production rules with fuzzy implication) and components for translation into linguistic and into fuzzy values (a fuzzy encoder and a fuzzy decoder, respectively).

Figure 7 shows a typical structure of a fuzzy controller.

Depending upon the type of traditional controller employed and the methods used to set up the knowledge base (with inference mechanisms), a fuzzy controller may be either an adaptive, a learning, a self-learning (self-organizing), or a fuzzy active expert system controller. If modifications of the traditional controller, in the form of adaptive, learning, or self-organizing PID controllers, are employed at the lower level of the hierarchy, the functional and dynamic characteristics of the execution level will, in that case, improve, but this will have no effect on the level of intelligence of the controller's

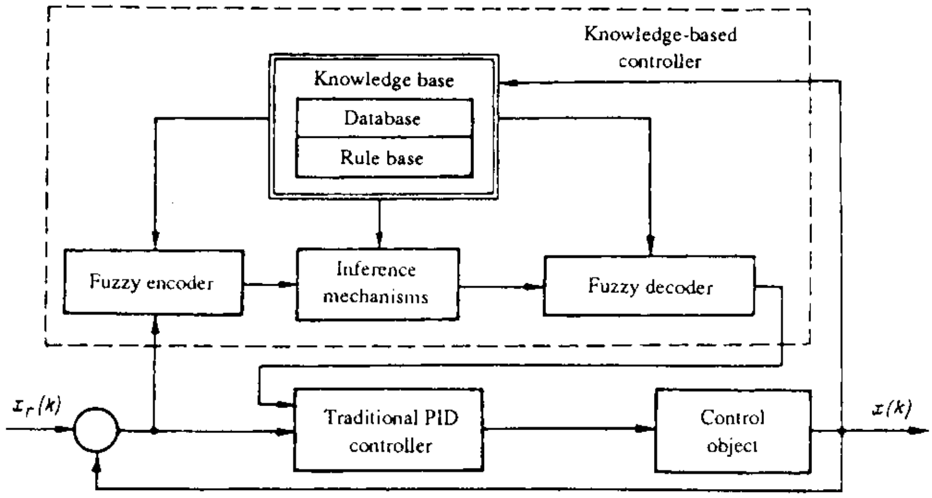

Fig. 7. Structural diagram of a fuzzy controller.

behavior. Changing the methods of setting up the knowledge base by increasing its level of complication (for example, by incorporating neuron network learning using mechanisms of approximate reasoning) can increase the level of intelligence of this type of controller right up to the level of intelligence in the large.

In such an approach to the design of fuzzy controllers, the main difficulty is that of selecting linguistic approximations of the functional and dynamic characteristics of the control object and the corresponding membership functions. Let us consider one possible procedural approach to the solution of this problem.

6. Informational Aspects of the Organization of Fuzzy Control Systems That Are Intelligent in the Small

In the theory of fuzzy simulators of control systems an imprecise (fuzzy) description of the dynamic behavior of an automatic control system caused by the linguistic approximation of the description of the system's transfer functions is compensated by a higher (i.e., at the semantic level) algorithm by taking into account qualitative attributes of the dynamic behavior of the controlled object on the basis of the linguistic variables. An information measure [29] expressed in the form

$$\alpha(A) = \frac{1}{\nu(\text{supp } A)} \int \Delta(\mu_A(x))d\nu(x),$$

is selected as the measure of uncertainty of the fuzzy set A. Here the entropy $\Delta Z = -Z \ln Z - (1 - Z) \ln (1 - Z)$; $\text{supp } A = \{x \mid \mu_A(x) > 0\}$, and $\mu_A(x)$ is the membership function of the fuzzy set A, $x \in A$. The decomposition of the set $F(x) = \bigcup_\lambda F_\lambda(x)$, where $F_\lambda(x) = \{A \subseteq F(x), \alpha(A) \leq \lambda\}$, into sets of level λ depends on the already established radius of uncertainty (entropy) $\alpha(A)$. Through the introduction of the measure of uncertainty $\alpha(A) \leq \lambda$ it becomes possible to establish the range of applicability of the linguistic approximation of particular simulators, which may be understood as measures of adequacy to the particular real-control objects under investigation with respect to an entropy criterion. Methods of structural analysis (decomposition) based on the measure $\alpha(A)$ and optimization of fuzzy simulators of control systems on the basis of the theory of differential inclusions (corresponding to the Hamilton-Jacobi-Bellman equation) were considered in [34]. An important relation was established between fuzzy differential inclusions, Lyapunov functions, and methods of optimal control based on "viscous" solutions of the Hamilton-Jacobi-Bellman equations. This relation enabled researchers to develop one possible approach to overcoming the drawbacks of heuristic methods of selecting and evaluating the membership functions $\mu(x)$ that determine the knowledge held by an intelligent control system. It also became possible to evaluate the procedures of linguistic approximation of a controlled object from the point of view of Definition 2 (intelligence in the small).

We will now briefly consider the distinctive features of the theory of fuzzy differential inclusions using methods from the theory of "survivability" of the orbits of dynamic systems and their application to the problem of determining optimal controls described by the function $\mu(x)$ as "viscous" solutions of the corresponding Hamilton-Jacobi-Bellman equation [34].

In the theory of fuzzy differential inclusions the "fuzzy dynamic" of a particular controlled system with feedback of the type $\dot{x} = f(t, x, u(x))$ is reduced to the form $\dot{x} \in F(x), x \in X, u \in U(x)$ and then replaced by the fuzzy graph described by the membership function $\mu_F(x, \dot{x}): X \times X \to R_+ \cup \{+\infty\}$. Moreover, a price function of the control objective $V: X \to R_+ \cup \{+\infty\}$ exists in which the domain of existence $\mathrm{Dom}\{V\} = \{x \in X \mid V(x) < \infty\}$ and $\mathrm{Dom}\{V\} \subset \mathrm{Dom}(\mu_F(x, \dot{x}))$. The latter relation means that $V(x)$ is identified, in terms of the domain of definition, with the function $\mu_F(x, \dot{x})$. Thus, the membership function $V(x)$ describes the set of optimal orbits of a designated dynamic system. Let us consider certain necessary mathematical definitions for describing the properties of the function $V(x)$.

We will introduce the concept of a tangent epiderivative of the function V at the point x in the direction μ (as an analog of the Lie derivative) of the following form:

$$D_\uparrow(V)(x)(u) := \lim_{h \to 0_+} \inf_{u' \to u} [V(x + hu') - V(x)]/h.$$

We denote by $T_k(x)$ the Buligande tangent cone, defined as

$$T_k(x) := \{\dot{x} = v \in X \mid \lim_{h \to 0_+} \inf [d_k(x + hv)/h] = 0\},$$

where $d_k(y) := \inf \|y - z\|$ is the distance from y to k. The properties of the function $V(x)$ are described by the epigraph

$$ep(V) := \{(x, \lambda_0) \in X \times R \mid V(x) \le \lambda_0\}; \; \lambda_0 = \sup_{x \in K} \inf_{v \in T_K(x)} \mu(x, v) < \infty.$$

Note in this connection that the number λ_0 determines the levels of the membership function $V(x) \le \lambda_0$ and, at the same time, its extremal properties as a criterion of realizability on the optimal orbits $x(t)$ and on the velocity vector $v(t) = \dot{x}$ of the flow of trajectories of the particular dynamic system.

The behavior of the function V is approximated in the form $V(x(t)) \le w(t), \forall t > 0$. The function $w(t)$ is defined as the solution of the following auxiliary differential equation:

$$\dot{w}(t) = -\varphi(w(t)), \; w(0) = V(x(0)),$$

i.e., the initial conditions coincide, and the function $(w(t))$ is a majorant of $V(x), \forall t > 0$. Then the Buligande tangent cone may be written in the form $T_V^\varphi(x) := \{v \in X \mid D_\uparrow V(x)(v) + \varphi(V(x)) \le 0\}$.

The nonnegative function V with tangent epiderivative is the Lyapunov function associated with the function φ if (and only if) V satisfies the viscous solution of the Hamilton-Jacobi-Bellman equation in the tangent cone T_V^φ, i.e., $\forall x \in \mathrm{Dom}(V)$, we have

$$\inf_{v \in F(X)} [D_\uparrow V(x)(v) + \varphi(V(x))] \le 0. \tag{6.1}$$

We emphasize once again that the function $V(x)$ is a membership function and, simultaneously, a Lyapunov function if condition (6.1) is satisfied. The solution of Eq. (6.1) determines the form of such a set of membership functions V of a pencil of fuzzy optimal orbits $x(t)$. Moreover, the pencil of fuzzy orbits $x(t) \in \mathrm{Dom}(V)$ itself possesses the property of stable survivability in the sense of satisfying the relation $\forall x \in K, F(X) \cap T_K(x) \ne \varnothing$. This relation asserts that for every orbit $x(t)$ belonging to the subset $\mathcal{X}$ (in the domain of definition of the function V), the intersection of the set of solutions of a fuzzy differential inclusion and a tangent cone is nonempty. Thus, in the set of solutions of the fuzzy differential inclusion $\dot{x} \in F(x)$ a pencil of orbits x exists in the sense of solutions of (6.1) with membership function $V(x)$ describing the domain of attraction (attractor) under designated initial conditions of the motion of the controlled system. From the result we have presented it follows that the problem of describing a feedback-controlled dynamical system in the form of a fuzzy differential inclusion in which the right-hand side—a fuzzy subset with membership function $V(x) \in [0, +\infty]$, which we have considered as the price function of the control and, at the same time, as a Lyapunov function—reduces to investigating the viscous solutions of the corresponding Hamilton-Jacobi-Bellman equation (6.1) of optimal control theory. Equation (6.1) determines the form of the membership function $V(x)$ with respect to which the pencil of stable optimal orbits of the controlled system is specified, and is an analog of the Focker-Planck-Kolmogorov equation that defines the probability distribution function in terms of the parameters of a controlled dynamic system under specified probabilistic characteristics of the actions.

In the third part of this paper we will consider questions related to the linguistic approximation and construction of optimal fuzzy control algorithms following the criterion (6.1) for the corresponding fuzzy controllers of the orbits of a controlled dynamic system.

Once the form of the membership function $V(x)$ is determined to be the Lyapunov function from the solution of (6.1), a definition of intelligence in the small may be derived from the relation min $\alpha(\mu_X(x)) \leq \lambda$ as measures of the uncertainty of the knowledge (following Definition 2) used in the linguistic approximation of a controlled object.

CONCLUSION

In this paper a class of intelligent control systems has been identified and defined on the basis of traditional simulators of automatic control theory. Principles for the structural organization of automatic control systems with different degrees of intelligence have been developed. New concepts of intelligence in the small and of intelligence in the large that make it possible to improve the quality of the dynamic characteristics of previously designed systems and to enlarge their functional potential, particularly under conditions of undefined environments (in particular, in a dynamically varying external world) have been introduced. Using the formalizations of the concepts of levels of intelligence proposed, a foundation was created for setting up a modern procedure for developing control systems with different degrees of intelligence by using the tools of modern CAD systems.

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