DEEP MACHINE LEARNING SW FOR INTELLIGENT CONTROL. PART II: KNOWLEDGE BASES DESIGN FORROBUST INTELLIGENT FUZZY CONTROLLER[1]

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ABSTRACT

The article describes the technology of knowledge base design of the fuzzy controllers developed with the application of the "Soft computing optimizer"™ toolkit software based on soft computing. The possibility of setting and communication the knowledge base using remote connection to the control object is considered. Setting and communication of knowledge bases of the fuzzy controllers is implemented through the remote connection with the control object in the on line mode using the Bluetooth orWiFi technologies. Remote transmission of knowledge bases allows designing many different built-in intelligent controllers to implement a variety of control strategies under conditions of uncertainty and risk. For example,two different models of robots - inverted pendulumand unicycle robot demonstrated. A comparison of the quality control in the fuzzy controllers and classical controllers in various control modes presented. The ability to connect and work with a real control object, without using than model investigated. The results of the experiments demonstrate the possibility of the ensured achievement of the control goal of robots applying soft quantum computing technologies in the design of knowledge bases of fuzzy controllers embedded in the loop of control systems. The developed software toolkit as SCOptKB™allows to design and setup complex ill-defined and weakly formalized technical systems on line.

KEYWORDS

Intelligent control systems, fuzzy controller, essentially nonlinear model, globally unstable model, stochastic simulation, soft computing.

1. INTRODUCTION

One of the key tasks in modernintelligent robotics is to develop technologies for intelligent control of robotic systems that allow to solve intelligent hierarchical control tasks through the

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[1] Nikolaeva A.V., Ulyanov S.V., Litvintseva L.V., Ulyanov V.S. Deep Machine Learning SW for Intelligent Control. Part I: Soft computing KB optimizer supremacy Pt I // Intern. J. Software Engineering and Applications. – 2019 (in print)
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redistribution of knowledge and control functions, for example, traditionally, between a leader and a slave ("master – slave" system) for example, a computing teaching server and a remote control object.Modern approaches to solving this problem based on the theory of multi-agent systems, the theory of artificial intelligence, intelligent control and many others [1-6].

In this article, different information software nodes of such a system, as a production rules, have a different level of intelligent computing (knowledge, algorithms, and computational bases) and various resources in designing. Each node should be able to modify its behaviour depending on the circumstances, as well as to plan its communication and cooperation strategies with other nodes. Here the indicators of the level of cooperation are the nature of the distribution of tasks, the unification of various information resources and, of course, the possibility of solving a common problem in a given time [2, 3]. We will consider the possibility of extracting knowledge using a mathematical model of the control object and extracting knowledge from the behaviour of the control object itself, that is, from real-time behaviour signals in real time.

Under conditions of uncertainty or inaccuracy of the initial information, unforeseen situations or information risk, the traditional (using the principle of global negative feedback) and industry-wide PID controller often fails to cope with the control task. At the same time, there is no solution to the problem of the global robustness of the PID controller so far, despite the urgency of this problem.

The use of fuzzy controller (FC) in combination with a PID controller led to the creation of hybrid fuzzy ICSs with different levels of intelligence, depending on the completeness and correctness of the designed knowledge base (KB). This allowed to improve the quality of control, but does not completely solve the problem of robust control in unforeseen situations. The use of the soft computing technology (based on the genetic algorithms, neural networks and fuzzy logic) has expanded the areas of effective use of PID with FC by adding new functions in the form of teaching and adaptation (figure 1).

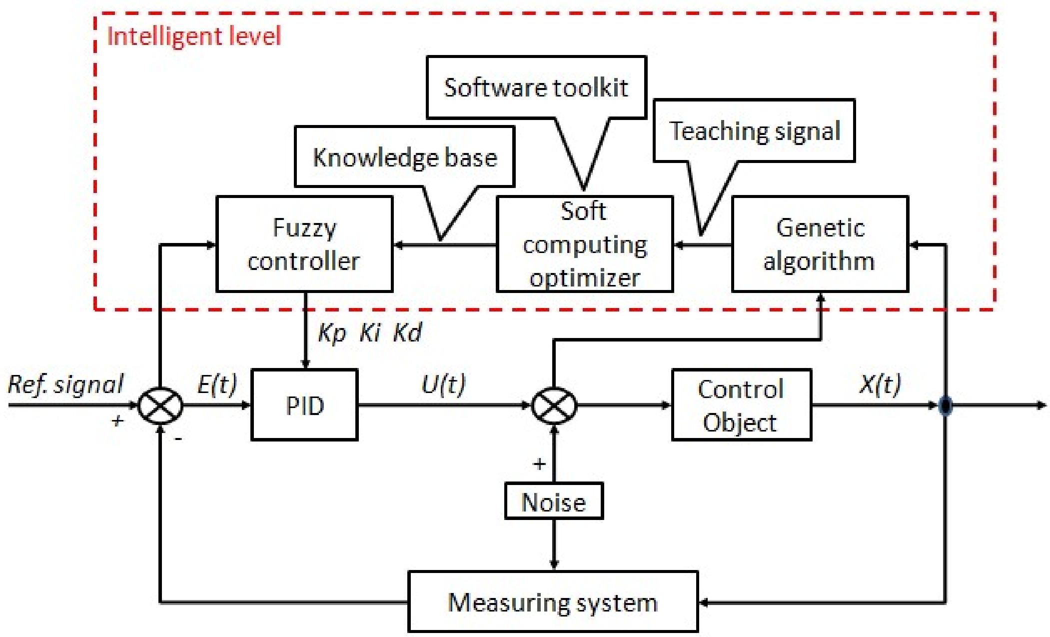


Figure1. Main steps of design intelligent control system

The developed intelligent toolkit - Soft Computing Optimizer (SCOptKB™) [7, 8] (figure 1), allowed to design robust KBs based on the solution of one of the problems of the theory of artificial intelligence difficult to solve algorithmically - extraction, processing and formation of the objective knowledge without using expert estimates. In this SCO, three GAs are used that allow designing an optimal structure of a FC (the type and number of the MFs, their parameters, and the number of fuzzy inference rules), that approximates the teaching signal with the required error.In this case, the teaching signal can obtained directly from the control object functioning in the learning mode. At the same time, an optimal structure of the fuzzy neural network is automatically designed and a model is formed of the universal approximator in the form of a fuzzy controller with a finite number of production rules in the KB.SCO on soft computing is a new effective software toolkit for constructing KB robust ICS using the presented criteria based on information and thermodynamic entropy.

Such a structure simultaneously includes the following control qualities: controllability, accuracy and stability (lower control level), as well as teaching and adaptation (upper intelligent control level - fuzzy controller with knowledge base). The SCO input is a teaching signal (TS), which can be obtained either at the stage of stochastic modelling of the control object (CO) behaviour (using its mathematical model), or experimentally, i.e. directly from the results of measurements of the dynamic parameters of the CO physical model. The TS is a source of knowledge and is an array of data divided into input and output components, each of which, in turn, consists of one or more signals. In general, terms, each of the component signals is a selective (representative) trajectory of a random process. It is implied that at each moment of time, there is some correlation between the input and output signals

Structurally, SCO consists of interrelated genetic algorithms (GA1, GA2, GA3) that optimize individual components of KB [7]. The basic optimization steps and the structure of the SCO are shown in figure 2.

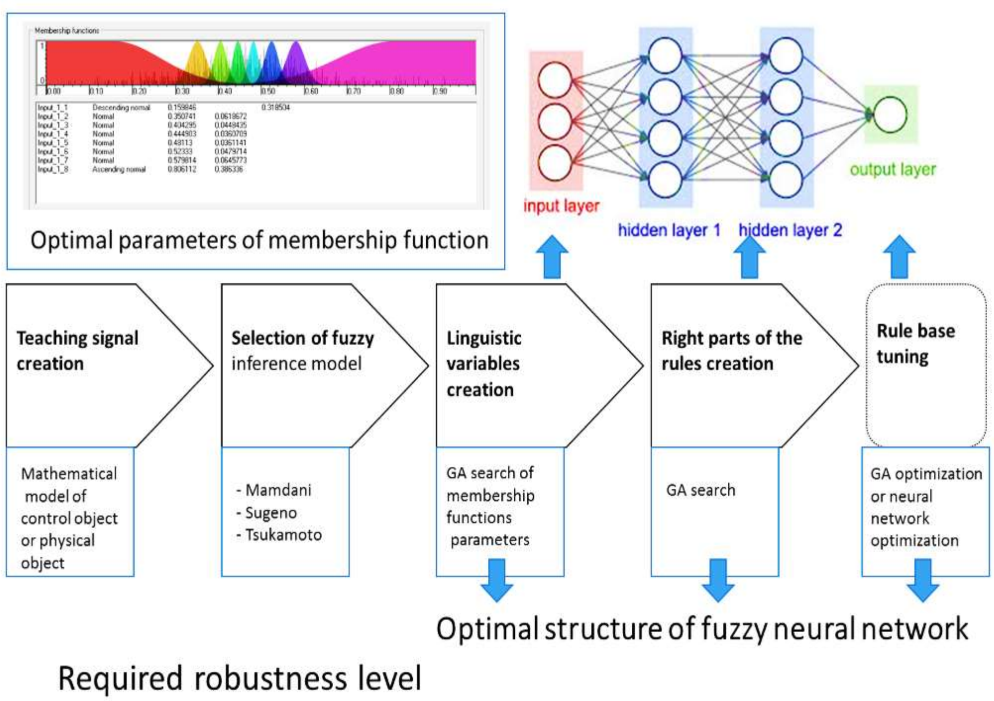


Figure2.Main stages of the knowledge base design on Soft Computing Optimizer (SCO)

Block FC is the central element of the ICS and generates control signals of the time-dependent (control laws) gain factors, *Kp, Ki, Kd* (coefficient gain schedule) of the PID controller, used to stabilize an inverted pendulum and other robots, including unicycle.The functional structure of the ICS with FC and SCO blocks on soft computing shown in figure1.

At the same time, the sources of teaching signals (TS) are on the one hand the physical environment measured by sensors with the ability to influence it with actuators and translate the system into the required state, on the other hand, the information (including model) representation of individual systems functioning among themselveswith the set accuracy of approximation.

Key stages of knowledge extraction from physically measured control signal and teaching with reinforcement are hardware and software implementation of such algorithm, which allows extracting and forming KB of cognitive-intelligent controller, while connecting to the COon all stages of KB design. In the process of knowledge extraction, the classification of input control situations and verification of control actions on the CO carried out. The learning process itself causes the expenditure of physical resources and a decrease in the quality of control, by checking the various trajectories of control and commands, while the information environment forms the structure of the KB. Note that in the space of the formed solutions, all the features of the physical implementation of the system (noise, backlash, errors in the manufacture of parts and environmental conditions) taken into account. As a result, the loss of resource in the learning process compensated by knowledge, formalized in the form of KB, while laying the accuracy and reliability of control in the learning situation, taking into account the physical characteristics of the system.

Modelling the behaviour of the system, firstly, allows you to expand the class of problems solved by increasing the number of simulated situations (changes in mass, friction, various kinds of noise sensors and modelling the influence of the environment), and secondly provides the ability to search for optimal trajectories in given situations modelling. However, the previous process of verification and identification of the model, as well as the process of search and approximation of optimal trajectories in the KB, require significant computational resources and strongly depends on the level of complexity of the described system, its correctness, the number of structural elements and connections between them. Moreover, in the event of unforeseen situations-not inherent in the KB ICS, the application of such an approach will cause significant time delays in the feedback loop, which is quite critical from the point of view of control of these systems.

Consider the example of the process of designing an intelligent control system of inverted pendulum. In this example, we consider the possibility of creating an intelligent robust control system with an increased level of robustness due to the applicationon next step of design IT (Part III) of quantum computing and various hidden quantum information resources in the process of extraction and formation of KB.

2. INFORMATION DESIGN TECHNOLOGY OF INTELLIGENT CONTROL SYSTEM WITH SCO

The technology of application of the SCO allows combining into a single control system several KB obtained from various information sources, which allows taking into account both the physical features of the control object (CO) and the model representation of the system.

The input of the SCO is a teaching signal (TS).TS can be obtained either at the stage of stochastic simulation of the CO behaviour (using its mathematical model); or experimentally, i.e. directly from the results of measurements of the dynamic parameters of the physical model of the CO.

TS is a source of knowledge and is an array of data divided into input and output components, each of which, in turn, consists of one or more signals (Fig. 3).

If some control signal approximated, the input components may be a control error, an error integral and its derivative, and the output component is the desired control action value, or some adjustable control system parameters, for example, the gain coefficient of the PID controller.

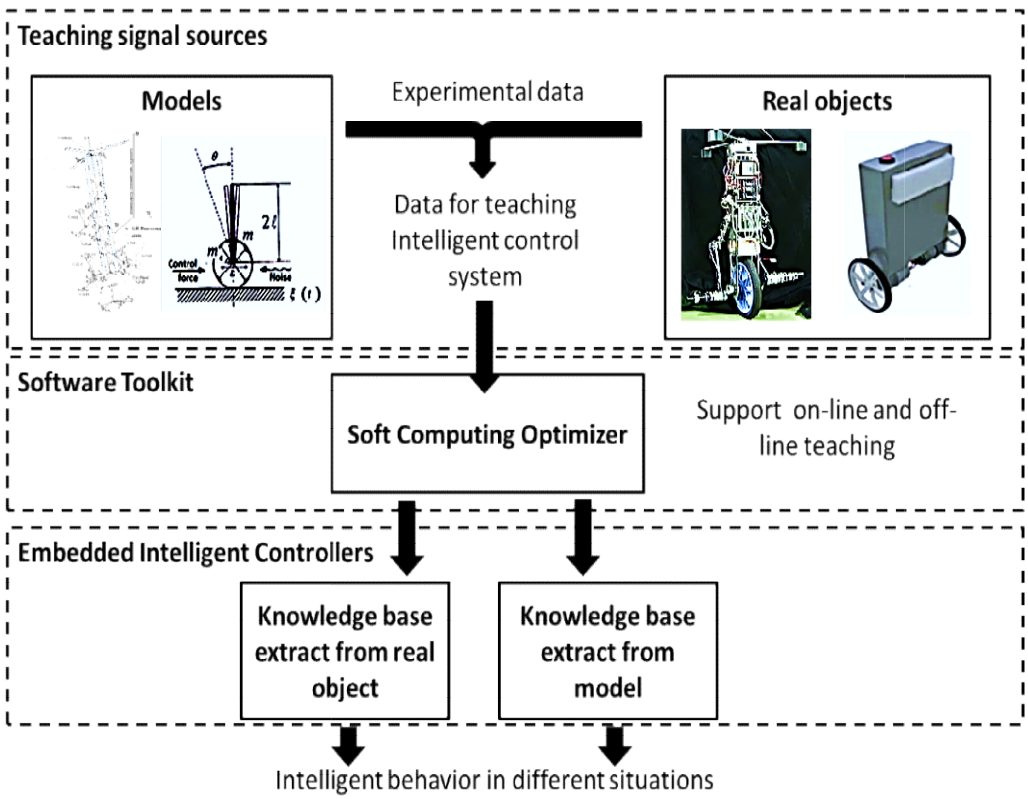
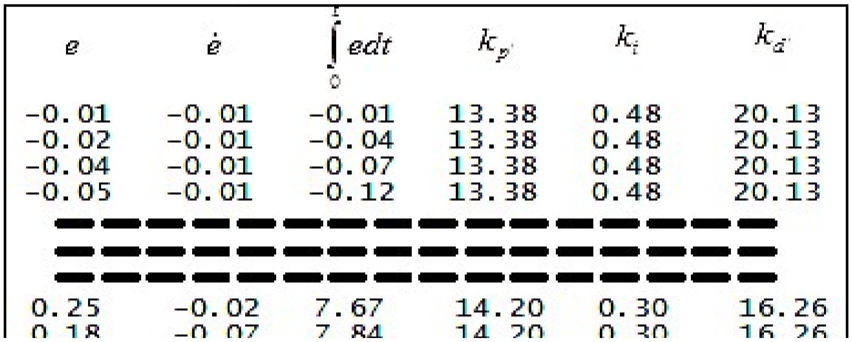


Figure 3. Information technology designrobust ICS with SCO

Onfigure 4, the input data for FC is the error vector, which consists of the control error$e(t)$, the integral of the control error$ie = \int edt$, and the rate of change of the control error$\dot{e}(t)$. Output FC's data is a vector consisting of the coefficientgain schedule,k_p, k_d, k_i, PID controller, the values of which are used in the formation of the control action in the form of:

$$u(t) = k_p(t)e(t) + k_i(t)\int_0^t e(\tau)d\tau + k_d(t)\dot{e}(t) \qquad (1)$$

Consider the possibility of using GA-PID controller to obtain TS and further approximation of the signal on the neural network using SCO.



e	$\dot{e}$	$\int_0^t edt$	k_p	k_i	k_d
-0.01	-0.01	-0.01	13.38	0.48	20.13
-0.02	-0.01	-0.04	13.38	0.48	20.13
-0.04	-0.01	-0.07	13.38	0.48	20.13
-0.05	-0.01	-0.12	13.38	0.48	20.13
0.25	-0.02	7.67	14.20	0.30	16.26
0.18	-0.07	7.84	14.20	0.30	16.26

Figure 4.Exampleofteachingsignal

One of the disadvantages of GA is the inability to use in the future solutions that do not fall into the next generation. When documenting solutions, for a third-party observer of the algorithm, this data turns into a huge array of hard-to-process information.

For figure5 on the left is the TS with the layout in the form of a graph of the angle of deviation and changes in gain.

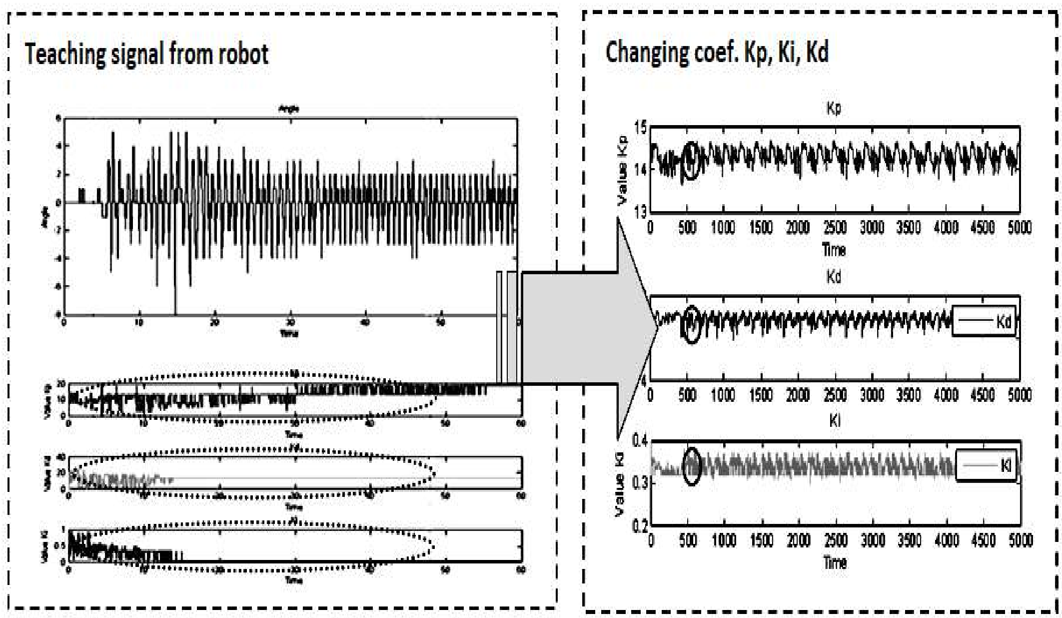


Figure 5. On the left TS from the layout (GA-PID controller), the right gain FC

This signal is derived from the GA-PID controller. The presented data set of the learning process of the CO and the selected areas are "knowledge" about the gain and their changes. It is obvious that the information about the learning process of the robot contains knowledge (in terms of the selected quality criterion) about the suitability of the tested solutions.

It is important to note that the amount of this knowledge grows in the learning process. In the first generations (with a random distribution of chromosomes in the search space), this knowledge is minimal, but with the passage of time and the change of generations, the amount of useful information increases, and the quality of control increases. This data set contains information about both the possible States of the CO (deflection angle)the gain for each time. Using the software tools as SCO,it is possible to allocate knowledge from the signal obtained in the process of GA in on line, with their further use in the KB of FC. Thus, the designed KB will contain knowledge about the physical features of the control object, backlash, noise, friction and implementation features. This type of training allows you to extract knowledge about poorlyformalized and poorly structured CO, for which it is difficult to design an adequate model.

The first three columns in figure5describe the control error, differential and integral errors, respectively, the last three-gaink_P, k_D, k_I.

In the second stage, the TS is fed to the SCO input, which approximates it using a user-defined fuzzy output model. The optimal representation of the membership functions of the linguisticvariable chosen.

The result of the stage of construction of input linguistic variables for four FCs presented on figure 6.

At this stage, the right parts of the rules optimized.

This uses GA2 (for TS with layout) and MATLABmodelling for TS obtained using model and layout.

For formation of the right parts of rules for KB, which TS received from a layout, GA 2 used.The fitness function at this stage is the minimum of the TS approximation error. The first layer of fuzzy neural network shows the number of input variables, the second-the number of membership functions for each variable, the third - the production rules of KB, the fourth - the values of the gain.

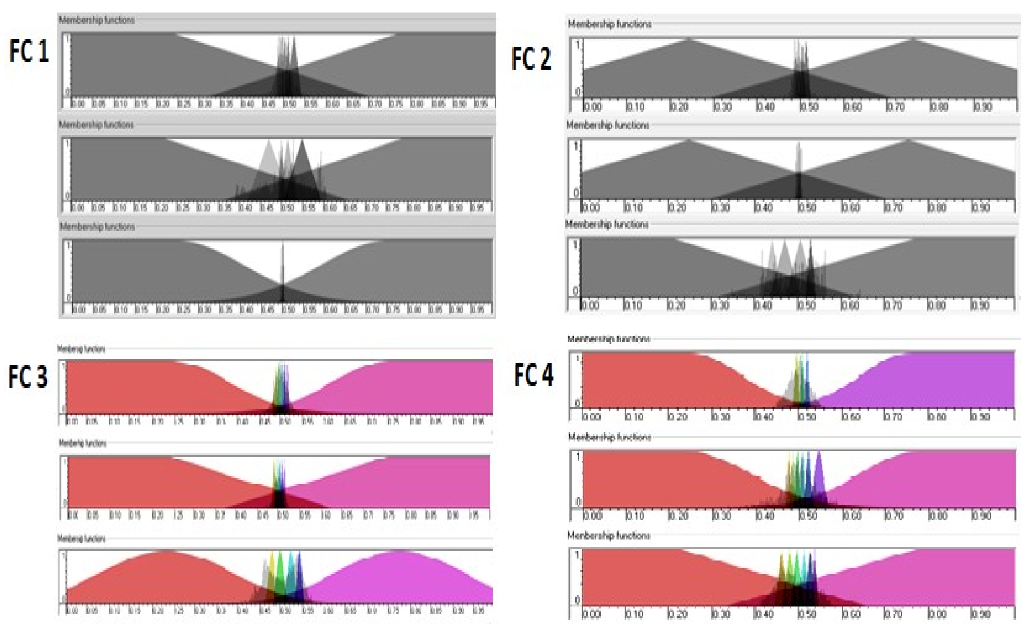


Figure6. Membership functions for input values of linguistic variables FC 1, FC 2, FC 3, FC 4

Figure7 shows the relationship between the training signal obtained using a mathematical modeland the gain of the fuzzy controller.

Remote control setting allows to adapting fuzzy control system to a specific (unexpected) control situation regardless of the time and location of the CO. This kind of self-organizing intelligent control system (ICS) with remote design of KB is important for elimination of consequences of accidents at the nuclear power plant, at analysis of blockages at earthquakes, train crash, for work in the polluted and radioactive environment, etc.

Let's consider the remote connection module of the SCO and the real CO for setting up the KB. A USB connection or a Bluetooth radio channel used for data transfer. The informationshared between the control system and the SCO to form a KB (figure 8).

Remote KB optimization carried out at the fourth stage of FC design. The implementation of the physical connection environment involves the use of additional equipment for receiving and transmitting data, for example, a Bluetooth radio channel, WiFi or cable connection, for example, USB.

It is assumed that the exchange of information between the control system and the SCO for the formation of KB (figure 8). The detailed process of setting up the functioning of such a system is presentedon figure 9.

The control system gets the readings from the sensors and sends them to the computer for further processing. By assuming input values, SCO evaluates the previous solution (KB FC) in the GA function and makes a fuzzyconclusion for verifying the next solution (KB FC). The result of the fuzzy conclusionsent to the remote device. After that, the control system, having processed the input values, generates a control action. Thus, the configuration of the KB FC realized on line. The connection profile uses the serial port. The transmission speed in this case is 115200 bps. In the process of functioning, numbers transmittedthrough the COM-portin the symbolic form. Connection to the SCO is carried out through the developed plug-in.

The remote KB transmission is the next step in the development of the wireless connection of the CO with the SCO. In this case, not control actions thattransferred from the SCO but the KBs. That is, information and knowledge of a higher level shared. The implementation of the connection environment involves the use of the IEEE 802.11 (Wi-Fi) standard and the TCP / IP protocol for data reception-transmission. Information shared between the control system and the SCO to form and transfer KB (figure 9).

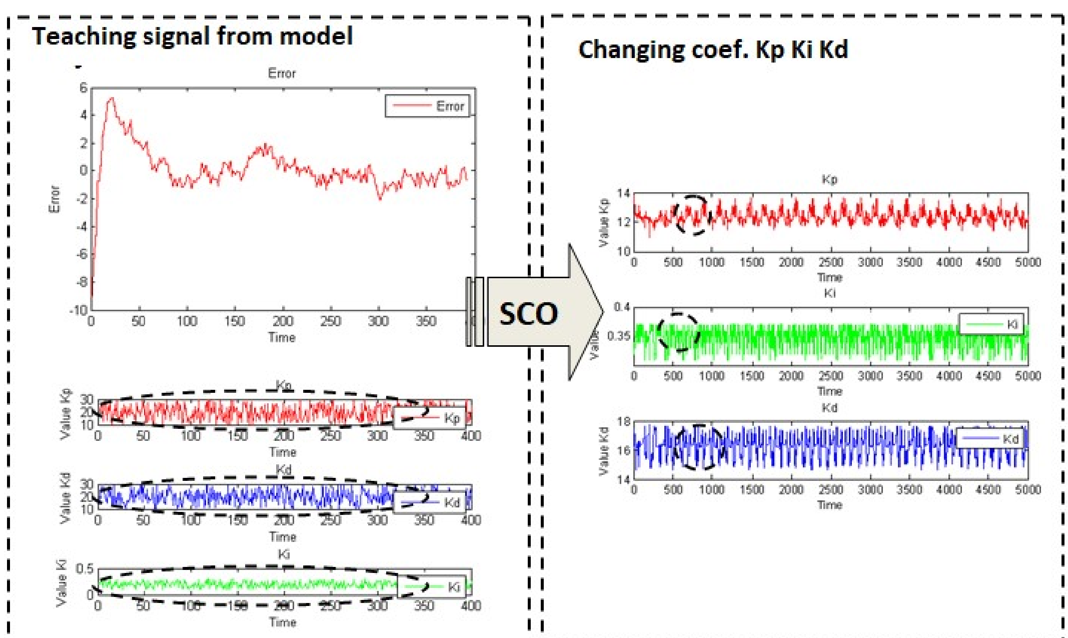


Figure7. TSfrom models and FC output gains

Figure 8. Connection diagram of a configurable device and knowledge base optimizer

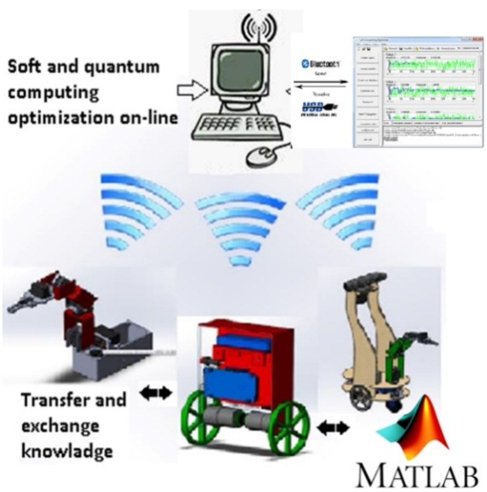
Figure 9. The algorithm works remote configuration

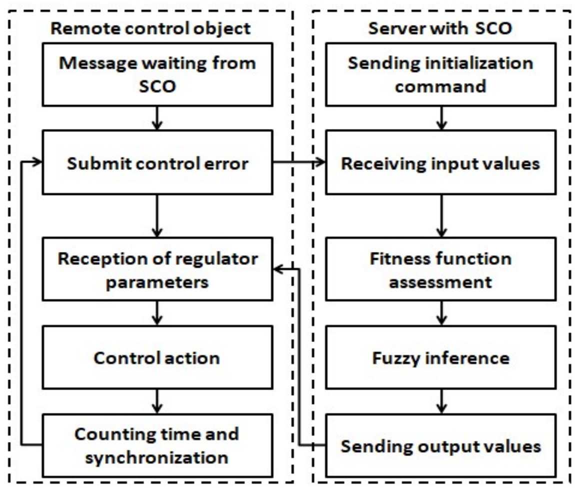
Structurally, from the point of view of the software engineering, the KB implemented by a structural type of data. Its size depends on the number of input and output variables, the number of membership functions of the linguistic variables and the number of production rules. At the speed of 1 Mbit / s, the transmission of a 10 KBwith internal delays takes no more than 100 ms, which allows to qualitatively rebuild the ICS for a given task in theon-line mode.

The technologies for remote configuration and transmission of knowledge bases allow the control object (CO) to accept the KB from the SCO block, or from other CO, which makes it possible to control structurally new objects such as robot teams, multi-agent systems, complex automated production facilities, etc. In addition, this technology allows the CO to update and adapt the KB for a specific control situation, including an abnormal situation.

The result of the TS approximation is the constructed KB for FC, including an optimal finite set of rules and optimally generated parameters of the membership function of the input and output variables of the FC.Thus, the result of designing is a required type of the universal approximator in the form of FC with an optimal structure of the KB.

EXAMPLE 1. CONTROL OF A DYNAMICALLY GLOBAL UNSTABLE OBJECT -





CART – POLE SYSTEM

Inverted pendulum it is a classical task of advanced control theory. A dynamic system has global dynamic instability; in the absence of a control force, an unlimited increase in the deflection angle occurs, i.e. the pendulum falls. The task of controlling the system is to, by acting on the trolley by means of a control force, hold (stabilize) the pendulum in a vertical position (the angle of deviation of the pendulum axis from the vertical should be kept close to 0 under changing environmental conditions).

The equations for entropy production rate are as follows:

$$\dot{S}_{\theta} = \frac{k\dot{\theta}^2 + 1/2ml\dot{\theta}^3 \sin 2\theta}{l(m_c+m)\left[\frac{4}{3} - \frac{m\cos^2\theta}{m_c+m}\right]}; \quad \dot{S}_z = \frac{a_1}{m_c+m}\cdot \dot{z}^2; \dot{S}_u = k_d\dot{e}^2. \quad (2)$$

In equations of cart-pole system motion on figure 10 and entropy production rates (2) following definitions introduced: z andθ are generalized coordinates; g is the gravity constant ($9.8\ \mathrm{m/sec^2}$), is the mass of the cart, m is the inverted pendulum (called the "pole"), l is half the length of the pendulum, k anda_1 the coefficients of friction in z and θrespectively, a_2 is the elastic force of the cart, $\xi(t)$external stochastic noise, and u is the control force.

The structure of the computer model "cart-pole", designed in the environment of modelling MatLab/Simulink, shown in figure 11.

The model includes a PID controller, noise in the control and measurement system, as well as a unit that generates a signal for the controller.This computer model used to obtain a training signal and configure the KB using SCO. As a control model of this system, we will use the expression (1) to calculate the control effect. In accordance with this control scheme, we will use the PID controller in the global negative feedback loop.The controllers designed to function in a typical control situation. To compare the robustness of the developed control systems, we use an unexpected control situation. The situation modelled by the presence of noise in the coefficient of friction of the wheel on the surface and in the control action. As such, noise in the experiment a special coating is used, and the corresponding parameter values were set for themodels.

Consider the behaviour of PID and fuzzy controllers in a typical and unexpected control situation. Onfigure 12-14 the results of modelling and experiments in a typical control situation presented.

Table 1demonstrate a comparison of the KB by the number of rules, the number of functions belonging to the linguistic variable and the method of optimization in the software tools of the KB.

Research of quality of control of the PID-regulator and fuzzy controllers based on software tools of SCO was carried out with use of mathematical model and real CO. The controllers designed to function in a typical control situation. The parameters of the mathematical model used for modelling presented in table 2.

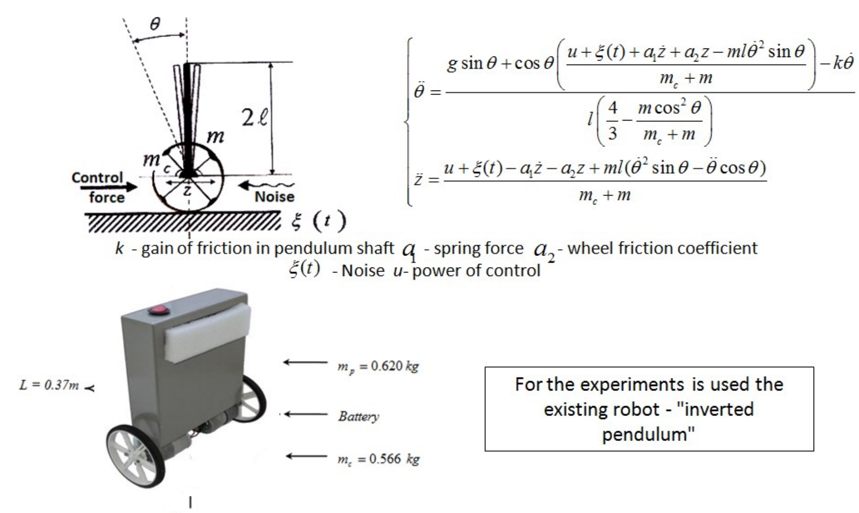


Figure10. Intelligent control system of inverted pendulum and mobile manipulator

Figure11. Modelling system structure: 1-fuzzy output unit; 2-PID controller; 3-control object; 4-noise generators

To compare the robustness of the developed control systems, we use an unexpected control situation. The situation modelled by the presence of noise in the coefficient of friction of the wheel on the surface and in the control action. As such, noise in the experiment a special coating is used, and the corresponding parameter values were set for the models.

Table 1. Comparison of KB

Knowledge №	Number of rules	Number of fuzzy sets	Optimization method
Knowledge base from model 1	245	8x6x6	simulation
Knowledge base from model 2	276	8x9x6	simulation
Knowledge base from robot 1	288	9x9x6	Approximation of TS
Knowledge base from robot 1	270	5x8x8	Approximation of TS

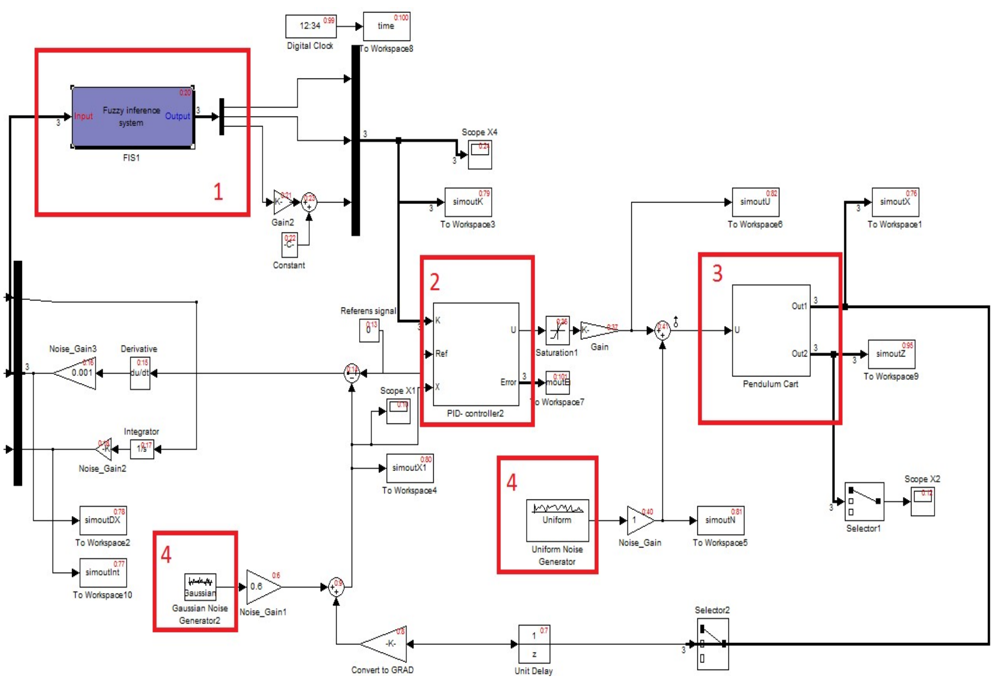
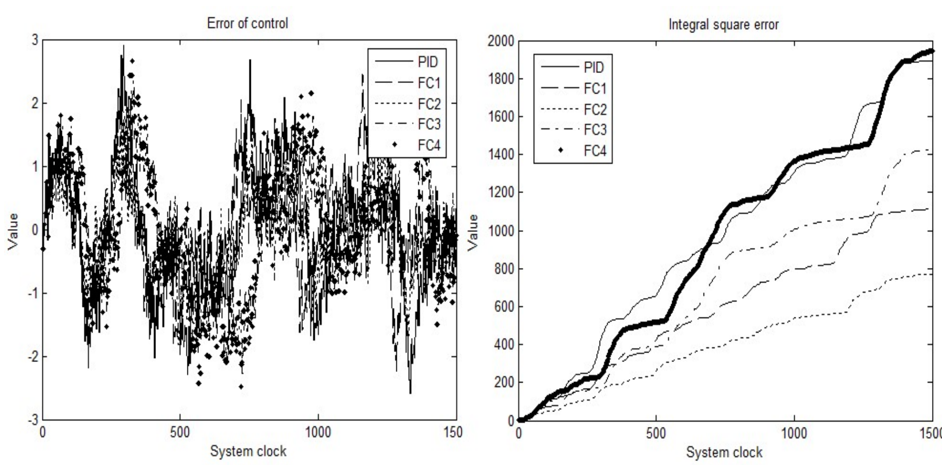


Table 2. Control situations, parameters of mathematical models

	Typical situation (C1)	Unforeseen situation (C2)
Initial angle	0deg	0deg
Initial velocity	1deg/c	1deg/c
Weight of the cart	0.56 kg	0.56 kg
Mass of the pendulum	0.63 kg	0.63kg
Length of the pendulum	0.07 m	0.07 m
Friction in fastening	2.75 + normalized noise with intensity 0.01 and an amplitude of 0.35	3.55 + normalized noise with intensity 0.01 and an amplitude of 0.35
Friction of the wheels	3.63 + Gaussian noise 15%	2.53 + Gaussian noise 15%
Elastic force	5.54Н/м	7.54Н/м
Noise in the control system	Uniform [-2.15 2.15], the intensity of 0.48	Uniform [-2.15 2.15], the intensity of 0.48
Noise in the measurement system	Gaussian noise, amplitude 0.22, intensity 0.01	Gaussian noise, amplitude 0.42, intensity 0.01
Delay on feedback control loop	0.01 c	0.01 c

Figure 12. Left error control, on the right the integral square error. Modelling in typical control situation



The results of the simulation and experiment in an unexpected situation presented graphically in figure 12-15.

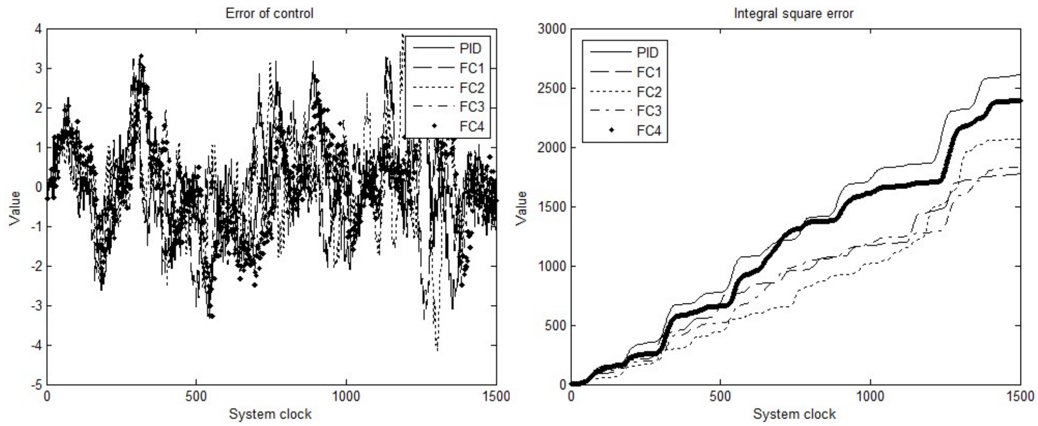


Figure 13. Left error control, on the right the integral square error. Experiment in typical control situation

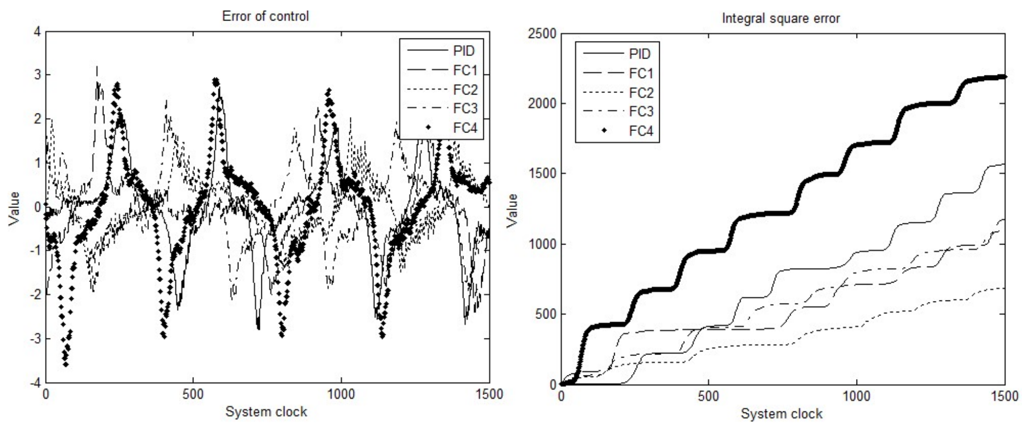


Figure 14. Left error control, on the right the integral square error. Modelling in unforeseencontrol situation

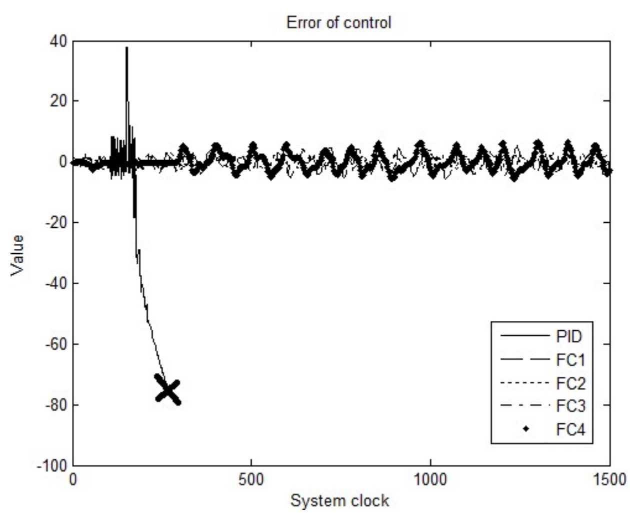


Figure 15. Control error. Experiment in unforeseen situation

Results of simulation demonstrated the supremacy of SCO in comparison with conventional PID controller.

EXAMPLE 2. CONTROL OF ROBOTICUNICYCLE

The knowledge extraction from a new movement types based on studding of mathematical model benchmarks. The robotic unicycle motion is one of such type of "benchmark movements" (benchmark model of nonlinear mechanics [9-13]), described as nonlinear nonholonomic, global unstable dynamic system. Development of an algorithm and control system for robotic unicycle benchmark required a new computation technology - computational intelligence.

The physical feature of robotic-unicycle is that skilful human being operator only realizes the real unicycle bike's control. This leads to the studding of the robotic unicycle as a biomechanical system including new approaches to the control system, such as intuition, instinct and emotions inherent to the human-operator (rider) and allowing to study the possibility of cognitive control by including the "human factor" in the control circuit. The control of the robotic unicycle motion is based on the coordination of the complex movement components (pedalling and movement of the rider's torso). Changing the components coordination type generates new types of movement (rectilinear movement, slalom, dance, jumping, etc.).

Previous studies conducted in the field of different unicycle robot's models controlling (see figure 16 [9-21]) considered the system only from the viewpoint of a mechanical model using classical control methods and/or a simplified, mixed fuzzy proportional-differential controller (FPD) with empirical tables of fuzzy decision rules (lookup tables) [11-13].

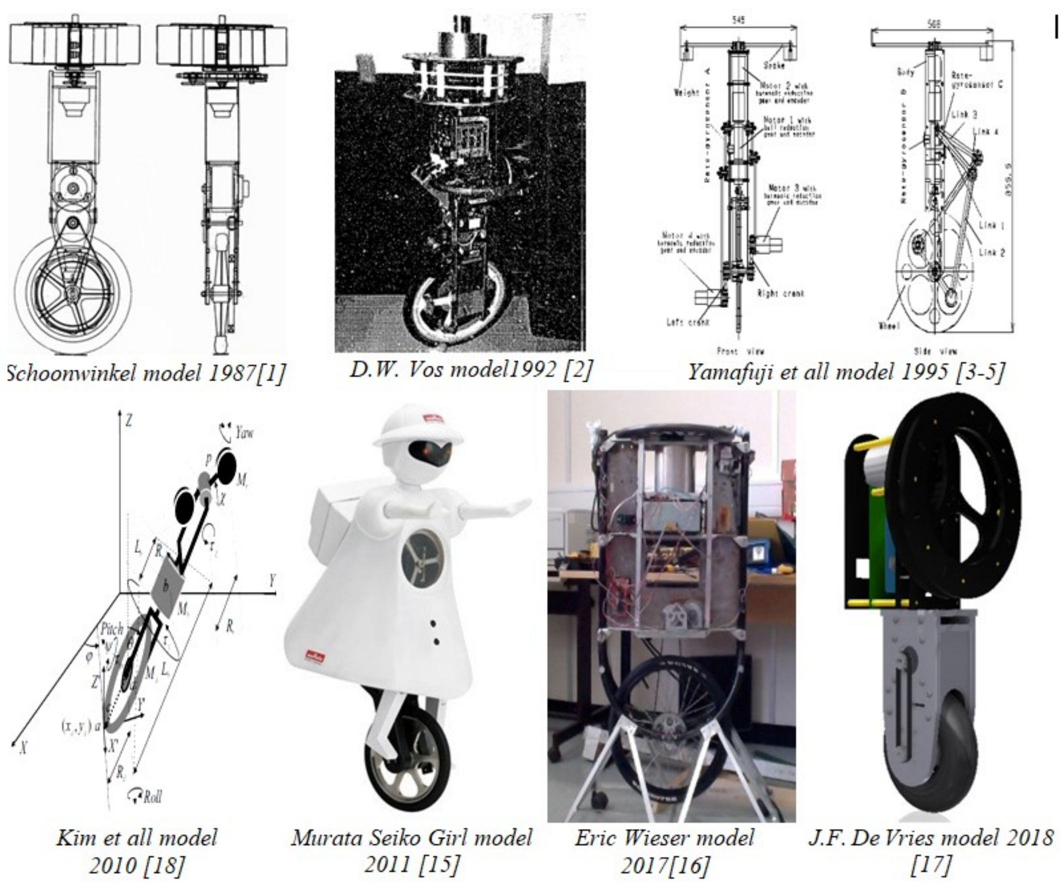


Figure16. Other models of unicycle robot for previous years.

However, this becomes an algorithmically insoluble problem for traditional control methods in the task of robust (stable) motion of the object.In addition, has resulted in new approaches appearance to solve this issue.

The conceptual structure of robotic unicycle intelligent control system research and development shown in figure 17.

To solve this controlling problem the cyber-physical model called as “Conceptual Logical Structure of the Distributed Knowledge Representation (Information Levels) in the Artificial Life of the Robotic Unicycle” (figure 17 a, b) as a biomechanical model of object movement and control was developed and proposed.

Studying the control problem of the robotic unicycle nonlinear biomechanical model, as well as the creation and "training" of a control system by means of available soft computing methods and algorithms was a main research goal.

To assess the control quality the new physical principle the minimum entropy production rate in the object’s movement and in the control system [11-14, 16-22] introduced. The physical measure of entropy production rate is applied as a fitness function in the genetic algorithm (GA). This approach ensures the global stability of the dynamic control object and control system’s robustness.

Basing on this approach the “Self-organizing structure of an artificial intelligent (AI), robust control system design with a new physical measure of control quality” (see below figure20) with a new type of intelligent feedback rooted in the principles of computational intelligent, as well as “Fuzzy Simulation structure of an intelligent control system design with soft computing algorithms ”(see Scheme 2 below) developed.

In previous studies, the problem of external and internal excitations in the mechanical and control system was not considered, see [18-23]. As a result, the global dynamic stability in object’s control was not achieved. In this studding the modelling and optimization of intelligent control system with simulation of stochastic external\internal excitations in the mechanical and control systems floor roughness’s, mechanical vibrations, zero sensors drift etc.) using the structure of the forming filters [24, 25] is represented.

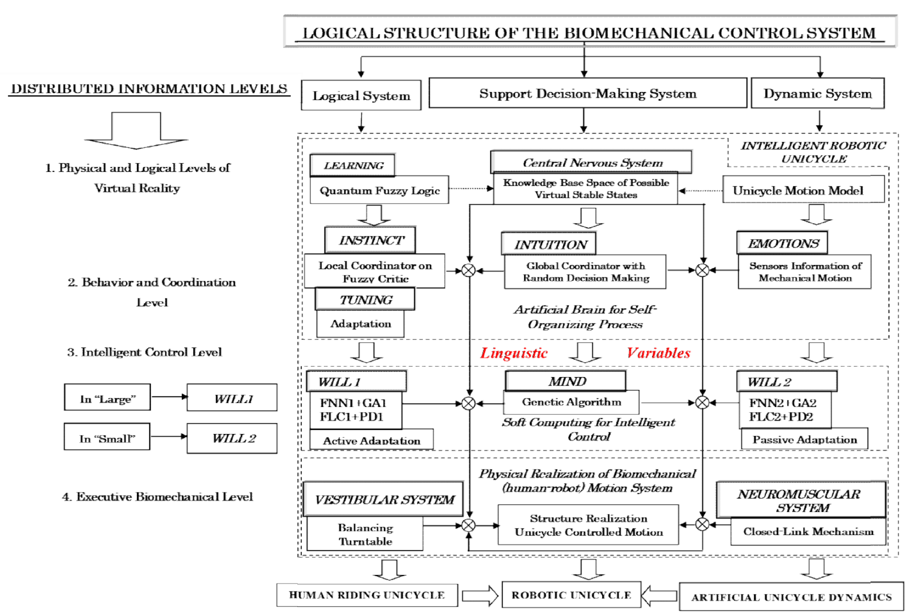


Figure 17 (a). Conceptual Logical Structure of Distributed Knowledge Representation (on Information Levels) in Artificial Life of the Robotic Unicycle.

The simulation and experiment results confirming the efficiency of the robotic unicycle control system.

For the purpose of development, the intelligent control system for non-holonomic, essentially nonlinear, global spatially unstable, highly linking constrained model, a new unicycle mathematical model was created for the "Real" unicycle's coordinate system figure 18.

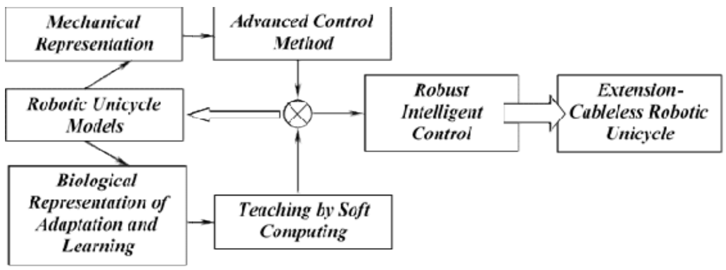


Figure 17 (b). The conceptual scheme of the Robotic Unicycle R&D.

For this coordinate system the following explanations for basic and generalized coordinates, generalized velocities and accelerationsderived:

Elemental Coordinates - $q_j(t) = [x0, y0, \alpha, \gamma, \beta, \theta w, \Psi, \theta 1, \theta 2, \theta 3, \theta 4, \eta]$; where j = 1,…,12, $\Psi(t) = \theta \quad (t) + \psi(const)$, $\psi(const)$ - initial position of pedal figure 18. (link 5,6).Hereinafter, the indices (i, j) denotes the serial numbers of elements in the corresponding vectors, matrices, and in the system equations

The*equation of non-holonomic constraints* in case of unslipping rolling between wheel and ground:

$$\frac{dx0(t)}{dt} = Rw \cdot \frac{d\theta w(t)}{dt} \cdot cos(\alpha(t)); \frac{dy0(t)}{dt} = Rw \cdot \frac{d\theta w(t)}{dt} \cdot sin(\alpha(t)). \qquad (3)$$

where*Rw*– wheel radius, $\frac{d\theta w(t)}{dt}$- velocity of wheel rotation, $\alpha(t)$ - yaw angle. The coordinates x0,y0 are eliminated by substituting of Eq.(3) to kinematic Lagrangian part.

GeneralizedCoordinates– $q_j(t) = [\alpha, \gamma, \beta, \theta w, \theta 1, \theta 2, \theta 3, \theta 4, \eta]$, j = 1,…,9.

In figure18 notation:α- yaw angle;γ- roll angle; β - pitch angle; C.M. – centre of mass; L 1,…,6 – links 1-6; θ_w, 1, …,4 – links rotation angles; ψ - initial position of pedals andthe current angle of pedal rotation (link 5,6) is included in equations as summa - $\Psi(t) = \theta w(t) + \psi(const)$.

Thus, the Lagrangian solvation with insertion represented above equations of nonholonomic/holonomic constraints and external forces of stochastic excitations, gives the following generalized stochastic equation of the robotic unicycle system motion with control:

$$\begin{cases} ME_{i,j}(q) \cdot \ddot{q}_j^T(t) = \tau^T{}_i + C^T{}_i(q,\lambda) + \xi^T{}_i(t) - (BT_{i,j}(q,\dot{q}) \cdot \dot{q}_j^T(t) + G^T{}_i(q) + D^T{}_i(\dot{q}))(a), \\ A_{i,n}(q) \cdot \lambda_n = Mc_{i,j}(q) \cdot \ddot{q}_j^T(t) + Bc_{i,j}(q,\dot{q}) \cdot \dot{q}_j^T(t) + Gc^T{}_i(q) + Dc^T{}_i(\dot{q}) - \tau c^T{}_i - \xi c^T{}_i(t)(b), \end{cases} \qquad (4)$$

where - i,j=1..9; vector of generalized accelerations $\ddot{q}_j(t) = [\ddot{\alpha}, \ddot{\gamma}, \ddot{\beta}, \ddot{\theta} w, \ddot{\theta} 1, \ddot{\theta} 2, \ddot{\theta} 3, \ddot{\theta} 4, \ddot{\eta}]$; vector of generalized velocities $\dot{q}_j(t) = [\dot{\alpha}, \dot{\gamma}, \dot{\beta}, \dot{\theta} w, \dot{\theta} 1, \dot{\theta} 2, \dot{\theta} 3, \dot{\theta} 4, \dot{\eta}]$ .In the system of equations(4), equation (a) is the dynamicalequation of motion for the whole unicycle model with stochastic excitations, and equation (b) is the description of Lagrangian multipliers λ_n, where *n*=1…4. Matrices, vectors and another terms of equations (4) are deeply described in [23].

*Stochastic excitation*appears in case of $\xi c_i(t)\&\xi_i(t)\neq 0$ and described via differential equation *of<u>Forming Filter</u>* as Gaussian (as in our case) random process with autocorrelation function $R(\tau_\xi') = \sigma_\xi^2 \cdot exp(- \quad _\xi \cdot |\tau_\xi'|)$. This disturbance is included into equation of motion for some generalized coordinates, and it is modelling the possible roughness of flow, jamming in closed-links mechanism, and inaccuracy of angular acceleration measuring (sensors zero drift).

Under these conditions' the ***<u>stochastic equation of motion</u>*** with parametric excitationsreceived. All of this gives a possibility to simulate behaviour of dynamic controlled system more realistically and determine the real parameters of intelligent controllers for error estimation and control robustness. Stochastic modelling via Forming Filters described below in [14].

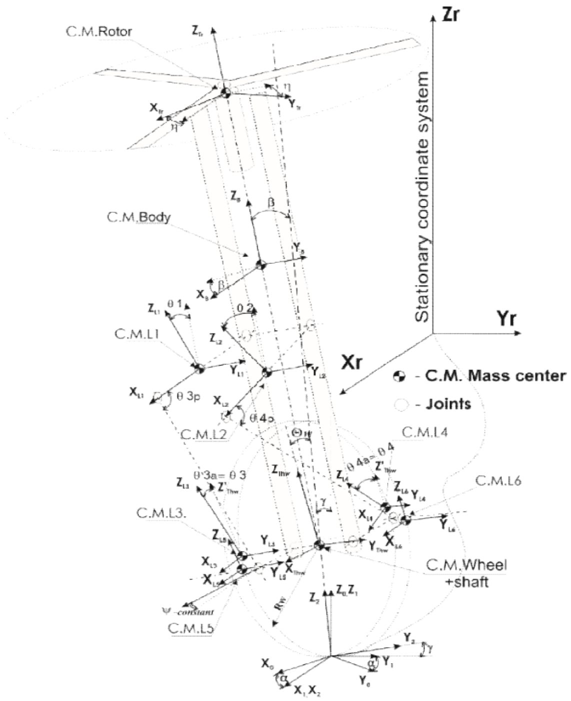


Figure 18. Coordinates description of the robotic unicycle model

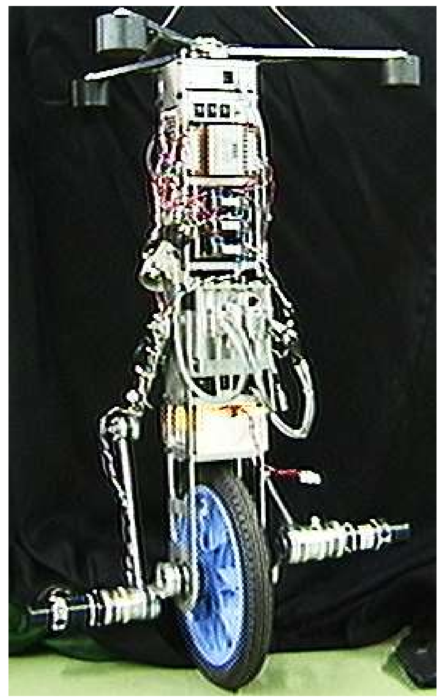


Figure 19. Robotic Unicycle model.

Stability estimation of Robotic Unicycle system is based onthe Salvadorytheorem about equilibrium of mechanical systems with dissipative forces of a $Q_i(q, \dot{q})$type along with full energy of system $E(q, \dot{q})$ as Lyapunovfunction $V(q,\dot{q}) \equiv E(q,\dot{q}) = T(q,\dot{q}) + U(q)$is used; where $T(q,\dot{q})$is system kinetic energy, $U(q)$ - potential energy of system. Under Lyapunov's theorem conditions,if the function $V(q,\dot{q})$ is: **1)** positively determined about any q,$\dot{q}$ and have 0 at (q,$\dot{q}$)=0, i.e.$V(q,\dot{q}) \geq a\|(q,\dot{q})\|\&V(0) = 0$, where **a** is a some continuous, strictly increasing function, satisfying to a condition a(0)=0; **2)** Derivativeof function *V*by time*t* is negative, i.e.$\dot{V}(q,\dot{q}) \leq 0$; when origin is stable[15]:

Thistheoremenables to assert about global instability of the robotic unicycle dynamic system. However, as discussed in [15], in case if the U(0) has maximum value it possible that the equilibrium will stable owing to occurrence of external forces, such as gyroscopic or similar that in our case is controlled torques.

This research proclaims that it is possible to create such intelligent control system, which can continuously stabilize dynamic motion of nonlinear robotic unicycle and the simulation results approved these are shown below.

The equations of the Robotic Unicycle system has controlled torquesin the case of PD controller for the Links mechanism, the controlled torque given as:

$$\boldsymbol{\tau_{(\theta 3)1} = -\tau_{(\theta 4)2} = -kp1(T) \cdot \beta(t) - kd1(T) \cdot \dot{\beta}(t)}, \tag{5}$$

and for the Rotor mechanism - as:

$$\boldsymbol{\tau_{(\eta)3} = kp2(T) \cdot \gamma(t) + kd2(T) \cdot \dot{\gamma}(t)}. \tag{6}$$

GA generates P(I)D controller's parameters $kp1(T), kp2(T), kd1(T), kd2(T)$, selecting them basing on the results of the fitness function calculations, each sampling time T = 0.05sec. This sampling time defined from real controller scheme of Robotic Unicycle.

The intelligent robust control system structuring. The development of robust control for complex dynamic systems motion has two ways of research: 1) the study of stable motion processes; and 2) the study of unstable motion processes of complex dynamic systems.

Such a global-spatially unstable dynamic object requires a new intelligent robust control algorithm based on knowledge description of essentially nonlinear, unstable dynamic system movements [9, 10]. The structure of the intelligent robust control algorithm in the conceptual form for the entire class of unstable dynamic control objects was described in [12,13, 19] and here we apply it to the problem of controlling the robotic unicycle.

The control structure with a new intelligent feedback type represented in figure20. It is based on the *scheme of a conventional control system with linear feedback P(I)D*, intelligent soft computing tools (fuzzy set theory, fuzzy neural networks (FNN), genetic algorithms (GA)); nonlinear model of the control object; entropy production rate calculating; stochastic simulation of random external/internal excitations.

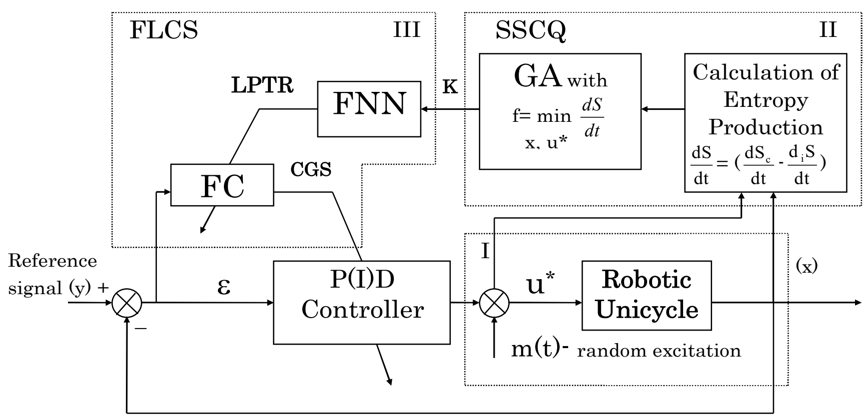


Figure 20. "Self-organizing structure of an artificial intelligent (AI), robust control system design with a new physical measure of control quality".

In the structure figure 20 the following designations are used: GA - Genetic Algorithm;f - Fitness Function of GA;S- Entropy of System;S_c - Entropy of Controller;S_i - Entropy of Controlled Plant;ε- Error;u*- Optimal Control Signal;m(t) – Disturbances (random external/internal excitations); FC - Fuzzy Controller;FNN - Fuzzy Neural Network;FLCS - Fuzzy Logic Classifier System; SSCQ - Simulation System of Control Quality; K - Global

Optimum Solution of Coefficient Gain Schedule (Teaching Signal);LPTR - Look-up Table of Fuzzy Rules; CGS - Coefficient Gain Schedule (in case of 2 PD controllers - K = (k_1, k_2, k_3, k_4)).

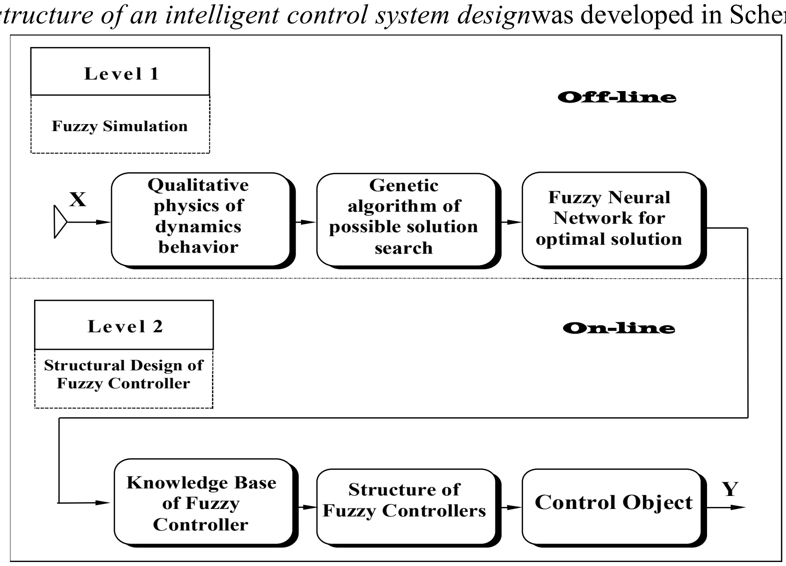
The self-organization control in this system, at the first stage, is provided by optimizing the control parameters of the P(I)D controller by selecting the best solutions with a genetic algorithm, in which the selection criterion is the best fitted solution, calculated using the fines function. To determine solution fitness's a new physical measure of control quality is used ***- the entropy production minimum rate***. This measure is a difference between entropy production of the control object itself and the control system included in this object. This allows adapting the parameters of the linear control system to a nonlinear control object [18 - 21].

The next adaptation stage is control system training to ensure its robustness. This step based on a fuzzy logic classifier that defines fuzzy rules for logical relationships of linear controller parameters. The classifier in this step is FNN for which the optimized control parameters obtained from the genetic algorithm output used as the training signals. This stage generates fuzzy lookup tables, adapted control parameters of the low-level controller P(I)D.

Scheme 1. Interrelation structure between a Stability, Robustness and Controllability of the system.

In this approach, for the task of nonlinear object controlling, the criterion of the control quality (controllability) is introduced as the entropy production function, which is directly interrelated with the Lyapunov function i.e. to a dynamic system stability, as it shown in [18,22,23]. The interrelation between these functions in an intelligent control system ensures its robustness, as shown in Scheme 1. Further, obtained lookup tables used by a fuzzy controller (FC) to control the linear controller parameters (PD).

Based on the intelligent control structure and interrelationship in Scheme 1, the *Fuzzy Simulation structure of an intelligent control system design*was developed in Scheme 2.



Scheme 2. Fuzzy Simulation structure of an intelligent control system design.

Simulation is decomposed into follow main stages: **Off-Line** and **On-Line**. At the first stage a controlled object as the mathematical model is created and the thermodynamic equations of its states are founded for entropy calculation. Further, the equations for entropy production are forming the GA's fitness function. The GA in computer stochastic simulation mode optimizing the P(I)D controller's parameters. The next step is the training of the control system based on the optimized controller parameters obtained from the GA and obtaining lookup tables (FC Knowledge Base) using the FNN.

In **On-Line** mode, the P(I)D controller's parameters of the robotic unicycle are changes by a fuzzy controller basing on the obtained lookup tables, in real time. The structure of the robot control system described below.

MATHEMATICAL SIMULATION AND EXPERIMENTAL RESULTS.

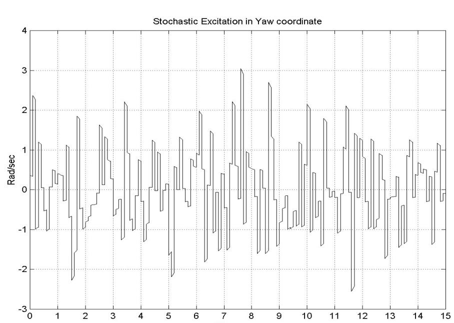
Soft Computing Simulation structure in MathLab Simulink® system is shown in Scheme 3. It consists from following main parts:

1. Block of main equations;
2. Block of random excitation;
3. Blocks of equation's coefficients;
4. Blocks of Lagrangian multipliers calculation;
5. Block of Intelligent control system based on Soft Computing – GA or FNN.

In all simulation cases, the real parameters of the robotic unicycle model were used see the figure19, and the corresponding stochastic effects: disturbing from the floor to the yaw rotation angle and jamming in the closed-links mechanism. (seefigure21).

Simulation results discussion. In figure22 shown the simulation result of Fuzzy PD controller with lookup tables obtained after learning process by FNN with pattern from GA – Soft Computing approach.

From represented results it is visible, that: 1) usage of the approach described above, with application of a minimum entropy production rate as fitness function in GA and learning process by FNN, is completely justified; 2) dynamic motion occurs more smoothly even the control signal's discretization time is use in PD-GA and Fuzzy PD controllers with sampling time = 0.05 sec.



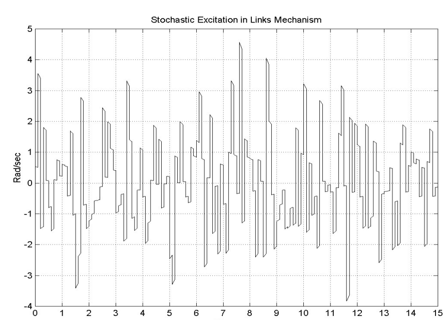
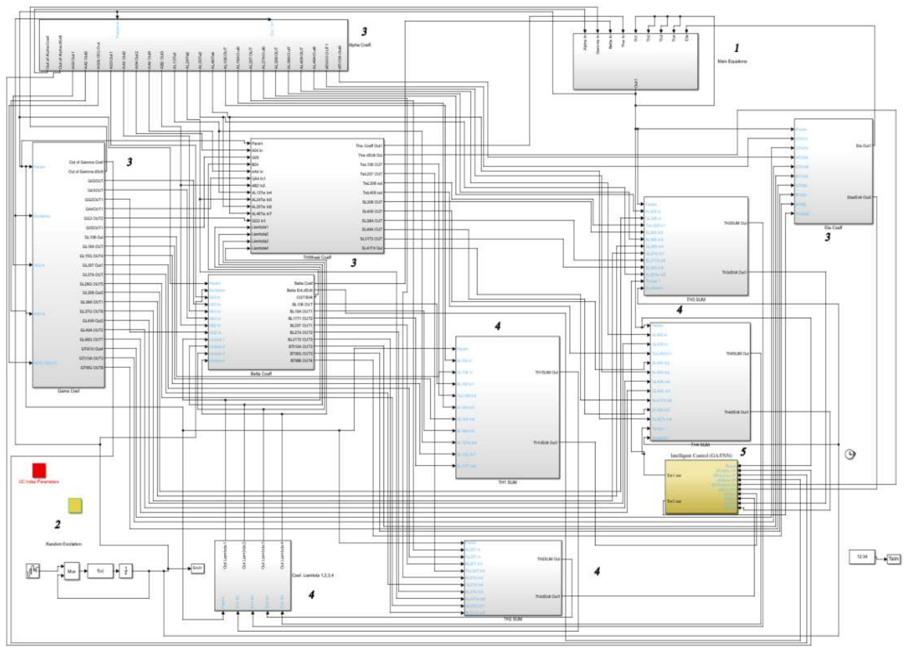


Figure 21. Simulated stochastic excitations - from a floor roughness's and jamming in closed-links mechanisms.

Scheme 3.MATLAB Simulink® diagram of the Robotic Unicycle computer simulation



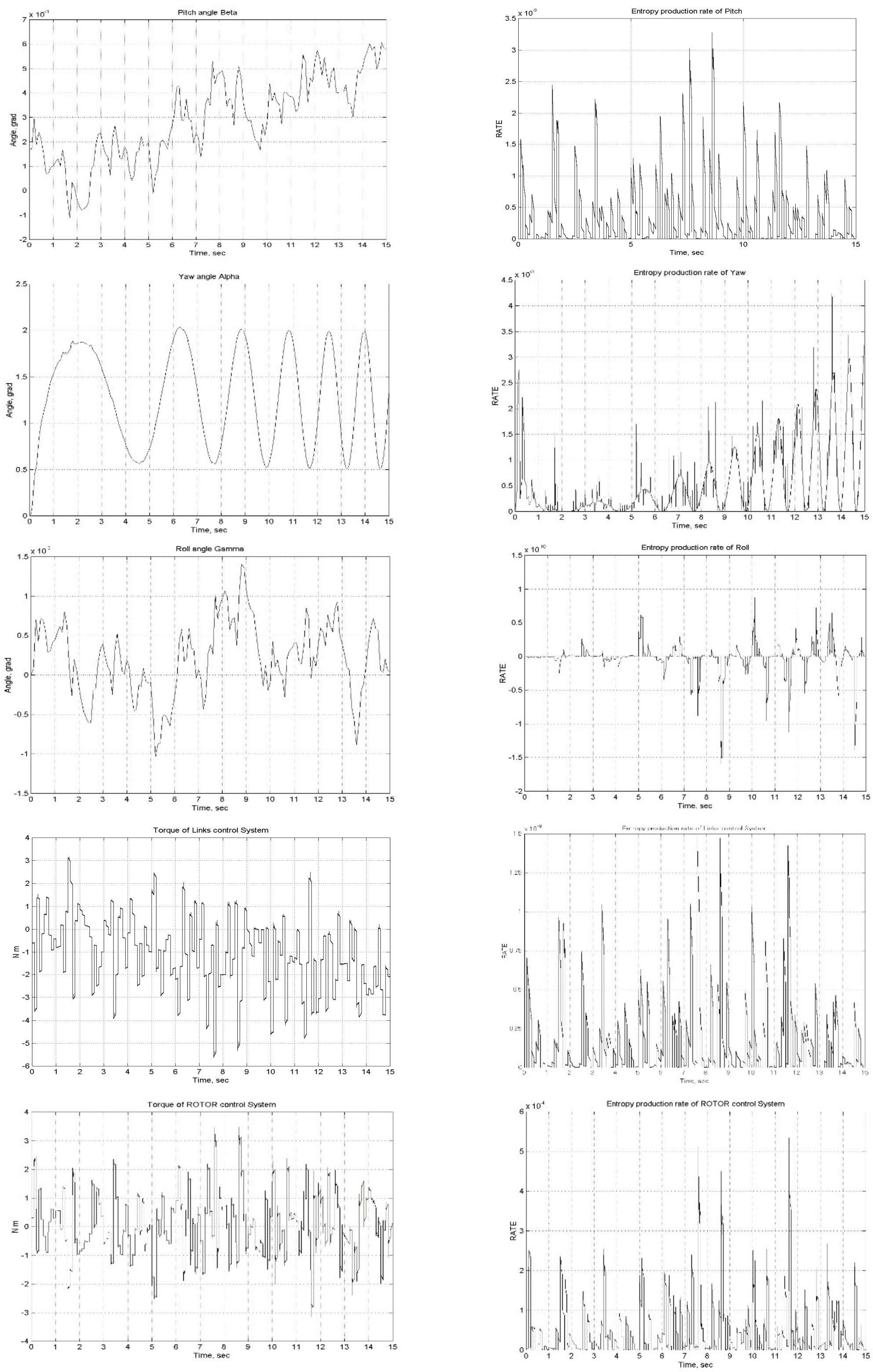


Figure 22. Stochastic simulation results of Robotic Unicycle ModelwithFuzzy PD controllers: a)

a

Temporal mechanical and thermodynamic behaviour of Robotic Unicycle - α, β, γ.
b) Temporalmechanical and thermodynamic behaviour of Fuzzy PD control system torques.

Entropy production rate for the Pitch angle after the learning by FNN decreased to 10 times. For the Yaw and Roll angles, Entropy production rate is 10 times less for PD-GA and 1000 times less for the Fuzzy PD than for cconventional PD controller.

However, such energy transmitting increases amplitude of Pitch angle in case of PD-GA controller that conducts to increase torque in Links control system. But, after learning by FNN the motion in the pitch direction becomes smooth with small amplitude. It confirms about learnability and intellectualization of the Robotic Unicycle control system.

Experimental Results Discussion. Created in 1997-2000, the Cableless Robotic Unicycle shown in Figure19. The experimental results represented in figure23, 24. The time of the full-scale experiment was limited to 8 seconds due to the adverse effect of the gyroscopic sensors drift signal and low capacity of existed accumulators.

However, it should be noted that sampling (more than 0.001 sec) of control signal from conventional PD, as it is present in real model, offers the Unicycle simulation system to "falling" after 8-10 sec.

In Figure 23 shows the experimental results for the cableless unicycle model. As it shown, the robot's lateral stability - in the roll direction γ, and posture in the pitch direction βis obtained.In Figure 24 shown the temporal behaviour of the fuzzy gains **kp1, kd2, kp2, kd2** for 2 PD controllers (Eq. 5, 6).

From the result in Figure 23c is observed that the robot's posture in the yaw direction α is changed rapidlyduring the experiment, which indicates a satisfactory redistribution of control energy that provides lateral stability of the robot (roll γ) and tracking stochastic excitations on the model (floor roughness's and jamming in closed-links mechanisms) by controlling the yaw angle α and pitch angle β.

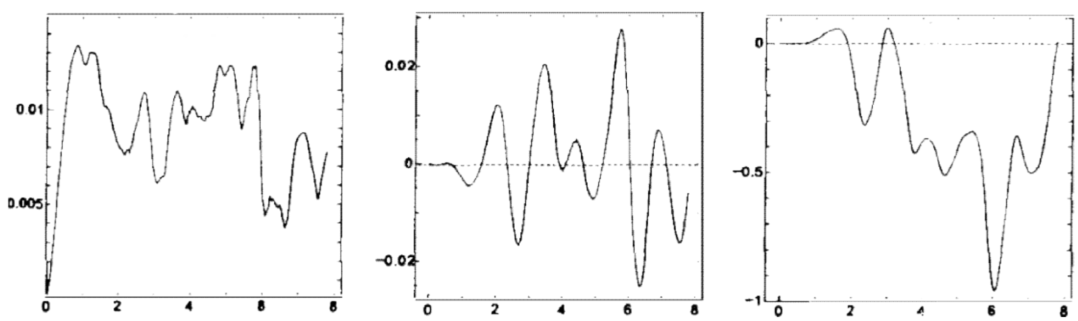


Figure 23. Experimental results, angles - *pitch β, roll γ and yaw α angles.*

a **b** **c**

Pitch angle β, rad

Roll angle γ, rad

Yaw angle α, rad

Time, sec.

Time, sec.

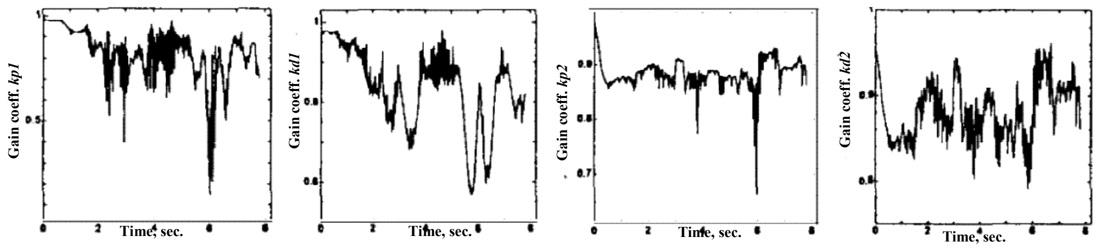


Figure 24. Experimental results of the fuzzy gains *temporal* behaviour kp1, kd2, kp2, kd2 for 2 PD controllers

Remark 1. The obtained experimental results were achieved using empirically generated fuzzification and defuzzification for the gain coefficients **kp1, kd2, kp2, kd2** of two fuzzy PD controllers, which were generated on the basis of preliminary results of GA simulation with the fitness function - reduction only the entropy production rate of the control system, i.e. incomplete simulation process of soft computing technology. The simulation results presented above were obtained later, upon completion of the Robotic Unicycle mathematical model development (figure18, 19;equation (4)), formation the soft computing process technology (figure 20, Scheme2), and most importantly, the appearance of this approach calculating possibility - appropriate computational capabilities, without which this process was extremely difficult or impossible.

Remark 2. Despite of this, the obtained result at this time and with those computational capabilities, leads to confirmation of quite satisfactory operation of the represented structure of the intelligent control system. The represented structure of the process, as well as the new developments in this direction, planned fully applied in the new prototype - an Autonomous Flexible Robotic Unicycle based on SCO with quantum soft computing technologies [26,27].

CONCLUSIONS

1. This work represents the basic idea of intelligent control of dynamical, globally unstable, nonlinear objects on the example of Robotic Unicycle and Inverted pendulum. The basis of this approach is a qualitative physical analysis of the robot dynamic movement with the introduction of intelligent global feedback in the control system and the implementation of instinct, intuition and cognitive mechanisms based on the FNN and GA.
2. The main components of an intelligent control system based on soft computing and robustness determination represented. Thus, there is an adaptation of the two fuzzy PD controllers' parameters to achieve a stable motion of the robotic unicycle over a long (finite) time interval, without changing the structure of the control system executive level, is achieved.
3. Use of a fuzzy gain schedule PD controller with look-up tables calculated by FNN, offers the ability to use instinct and intuition mechanisms in on line to intellectualize the intelligent control system levels.
4. Soft computational intelligence toolkit applied to design of self-organized conventional P(I)D controllers can increase the robustness of robotic dynamic unstable control object.
5. Practice and simulation results have shown that in conditions of uncertainty or inaccuracy of initial information, unforeseen situations or information risk, the

traditional (using the principle of global negative feedback) and widely used in the industry PID controller often fails to cope with the task of control.

6. The developed toolkit implements the mechanisms for creating, setting up and transmitting control parameters in the form of control signals received from the KBs of FC without destroying the lower executive level. The use of the soft computing and developed ICS design technologies reduces the influence of expert assessments in the process of teaching, training and setting up ICS.

The results of the conducted research showed that:

• Remote optimization of the KB together with the GA-PID controller allows building the ICS without mathematical modelling in the on-line mode.

• KB provides an increased reliability of the ICS in the on-line mode.

• The toolkit allows to setup complex control systems with a large number of control loops. The number of input variables and the size of the obtained KB limited only by the hardware characteristics of the computer and the CO.

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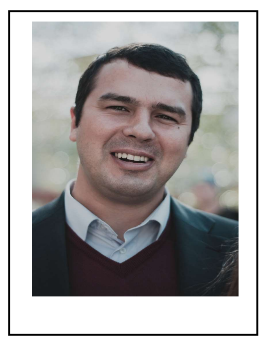

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Field of research: mathematical modelling, intelligent control systems, human-machine interfaces, quantum and soft computing.