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Industrial robotic intelligent robust control system: applying quantum soft computing technologies and quantum software engineering in unpredicted control situations

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Abstract. The strategy for designing intelligent control systems based on quantum and soft computing technologies is described. The synergetic effect of quantum self-organization of a robust knowledge base, extracted from imperfect knowledge bases of an intelligent fuzzy controller, is presented. The developed technology improves the reliability of intelligent cognitive control systems in unforeseen control situations, for example, with various types of interacting robots.

Benchmarks demonstrated the effective implementation of a quantum fuzzy inference circuit as a ready-made programmable algorithmic solution for lower-level control systems embedded in a standard board, demonstrated the quantum superiority of quantum intelligent control of classical control objects, expanding the Feynman-Manin thesis.

The correct physical interpretation of the process of controlling self-organization at the quantum level is discussed on the basis of quantum information-thermodynamic models of exchange and extraction of quantum (hidden) valuable information from/between classical particle trajectories in the "swarm of interacting particles" model. A new information synergetic effect is demonstrated: a robust knowledge base of a quantum fuzzy controller is created in real time from two unreliable knowledge bases of a fuzzy controller. This effect is purely quantum in nature and uses hidden quantum information extracted from classical states. The main physical and information-thermodynamic aspects of the model of quantum intelligent control of classical control objects are discussed.

Keywords*: quantum fuzzy inference, intelligent control in unpredicted situations, robustness, quantum algorithms, industrial robot.*

One of the intelligent control system application areas is the development of autonomous robots that are able to operate under conditions of information uncertainty and unpredicted control situations. Application area of robots ranging from household and business sectors to solutions of specific problems of military-industrial complexes and aerospace is mainly associated with monotonous or dangerous work. In 2011 during the accident at the Fukushima nuclear power plant, specialists used mobile robots on tracks with established U.S. company iRobot manipulators and also Monirobot machines designed by Japan's Nuclear Safety Technology Center in 1999 after an accident at the Tokaimura (The background of intelligent control system for the deactivation/decontamination of nuclei power plant was described in [1]) nuclear plant.

The principal feature in the construction of a multilink robotic manipulator is modularity which provides adaptability and reconfigurability of a dynamic structure in accordance with the problem to be solved.

Specialists has been considering the possibility of unstable industrial robots' control for a long time. But practical importance of controlling such objects has appeared relatively recent. The fact is that unstable *control objects* (CO) have many useful qualities (e.g. high-speed performance). It is possible if these objects are properly controlled. However, in a case of control failure, an unstable object can become a significant threat. In such situations, it is possible to apply the computational intelligence technologies, such as soft computing (including neural networks, genetic algorithms, fuzzy logic, etc.). The advantage of an intelligent control system is a capability to achieve a control goal if information about CO functionality is incomplete. The basis of any *intelligent control system* (ICS) is a *knowledge base* (KB) (including parameters of membership functions and set of fuzzy rules), therefore the main problem of designing

ICS is design of optimal robust KB, which guarantee high control quality in any complex dynamic systems provided there are the abovementioned control difficulties.

Development of a *fuzzy controller* (FC) is one of the most perspective areas of fuzzy systems. For CO developers, fuzzy systems are so attractive because of the fact that they are universal “approximator” systems with poorly known dynamics and structure. In addition, they allow controlling a dynamic object without expert. It should be noted that sometimes involving knowledge experts to create an ICS KB can contribute to achieving control goals. Even an experienced expert has difficulties to find an optimal KB of FC in situations of controlling nonlinear CO with stochastic noises (Optimal KB is a base with an optimal parameter of membership functions and a set of rules according to the approximation with required accuracy of an optimal control signal).

This work describes developing an intelligent control system for 1) a stroboscopic robot (with partially unstable generalized coordinates), 2) redundant planar manipulator with three *degrees of freedom* (DoF) and 3) an autonomous (globally unstable) dynamic mobile robot. Configuration redundancy provides many solutions for a dynamic inverse problem that allows operating CO in a hazard environment.

Design technology knowledge bases on soft computing

Application of fuzzy neural networks cannot guarantee achieving the required accuracy of approximation of a *teaching signal* (TS) received by a *genetic algorithm* (GA). As a result, an essential change in external conditions leads to losing accuracy of achieving the control goal. However, a new developed tool called *Soft Computing Optimizer* (SCO) can solve this problem [2]. It is possible to design a robust KB for controlling complex dynamic CO using the SCO design technology and previously received TS that describe the specific situation of control. The benchmarks of various CO and control systems based on this approach can be found in [3].

The designed (in the general form for random conditions) robust FC for a dynamic CO based on the KB optimizer with the application of a soft computing technology (stage 1 of the *information design technology* – IDT) can operate efficiently only for fixed (or weakly varying) descriptions of the external environment. This due to possible loss of the robustness property under a sharp change in the CO functioning conditions: CO internal structure, control actions (reference signal), a time delay in the measurement and control channels, under the change in conditions of functioning in the external environment, and the introduction of other weakly formalized factors in the control strategy. To control a dynamical object in different situations it is necessary to consider all of them, i.e. to design the required number of KB, the use of which will help to achieve the required robustness control level.

Nevertheless, how is it possible to determine what KB to apply in the current time?

A particular solution of a given problem is due to introducing a generalization of strategies in fuzzy inference models on a FC finite set designed in advance in the form of new *quantum fuzzy inference* (QFI) [2, 3].

ICS model based on QFI

With regard to computer science, the QA structure of QFI model (as a particular case of the general quantum control algorithm of self-organization) must include the following necessary QA features: preparing a superposition; selecting quantum correlation types; applying a quantum oracle (black box model) and transporting extracted information (dynamic evolution of an “intelligent control state” with minimum entropy); a quantum correlation over a classical correlation as a computing power source; applying an interference operator for answer extraction; quantum parallel massive computation; amplitude amplification of a searching solution; effective quantum solving of classical algorithmically intractable (unsolved) problems.

In this section, we will show that we can use ideas of mathematical formalism of quantum mechanics to discover new quantum control algorithms that classical computers can effectively simulate.

We will use a CO mathematical model described in MATLAB/Simulink. The kernel of the abovementioned FC design tools is a so-called SCO – SCOptKB™ that implements advanced soft computing ideas.

The QFI quantum algorithm implements the following actions [3]:

– the fuzzy inference results are processed for each independent FC;

– valuable quantum information hidden in independent (individual) KBs is extracted based on the methods of quantum information theory;

– in on-line mode, the generalized output robust control signal is designed in all KB sets of FC;

– in this case, the QFI output signal in the on-line mode is an optimal control signal of the PID controller varying gains, which involves the necessary (best) qualitative characteristics of the output control signals of each FC, thus implementing the self-organization principle.

Therefore, the domain of ICS structure efficient functioning can be essentially extended by including robustness, which is a very important characteristic of control quality. The control signal robustness is the background for maintaining the control reliability and accuracy under information uncertainty or a weakly formalized description of functioning conditions and/or control goals.

The QFI model based on physical laws of quantum information theory uses unitary invertible (quantum) operators for computing with the following names: superposition, quantum correlation (entangled operators), and interference. The fourth operator, measurement of result quantum computation is irreversible.

In the general form, the quantum computing model comprises the following five stages:

– preparation of the initial (classical or quantum) state $|\Psi_{out}\rangle$;

– execution of the Hadamard transform for the initial state in order to prepare the superposition state;

– application of the entangled operator or the quantum correlation operator (quantum oracle) to the superposition state;

– application of the interference operator;

– application of the measurement operator to the result of quantum computing $|\Psi_{out}\rangle$.

Fig. 1 shows the QFI functional structure.

This QFI model solves the problem of robust control of essentially nonlinear unstable CO in unpredicted control situations by extracting additional information from designed individual KB FC that are created for different control situations based on different optimization criteria.

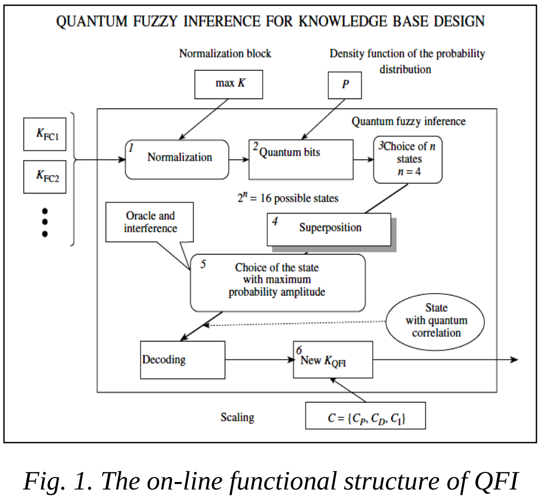


Fig. 1. The on-line functional structure of QFI

Thus, the quantum algorithm in the QFI model is a physical prototype of production rules, implements a virtual robust knowledge base for a fuzzy PID controller in software (for the current unpredicted control situation), and is a problem-independent toolkit. Fig. 2 shows an intelligent robust control system of essentially nonlinear CO.

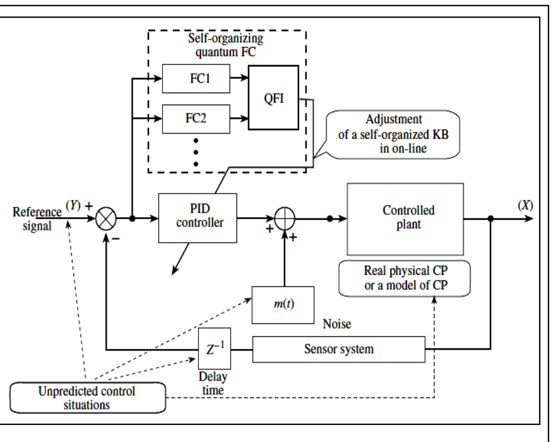


Fig. 2. A schematic diagram of a self-organizing ICS in unpredicted control situations

The next stage of this work will describe a benchmark using the developed ICS design technology.

Control object simulation with partial unstable general coordinates

A control object model. We have chosen the stroboscope robotic manipulator model as the modified Benchmark of the “Swing” dynamic system. A dynamic peculiarity of this system is the following: one generalized coordinate is locally unstable (angle) and another coordinate is globally unstable (length).

The model of a swing dynamic system (as a dynamic system with globally and locally unstable behavior) is shown in Fig. 3.

Swing dynamic system behavior (as an essentially non-linear dynamic system) under control is described by second-order differential equations for calculating the force to be used for moving a pendulum:

$$\begin{aligned} &\ddot{x} + \left(2\frac{\dot{y}}{y} + \frac{c}{my^2}\right)\dot{x} + \frac{g}{y}\sin x = u_1 + \xi_1(t), \\ &\ddot{y} + 2k\dot{y} - y\dot{x}^2 - g\cos x = \frac{1}{m}(u_2 + \xi_2(t)). \end{aligned} \tag{1}$$

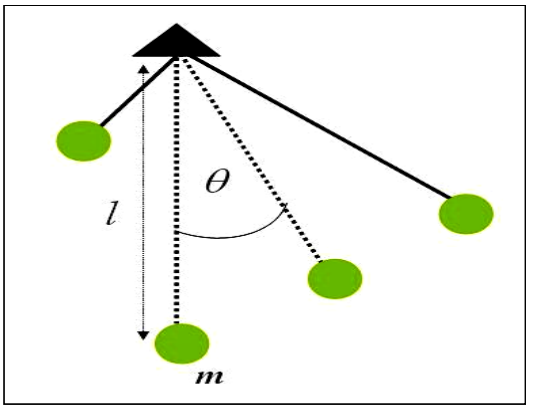


Fig. 3. A swing dynamic system

The equations of the entropy production rate are the following:

$$\frac{dS_\theta}{dt} = \left(2\frac{\dot{l}}{l} + \frac{c}{ml^2}\right)\dot{\theta}\cdot\dot{\theta};\quad \frac{dS_l}{dt} = 2k\,\dot{l}\cdot\dot{l}. \qquad (2)$$

A swing motion described by Eqs (1), (2) shows that a swing system is global unstable along the generalized coordinate l and local unstable along the generalized coordinate θ. In addition, model (1) has nonlinear essentially nonlinear cross links affecting the local unstable by the generalized coordinate x. In Eqs (1), (2) x and y are generalized coordinates; g is the acceleration of gravity, m is a pendulum weight, l is a pendulum length, k is elastic force, c is a friction coefficient, $\xi(t)$ is external stochastic noise, u_1 and u_2 are control forces.

Dynamic behavior of the swing system (free motion and PID control) is demonstrated in Fig. 4.

A control problem: to design a smart control system to move the swing system to the given angle (reference x) with the given length (reference y) in the presence of stochastic external noises and a bound limitation on control force.

A swing system can be considered as a simple prototype of a hybrid system consisting of a few controllers with the problem of organizing a coordination process between controllers (a coordination control problem).

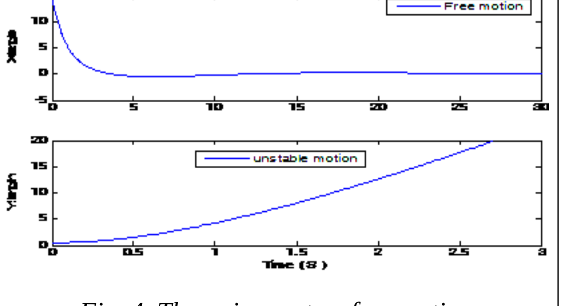


Fig. 4. The swing system free motion

A control task: to design robust KB for fuzzy PID controllers capable to work in unpredicted control situations.

Let us consider the excited motion of the given dynamic system under two fuzzy PID-controllers and design two KBs for making a teaching situation:

Noise x: Gaussian (max amplitude = 1);
Noise y: Gaussian (max amplitude = 2);
Sensor's delay time_x = 0.001 s;
Sensor's delay time_y = 0.001 s;
Reference signal_x = 0;
Reference signal_y = 2;
Model parameters = $(k\ m\ c)$ = (0.4 0.5 2);
Control force boundaries: $|U_x| \le 10(N)$, $|U_y| \le 10(N)$.

We investigate robustness of three types of spatial, temporal and spatiotemporal QFI correlations and choose the best type of QFI for the given CO and given teaching conditions.

Figs 5 and 6 show the comparison of the control performance of three *quantum fuzzy controllers* (QFC) based on three types of QFI (spatial, temporal and spatiotemporal QFI correlations) for the teaching situation.

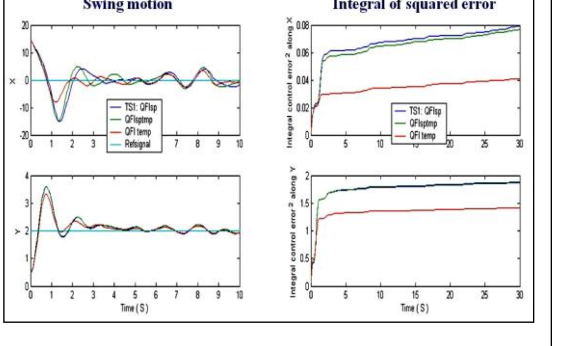


Fig. 5. A comparison of three quantum correlation types

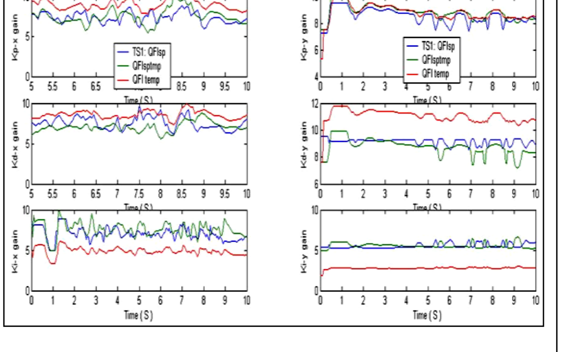


Fig. 6. A comparison of control laws

A temporal QFI is better in terms of a minimum control error criterion. We choose a temporal QFI for further investigations of QFI process robustness property using modelled unpredicted control situations.

Let us consider a comparison of dynamic and thermodynamic behavior of our CO under different types of control: FC1, FC2, and QFC (temporal).

A comparison of FC1, FC2 and QFC performances is shown in Figs 7 and 8.

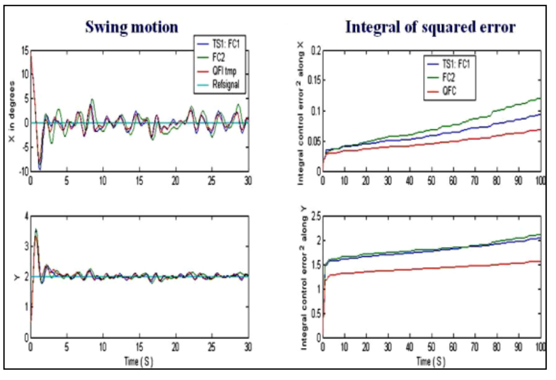


Fig. 7. A swing motion and integral control error comparison in TS situation

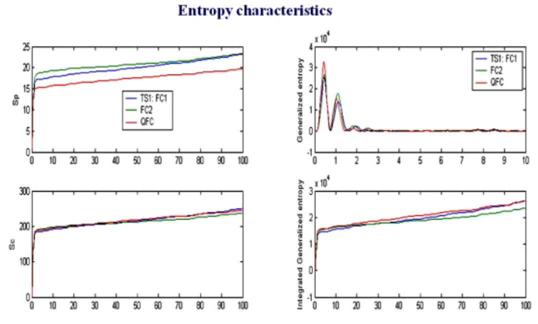


Fig. 8. A comparison of entropy production in a control object (Sp) and in controllers (left) and a comparison of generalized entropy production (right)

According to the minimum control error criterion under a teaching condition, QFC has better performance than FC1, FC2.

Now we consider the behavior of our CO in unpredicted control situations and investigate the robustness property of designed controllers (Table 1).

The unpredicted situation 1. Comparison of FC1, FC2 and QFC performances in the situation 1 (Figs 9–11).

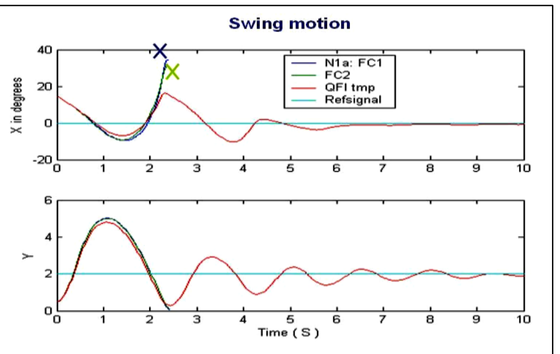


Fig. 9. A swing motion and integral control error comparison in the unpredicted control situation 1

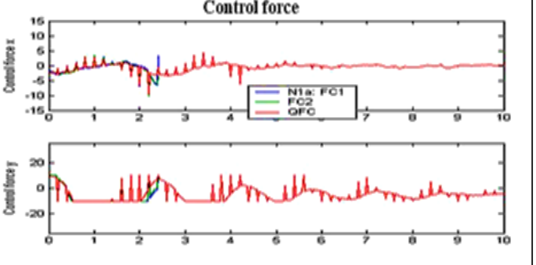


Fig. 10. Control forces comparison in the unpredicted control situation 1

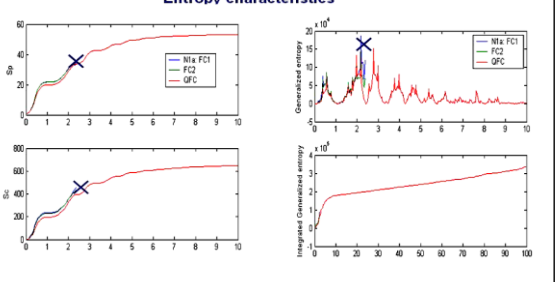


Fig. 11. Comparison of entropy production in control object (Sp) and in controllers (left) and comparison of generalized entropy production (right) in unpredicted control situation 1

Table 1

Unpredicted control situations

Unpredicted situation 1	Unpredicted situation 2
Noise x: Gaussian (max amplitude = 1)	Noise x: Rayleigh (max amplitude = 1)
Noise y: Gaussian (max amplitude = 2)	Noise y: Rayleigh (max amplitude = 2)
Sensor's delay time_x = 0.008 s	Sensor's delay time_x = 0.001 s
Sensor's delay time_y = 0.008 s	Sensor's delay time_y = 0.001 s
Reference signal_x = 0; Reference signal_y = 2	Reference signal_x = 0; Reference signal_y = 2
Model parameters = (k m c) = (0.4 0.5 2)	Model parameters = (k m c) = (0.4 0.5 2)
Control force boundaries: $|U_x| \le 10(N)$, $|U_y| \le 10(N)$	Control force boundaries: $|U_x| \le 10(N)$, $|U_y| \le 10(N)$

FC1 and FC2 controllers failed in the situation 1; QFC is robust.

The unpredicted situation 2. A comparison of FC1, FC2 and QFC performances in the situation 2 (Figs 12–14).

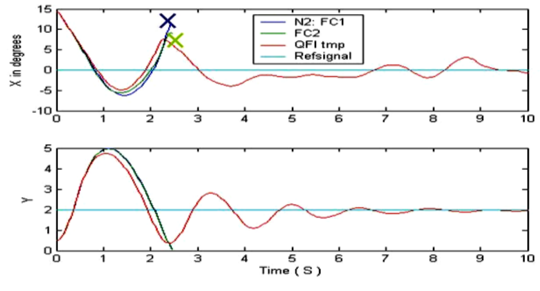


Fig. 12. A swing motion and integral control error comparison in the unpredicted control situation 2

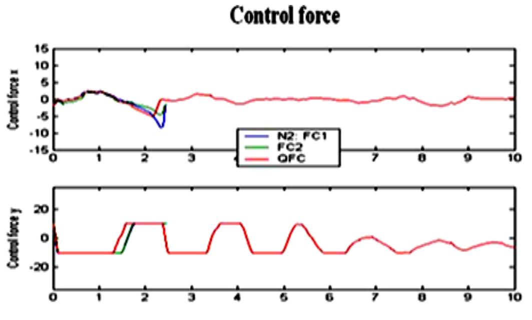


Fig. 13. Control forces comparison in the unpredicted control situation 2

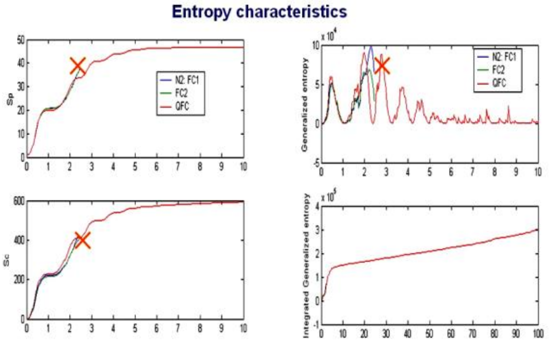


Fig. 14. A comparison of entropy production in a control object (Sp) and in controllers (left) and a comparison of generalized entropy production (right) in the unpredicted control situation 2

FC1 and FC2 controllers failed in the situation 2. QFC is robust.

A general comparison of control quality of designed controllers. Now we consider a general comparison of control quality of four designed controllers (FC1, FC2, QFC based on temporal QFI with 2 KB). We will use two types of the control quality criteria: a dynamic behavior performance level and a control performance level.

A control quality comparison is shown below in Figs 15, 16. Here we have as results:

– QFC is robust in all situations;

– FC1 controller is not robust in 2, 3 situations;

– FC2 controller is not robust in 2, 3 situations.

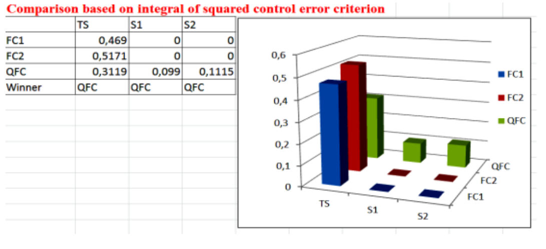
Thus, ICS with QFI based on two KB and a temporal correlation type have the highest robustness level (among designed controllers) and show the highest self-organization degree.

The simulation results lead to an unexpected (for the classical logic and the ICS design methodology) conclusion: we can get robust FC online from two not robust (in unpredictable situation) controllers (FC1 and FC2) using QFI.

Let us consider ICS for 3 DoF redundant planar manipulator developed by sequential increasing of intelligence. Configuration redundancy provides many solutions of the inverse dynamic problem that allows operating the CO in a changing environment.

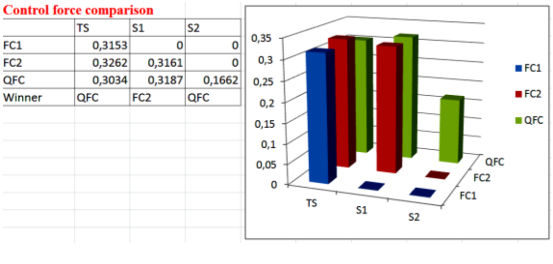
A three-degree-of-freedom manipulator

A behavior manipulator is a mechanism that performs motor functions similar to the movement of a human hand. However, a human hand has 27 DoF, while the majority of manipulators have a limit in 3–6 DoF, which are sufficient for a number of practical applications.



	TS	S1	S2
FC1	0,469	0	0
FC2	0,5171	0	0
QFC	0,3119	0,099	0,1115
Winner	QFC	QFC	QFC

Fig. 15. A comparison based on an integral of squared control error criterion



	TS	S1	S2
FC1	0,3153	0	0
FC2	0,3262	0,3161	0
QFC	0,3034	0,3187	0,1662
Winner	QFC	FC2	QFC

Fig. 16. A comparison based on simplicity of control force

In this work, a redundant 3 DoF planar manipulator acts as CO.

Figure 17 shows a CO scheme, where q_1, q_2 and q_3 are positions of manipulator links (the index indicates the number of links from the base of the manipulator), (p_x, p_y) are coordinates of manipulator capture device corresponding to the axes (X, Y).

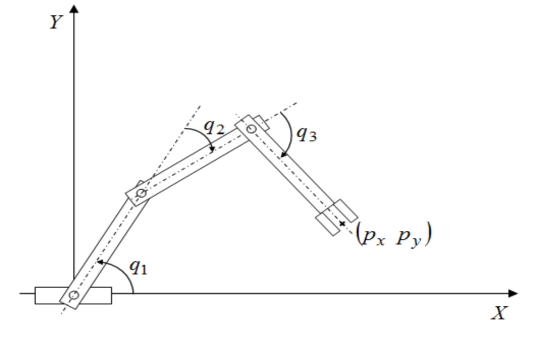


Fig. 17. Three degrees of a freedom manipulator

The task of the robot arm with three degrees of freedom is to position a capture device at a given point (p_x , p_y) by setting the position of the robot arm links using angles q_1, q_2 and q_3 at a given level. The equation relating to the position of the links and the capture device point is described as following:

$$\begin{cases} p_x = l_1 \cos(q_1) + l_2 \cos(q_1 + q_2) + \\ \quad + l_3 \cos(q_1 + q_2 + q_3), \\ p_y = l_1 \sin(q_1) + l_2 \sin(q_1 + q_2) + \\ \quad + l_3 \sin(q_1 + q_2 + q_3). \end{cases} \tag{3}$$

Since a reference signal of the model is the value of the positions of the manipulator links – q_1, q_2 and q_3, in [3] the author has introduced a method of calculating these positions under known Cartesian space coordinates (p_x , p_y), i.e. the solution method for the inverse dynamics problem of 3 DoF redundant manipulator.

A manipulator mathematical model is developed using n DoF manipulator dynamic equations [4]. The example of a simplified 3 DoF redundant manipulator mathematical model was considered in [5]. Earlier in [3], there was a description of MATLAB-simulation based on GA of ICS for redundant robot manipulator.

After preliminary research, the models of ICS 3 DoF manipulator module was designed (Fig. 18).

Developing CO takes into account the limitations on the ICS module models for the real world. These models (with their software and hardware implementation) are discussed further in this paper.

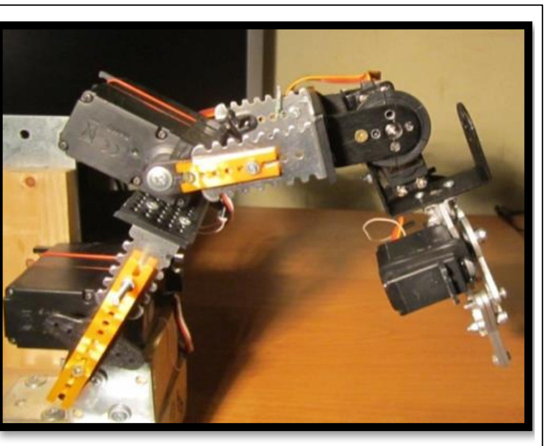


Fig. 18. A three DoF manipulator module

The aim of this work is to design ICS for a robot manipulator, which allows guaranteed control in unexpected (unpredicted/hazard) situations online due to applying the proposed quantum control algorithms. Despite its importance, the development of the design algorithm of robust ICS that can operate efficiently at risk is a complex and poorly studied area.

Earlier this objective was achieved by expert systems. Soft computing technologies are applied to eliminate the knowledge subjectivity [2]. They are the basis of computational intelligent tools named SCO of knowledge bases [3].

1. *The development of the ICS model based on SCO of KB* for a 3 DoF redundant planar manipulator. The basis for a soft computing technology is fuzzy logic, which does not use the law of the excluded middle. Introducing a subjective qualitative scale into the theory of fuzzy systems and displaying it in the form of a linguistic approximation of quantitative characteristics causes some logical difficulties, such as: the objective determination of the kind of a membership function and its parameters in the production rules of KB, the definition of the FNN optimal structure at training tasks, the use of GA in multi-objective control, etc. SCO of KBs have tried and resolved the above problems [3]. Computational intelligent design tools allow designing robust KB based on solving one of the algorithmically intractable problems of the artificial intelligence theory – extracting, processing and forming objective knowledge without applying expert estimations.

The main element of intelligent improvement of ICS based on SCO is FC, which adjusts PID gains depending on current conditions online.

Figure 19 demonstrates a schematic structure of ICS based on SCO.

KB – design process has described in [2].

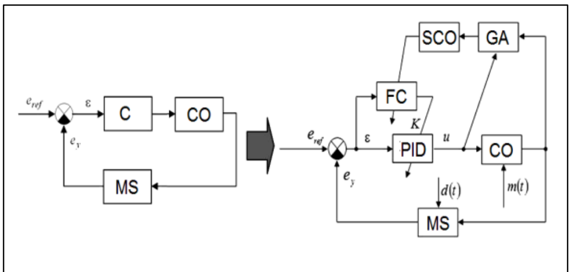


Fig. 19. The transition to ICS based on SCO of KBs

A group of ten test points was selected to test the developed ICS robustness in the manipulator workspace (Fig. 20).

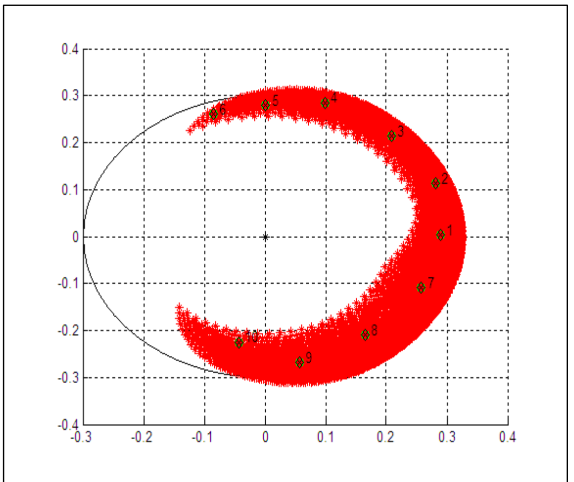


Fig. 20. Test space

Let us consider the following unpredicted control situations:

Situation 1. At the moment 0,2 the second position of link 2 forcedly changes to the value q_2 = 67 deg.

Situation 2. For ICS based on GA let us change the initial condition: q_1 = 60 deg, q_2 = 57 deg, q_3 = –43 deg.

The following criteria evaluate ICS behavior performance:

– the percentage of solving positioning tasks for a manipulator capture device (a problem is considered solved if each of the three links is positioned with zero error within the allowed time frame);

– the elapsed time to solve the positioning problem (limit – 10 s; if the problem is not solved for given time, then the positioning time is specified with a minimum error).

An upward manipulator position (q_1 = 60 deg; q_2 = 0 deg; q_3 = 0 deg) is taken as the initial condition. For demonstration ICS based on SCO performance the following KB of FC was created:

– GA model for creating a training signal and three GA of SCO were described in [6];

– sugeno 0 fuzzy inference model;

– fuzzy AND operation is simulated as a product operator;

– the number of input variables is 9;

– the number of output variables is 9;

– the optimization technique is an error backpropagation algorithm.

Testing results of the developed ICS based on SCO are represented in Tables 2 and 3.

Table 2

Experimental results of ICS based on SCO for points 1–5

Positioning error and task		**Points of test space**				
		1	**2**	**3**	**4**	**5**
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		0,26	0,28	0,32	0,24	0,42

Table 3

Experimental results of ICS based on SCO for points 6–10

Positioning error and task		**Points of test space**				
		6	**7**	**8**	**9**	**10**
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		0,34	0,36	0,4	0,6	0,64
Solution of positioning task (Table 7)		100 %				

Based on the testing results it may be deduced that ICS based on SCO copes with the positioning task with given accuracy in all ten experiments. Moreover, if for ICS based on GA the average positioning task solution time is 5,082 s, then for ICS based on SCO this characteristic is 0,386 s. That is, the average positioning task solution time under ICS based on SCO is reduced by 13,17 times.

Let us consider the behavior of ICS based on SCO in the uncertain situations introduced above.

Figs 21 and 22 illustrate the results of forced changing of the link 2 position (Situation 1) for the test point 1. Therefore it can be seen that the positioning task has been solved in 0,88 s (the maximum time is 10 s).

Let us change the initial condition for the test point 10 (Situation 2).

Figs 23 and 24 show that the positioning task was solved in 0,76 s.

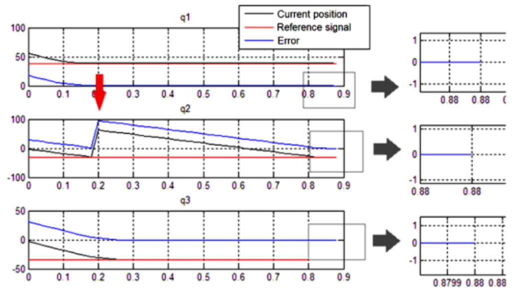
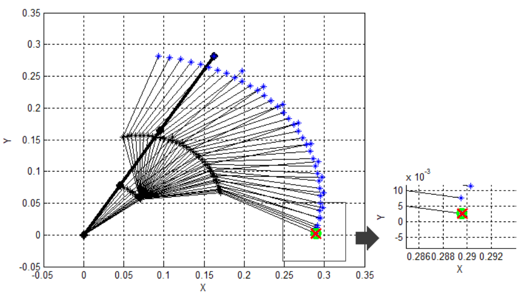


Fig. 21. External influence reaction of ICS based on SCO



Fig, 22. Manipulator behavior motion trajectory

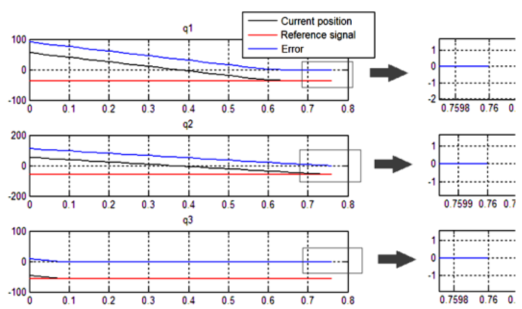


Fig. 23. Perturbation of initial condition changing

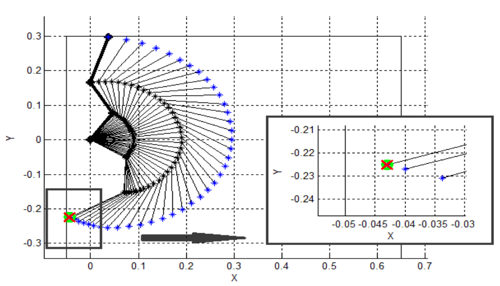


Fig. 24. A manipulator behavior motion trajectory

Obviously, in uncertain situations the positing time of a manipulator capture device for ICS based on SCO increases (by 3,38 times for Situation 1 and by 1,19 times for Situation 2), but its value does not exceed 0,9 s while for ICS based on GA the positioning task is not solved even during allotted time (10 s).

Therefore, ICS based on SCO versus ICS based on GA besides reducing positioning time at known control situations on the average 13, 17 times also ensures sustainable management in unforeseen situations by dynamical adjusting the control parameters.

Fig. 25 depicts PID gains dynamics obtained online for the last control example.

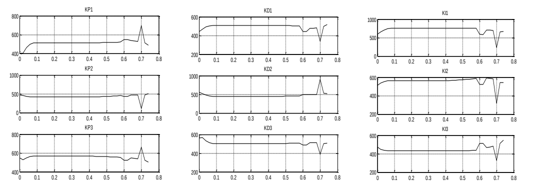


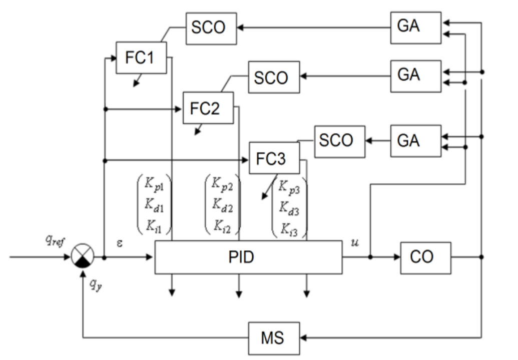
Fig. 25. PID gains

Remark. The PID controller is often implementted in software, and the control problem is reduced to finding the PID controller coefficients K_P, K_I, K_D, which provide the desired motion state. The considered CO (a 3 DoF planar manipulator) requires the control action vector $u = [u_1\ u_2\ u_3]$ with the dimension equal to the number of DoF. When we select PID as a regulator to identify each component of the vector u, we need three terms. Thus, it is necessary to determine nine coefficients of the PID controller to control the 3 DoF manipulator. We assume that the range of coefficients is determined by the interval $K = [0 \dots 1000]$ with up to 1 accuracy. Then the number of possible sets of PID controller coefficients is 1001^{3*n}, where n is the number of degrees of freedom of a manipulator. For the case with the 3 DoF manipulator there are 1009036084126126084036009001 variants. Using a GA [6] with the size of the initial population of 200 individuals allows finding the solution that is close to the optimum in less than 20 iterations. However, when we need to increase the number of DoF, each degree will increase the dimensionality of the search space up to three that will lead to an increasing time of the search algorithm execution. Thus, it may lead to the fact that the PC resources are not enough.

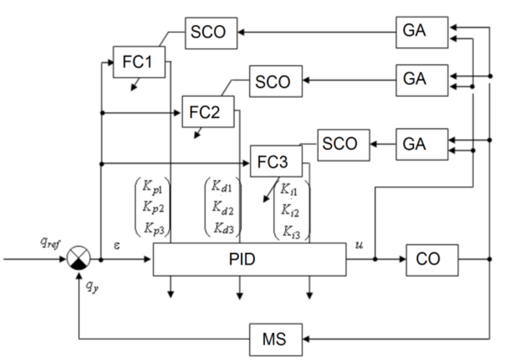
To reduce the dimensionality of the search space of control parameters of the 3 DoF manipulator, we have developed the control structure with split control based on three FC and KB obtained by the tools named SCO.

2. *Structures with split control.* A logical solution of the problem of controlling the 3 DoF manipulator would be to create the structure of an

ICS with three FC. Depending on the control type, the structures can be divided into control systems for individual links (ICS structures for three links, Fig. 26a), and the control structures by error types (ICS structures for proportional, integral and differential coefficients, Fig. 26b).



a) for three links



b) for proportional, integral and differential coefficients

Fig. 26. ICS structures

Depending on the method of obtaining KB for FC, it is possible to distinguish parallel and cascade structures of ICS based on SCO.

ICS parallel structures perform independent control of FC. Obtaining KB for FC includes several stages:

– obtaining parameters 1–3 (three outputs of the first FC): parameters 4–9 are assumed constant;

– obtaining parameters 4–6 (three outputs of the second FC): parameters 1–3, 7–9 are assumed constant;

– obtaining parameters 7–9 (three outputs of the third FC): parameters 1–6 are assumed constant.

Thus, obtaining KB for each of the three FC is independent. Parallel structures are simple to implement and, importantly, the need to change KB of the one of FCs does not require changes in other KBs.

Cascade structures of ICS based on SCO perform sequentially guided fuzzy control. Obtaining KB for FC includes several stages:

– obtaining parameters 1–3 (three outputs of the first FC): parameters 4–9 are assumed constant;

– obtaining parameters 4–6 (three outputs of the second FC): parameters 7–9 are assumed constant, parameters 1–3 are generated by the first FC with KB get on the previous step;

– obtaining parameters 7–9 (three outputs of the third FC): parameters 1–6 are generated by the first and the second FCs with KBs get on the previous steps.

In the cascade structures, each subsequent generated KB accounts previously obtained KBs. However, the need to change the KB of one of FC will require changes in the previous KBs. In addition, the procedure for determining the parameters plays an important role.

As an example, let us consider the parallel ICS structure for three links based on SCO since it is simpler to implement and optimize.

3. ***Developing the ICS model*** based on SCO with split control. In order to check the robustness of ICS model with split control on the example of the proposed parallel ICS structure based on SCO for three links we selected ten test points from the manipulator workspace.

ICS behavior performance is evaluated by the following criteria:

– the percentage of the solution of positioning tasks for a manipulator capture device (a problem is considered solved if each of the three links is positioned with zero error within the allowed time frame);

– allowed time to solve the positioning problem (the limit is 10 s if the problem is not solved in the given time, then the positioning time is specified with a minimum error).

The initial condition is the following position: q_1 = 60 deg, q_2 = 0 deg, q_3 = 0 deg.

The results of ICS based on SCO for three links performance are shown in Tables 4 and 5.

Table 4

Experimental results of ICS based on SCO with split control for points 1–5

Positioning error and task		**Points of test space**				
		1	**2**	**3**	**4**	**5**
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		6,66	0,28	1,04	0,52	0,44

Table 5

Experimental results of ICS based on SCO with split control for points 6–10

Positioning error and task		Points of test space				
		6	7	8	9	10
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		0,36	8,44	0,38	0,58	0,64
Solution of a position task (See Table 1)		100 %				

It follows from Tables 4 and 5 that ICS based on SCO with split control solves the positioning task for all considered points. The average time of the positioning task solution is 1,934 s.

Continuing the research on ICS based on SCO with split control, let us consider a few unpredicted control situations.

Situation 1. At the moment 0,2 s the position of link 2 forcedly changes to the value q_2 = 67 deg (Fig. 27).

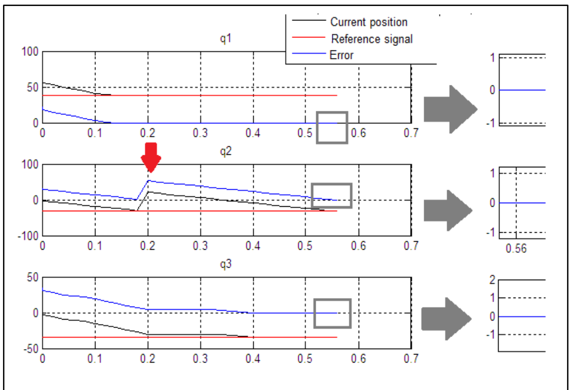


Fig. 27. External influence and its perturbation

The result of this action (Fig. 27 based on an example of test point 1) is that solving the positioning task takes 0,56 s. It should be noted that typically solving the positioning task takes 6,66 s (in 11,89 times slower), i.e. for this example, external influence has significantly reduced the positioning time.

Situation 2. Initial conditions are changed respectively: q_1 = 60 deg, q_2 = 57 deg, q_3 = –43 deg (earlier there were q_1 = 60 deg, q_2 = 0 deg, q_3 = 0 deg).

After the changes in the initial conditions, the positioning problem was not solved at all (Fig. 28).

Situation 3. Initial conditions changed respectively: q_1 = 60 deg, q_2 = 57 deg, q_3 = –43 deg. Furthermore, at the moment 0,2 s position of link 2 forced changes to the value q_2 = 67 deg (Fig. 29).

Such changes (Fig. 29 shows the example of the point 7 of manipulator workspace) did not solve the positioning problem.

Thus, under certain conditions, ICS based on SCO with split control is good enough to solve the positioning task of the manipulator capture device. However, Situation 2 and Situation 3 demonstrated that the proposed ICS becomes unable to perform certain tasks in unpredicted cases.

Solving the problem of CO management in unpredicted situations is possible using a strategy of improving the robustness of the designed FC by using new types of computations based on the quantum computing methodology. Implementing the property of ICS namely KB self-organization is achieved by introducing a generalization strategy in fuzzy inference models in the form of a new QFI [2].

QFI algorithm is implemented in the intelligent tool named *quantum computing optimizer* (QCO).

4. *Development of the ICS model based on QCO.* There is a generalized methodology for selecting a strategy to switch the flow of control sig-

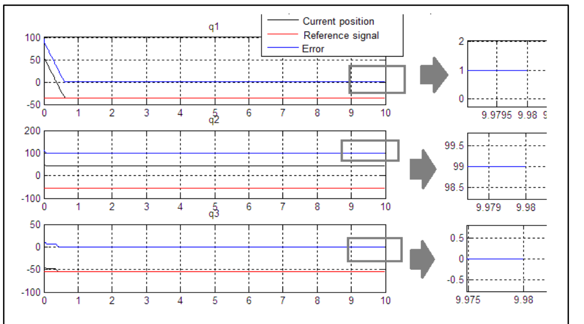


Fig. 28. The consequences of changes in the initial conditions

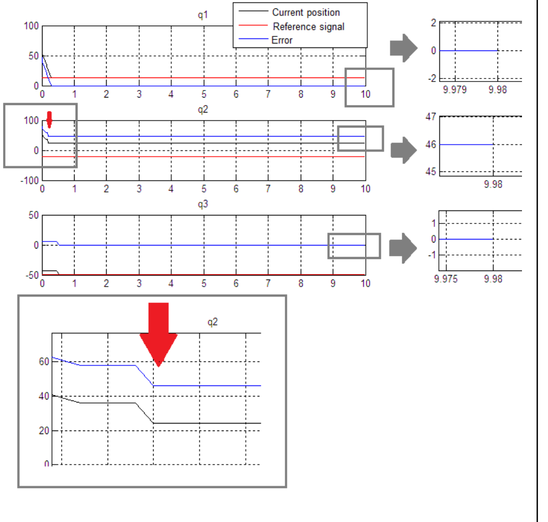


Fig. 29. The consequences of changes in the initial conditions and external influence

nals from the output of the various KBs of FC designed for different control situations [3].

This methodology is illustrated in Fig. 30: FCs for different control situations designed in the first stage are generalized by QFI methodology in the second stage. Hence, "generalized" KB guaranties the management in all control situations.

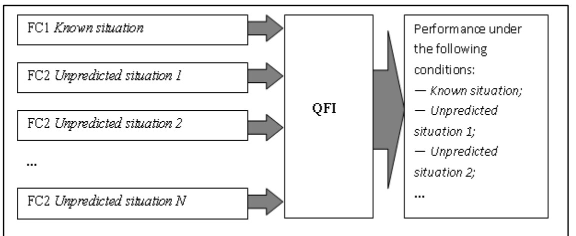


Fig. 30. A methodology of selecting a generalized strategy to switch the flow of control signals from the output of the various FC KB for different control situations

The developed QFI model is seen as a new kind of a quantum search algorithm [3, 6–16] acting on the generalized space of knowledge bases of FCs. QFI uses and implements processes of extracting hidden quantum information from the individual classical KB of FC based on physical laws of the quantum information theory and quantum computing.

When applied to the developed ICS based on QCO to control the 3 DoF manipulator, we use the following methodology: extracting hidden information from relationships of existing FCs (ICS structure with split control) for three links of a manipulator with KB obtained for known control situations (Fig. 31).

The ICS model based on QCO is designed in accordance with this methodology. Further, we consider the spatial, temporal and spatiotemporal correlation investigations [3].

The results of ICS based on QCO performance in known situations control (applying spatial, temporal and spatiotemporal correlations) are shown in Tables 6–11 correspondingly.

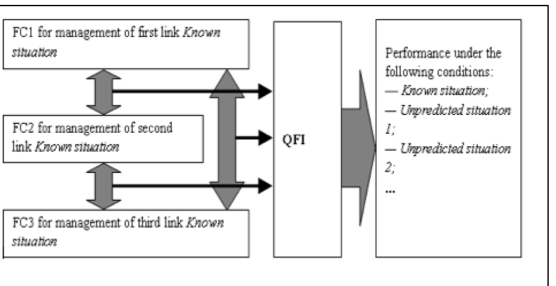


Fig. 31. The methodology of extracting hidden information from relationships between KB designed for known control situations

Table 6

Experimental results of ICS based on QCO with spatial correlation for points 1–5

Positioning error and task		**Points of test space**				
		1	**2**	**3**	**4**	**5**
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		0,26	0,28	0,34	0,26	0,44

Table 7

Experimental results of ICS based on QCO with spatial correlation for points 6–10

Positioning error and task		**Points of test space**				
		6	**7**	**8**	**9**	**10**
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		0,36	0,36	0,4	0,58	0,64
Solution of a position task (See Table 2)		100 %				

Table 8

Experimental results of ICS based on QCO with spatiotemporal correlation for points 1–5

Positioning error and task		**Points of test space**				
		1	**2**	**3**	**4**	**5**
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		0,24	0,28	0,34	0,24	0,44

Table 9

Experimental results of ICS based on QCO with a spatiotemporal correlation for points 6–10

Positioning error and task		**Points of test space**				
		6	**7**	**8**	**9**	**10**
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		0,36	0,36	0,4	0,58	0,64
Solution of a position task (See Table 4)		100 %				

Table 10

Experimental results of ICS based on QCO with a temporal correlation for points 1–5

Positioning error and task		Points of test space				
		1	2	3	4	5
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		0,24	0,28	0,34	0,24	0,44

Table 11

Experimental results of ICS based on QCO with a temporal correlation for points 6–10

Positioning error and task		Points of test space				
		6	7	8	9	10
Positioning error for a link, deg	1	0	0	0	0	0
	2	0	0	0	0	0
	3	0	0	0	0	0
Positioning task completion time, s		0,36	0,34	0,4	0,58	0,64
Solution of a position task (See Table 6)		100 %				

It follows from Tables 6–11 that in the case of ICS based on QCO in known control situations, when we select any of the three correlations, positioning tasks are solved in 100 % of cases, the average positioning time is:

– 0,392 s for spatial correlation (on average in 4,93 times faster than for ICS based on SCO with split control);

– 0,782 s for spatiotemporal correlation (on average in 2,47 times faster than for ICS based on SCO with split control);

– 0,374 s for temporal correlation (on average in 5,17 times faster than for ICS based on SCO with split control).

Let us consider the behavior of ICS based on QCO in the above considered control situations.

Situation 1: at the moment 0,2 s the position of link 2 is forcibly changed to the value q_2 = 67 deg (Fig. 32).

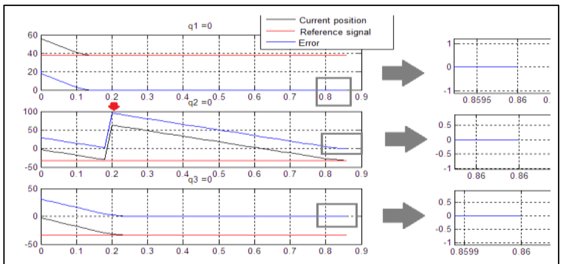
The result of this action (Fig. 32 is based on an example of the test point 1) demonstrates the positioning task solution for different correlation types in:

– 0,88 s (spatial correlation);

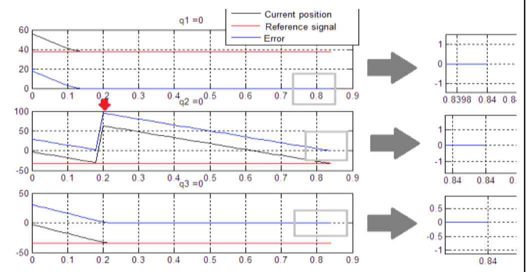
– 0,86 s (spatiotemporal);

– 0,86 s (temporal correlation).

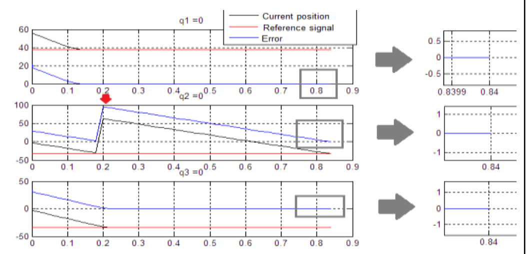
Situation 2: initial conditions are changed respectively: q_1 = 60 deg, q_2 = 57 deg, q_3 = –43 deg (earlier in a known situation there were q_1 = 60 deg, q_2 = 0 deg, q_3 = 0 deg) (Fig. 33).



a) spatial correlation



b) spatiotemporal correlation



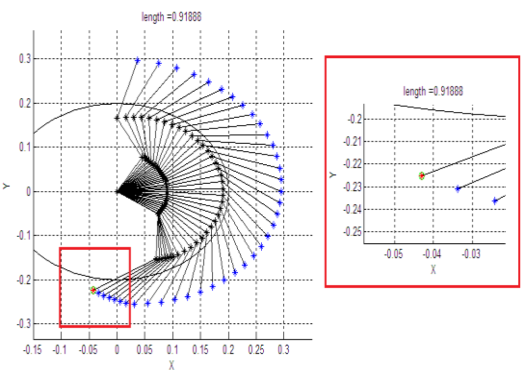
c) temporal correlation

Fig. 32. External influence and its perturbation

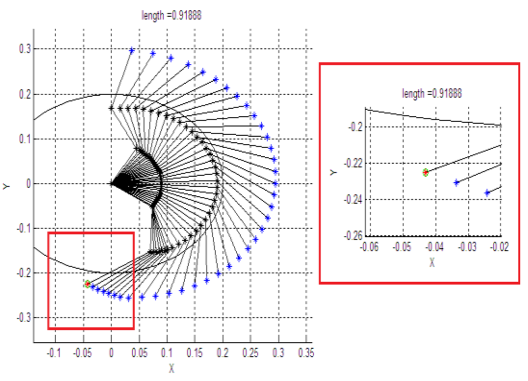
The result of this action (Fig. 33 is based on an example of the test point 10) is that the positioning task is not solved only for QFI based on temporal correlation.

Situation 3: initial conditions are changed respectively: q_1 = 60 deg, q_2 = 57 deg, q_3 = –43 deg. Furthermore, at the moment 0,2 s the position of the link 2 is forcibly changed to the value q_2 = 67 deg (Fig. 34). The result of this action (Fig. 34 is based on the example of the test point 7) is that the positioning task is not solved for QFI based on temporal and spatiotemporal correlations. Thus, in known situations ICS based on QCO provides the successful solution of the positioning task and allows reducing the transition time in 2,47 times (minimum).

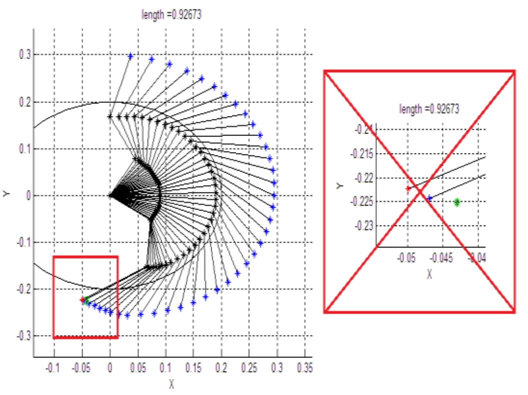
With proper selection of a correlation type, ICS based on QCO provides a guaranteed control in unpredicted control situations (for considered Situation 1, Situation 2 and Situation 3 we used spatial correlation).



a) spatial correlation



b) spatiotemporal correlation



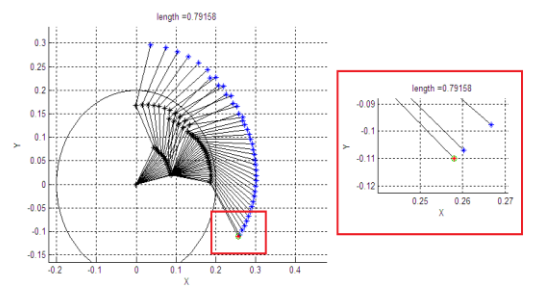
c) temporal correlation

Fig. 33. The consequences of changes in the initial conditions

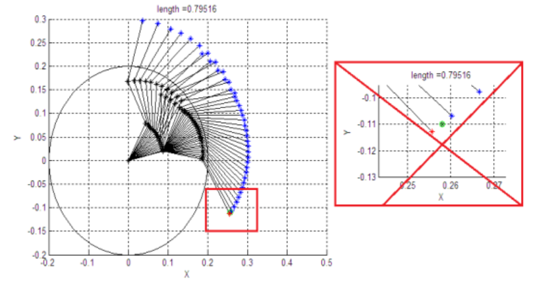
Fig. 35 shows simulation results based on SCO (Fig. 35a) and on QCO KB (Fig. 35b).

Based on the simulation result in Fig. 35 we can conclude that a FC based on QCO has better control quality performance.

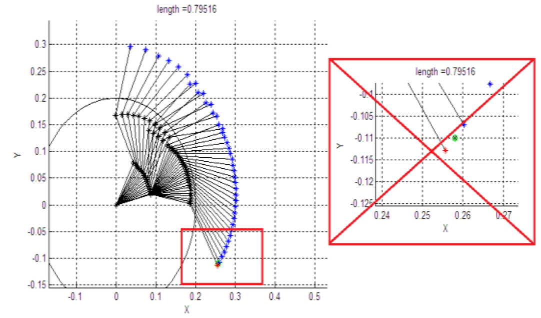
Let us consider the next Benchmark of robotic systems as "cart-pole" based on the quantum soft computing technology.



a) spatial correlation



b) spatiotemporal correlation



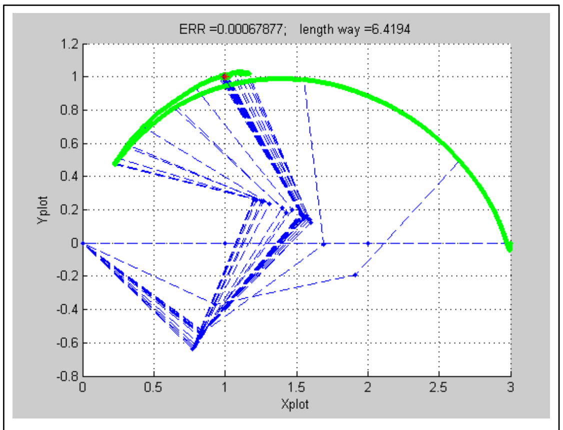
c) temporal correlation

Fig. 34. The consequences of changes in the initial conditions

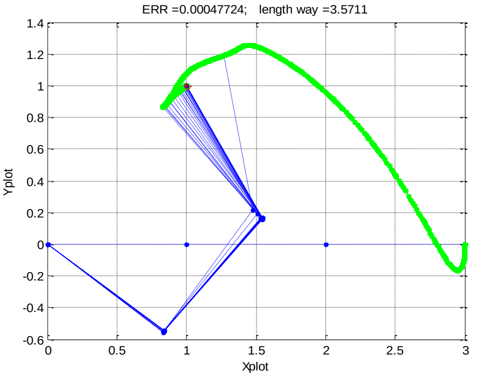
Modeling a mobile autonomous macro-robot based on the quantum soft computing technology

"Cart-pole" CO is a non-linear dissipative system. This is a typical task of the control theory, which demonstrates the control system quality. The task of control is the inverted pendulum stability in a vertical position. A solution of this task is a PID controller in a global negative back connection, but this control is ineffective and not robust. We use artificial intelligence methods for the most robust control. FC is a central element of ICS. They change P, I and D coefficients in PID controller using integration of the knowledge base.

1. ***Soft computing technology application.*** This base includes a fuzzy input and output value of a membership function in production rules.



a) SCO



b) QCO

Fig. 35. Robot manipulator simulation

The most relevant problem in intelligent control system design is obtaining an optimal and robust KB that guarantees a high level of control quality when complex dynamic systems control have all difficulties mentioned above. We use a SCO (http://www.qcoptimizer.com/) for FC design. The Soft Computing applied to ICS design represents a combination of the following approaches: the Fuzzy Systems Theory for a fuzzy control, Genetic Algorithms for global optimization of control laws, and Fuzzy Neural Networks for physical implementation of optimal control laws and for knowledge base design of FC using the extraction of necessary information by learning and adapting methods.

As a result, we have a completed base from SCO described as following: Fuzzy Inference Type – Sugeno, Membership Function (MF) – Triangle, Number of MF – [3 3 5], Number of rules – 15 from 45.

The experiments involved using a robot (laboratory (up) and experimental (down) devices) that is shown on Fig. 36.

This paper describes modeling CO behavior (pendulum with a variable length) based on QFI. The obtained simulation results show that the designed KB of FC is robust in terms of control quality criteria such as minimum error control and entropy production, as well as the minimum applied control force. The presented design technology allows achieving a control goal even in unpredicted control situations.

A verification model with GA. Verification requires the model to know its parameters. In practice, it is often impossible to identify some of them, so an expert has to select settings manually. Table 12 presents a classification of parameters, some of which has been determined accurately, but it

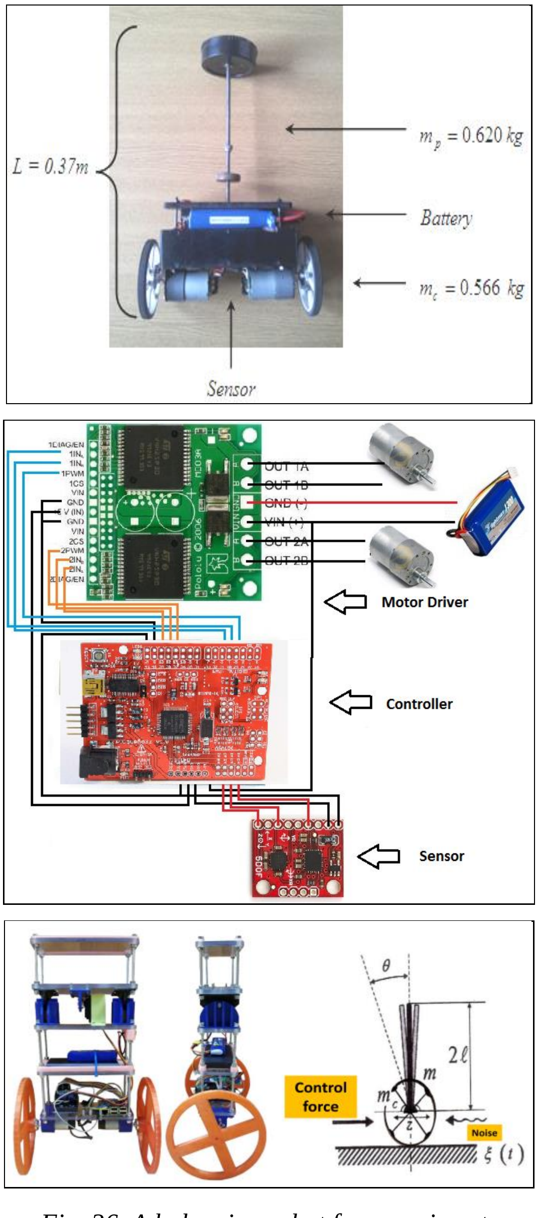


Fig. 36. A balancing robot for experiments

Table 12

Model parameters

	Chromosome
Known parameters	**Undefined parameters**
Mass of pendulum	Friction in pendulum shaft
Mass of cart	Spring force
Length of pendulum	Power gain (normalizing)
Control force boundaries	Noise of control force
Time step	Noise in sensors
PID gains	Wheel friction coefficient
Controller input and output data (2 000 points)	

was impossible to calculate a set of parameters with sufficient accuracy.

An underdetermined problem of finding parameter values can be solved by using the method described below, which is based on a GA. A GA can select model parameters so that the output data from a robot corresponds to the output values used in the MATLAB simulation. The difference between the variances of a Simulink MATLAB model and a real robot is used as a fitness function:

$$F(e,u) = 1/(1 + (\frac{(Var(e_{\text{mod}}) - Var(e_{rob})}{Var(e_{\text{mod}})})^2 + \\ + (\frac{(Var(ie_{\text{mod}}) - Var(ie_{rob})}{Var(ie_{\text{mod}})})^2 + \\ + (\frac{(Var(u_{\text{mod}}) - Var(u_{rob})}{Var(u_{\text{mod}})})^2), \quad (4)$$

where $Var(e_{mod})$ is a dispersion control error in a model, $Var(ie_{rob})$ is a dispersion control error of a robot, e is a control error, ie is an integral error, $Var(u_{mod})$ and $Var(u_{rob})$ is a dispersion of a control force model and a robot, respectively.

It is possible to achieve adequate model parameters using this fitness function. We apply GA that results in designing a new coefficient gain schedule of PID controller. After determining the gains, we test them on the robot. If the result is unsatisfactory, then we perform the same steps beginning with model verification. If the correction fails, it is recommended to change the number of undefined parameters by fixing one or more of them in a mathematical model if possible.

The verification scheme of the mathematical model is presented in Fig. 37.

The model verification result is presented in Fig. 38.

GA implementation online for creating teaching signal. The following discussion focuses on the technology of intelligent robust control systems based on quantum and soft computing. There are different ways to set controls. Typically, in the absence of a model a lot of experimentation and difficulties accompany control settings. One of the most important stages of this technology is a step of creating a teaching signal. To use our technology on real objects, it is nesessary to add tuner or adaptation blocks to the *automatic control system* (ACS). This way you can get useful information without resorting to the information of experts. The adaptation is the ability of technological devices or systems to adapt under changing environmental conditions or its internal structure, which increases the efficiency of their operations. Our design problem is to create an intelligent control system that can to cope with the changes in the external and internal conditions in operation by changing its parameters and structure in order to improve control and increase robustness.

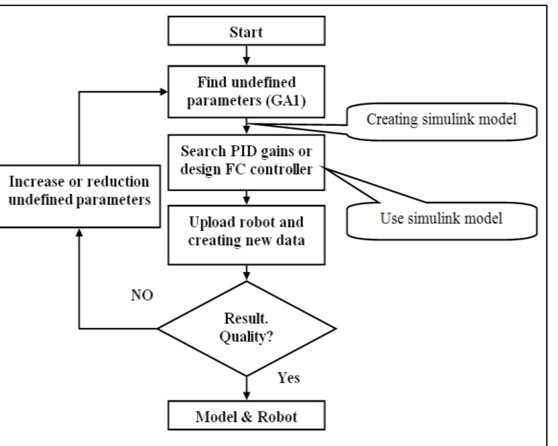


Fig. 37. A verification algorithm using GA

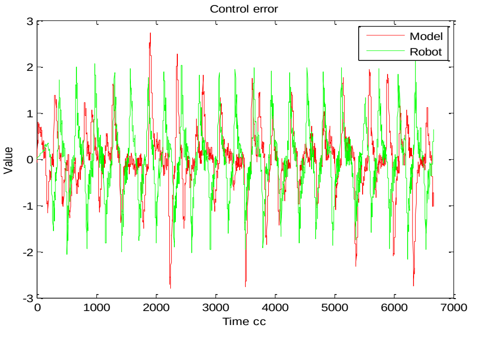


Fig. 38. A result of verification. A control error

In general, the ACS adaptation diagram is shown in Fig. 39.

To solve the control task, we have developed and implemented a control system based on GA and defining the following fitness function of chromosomes – a square integrated control error:

$$fit(P) = \frac{1}{1+(ae+b\int edt + c\dot{e})^2}, a+b+c=1, \quad (5)$$

where the coefficients a, b, c can have different weight values for each error. Each gain is valuated in a separate fitness function. In this case, larger values of the fitness function correspond to small values of control errors, hence, better quality of PID control. The range of integration is its working time for one of the solutions (each solution is the same working time). The GA scheme is shown on Fig. 40.

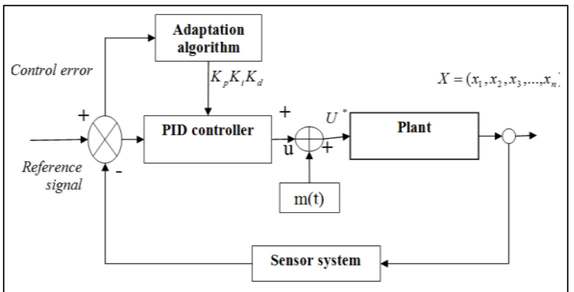


Fig. 39. ACS with adaptation block

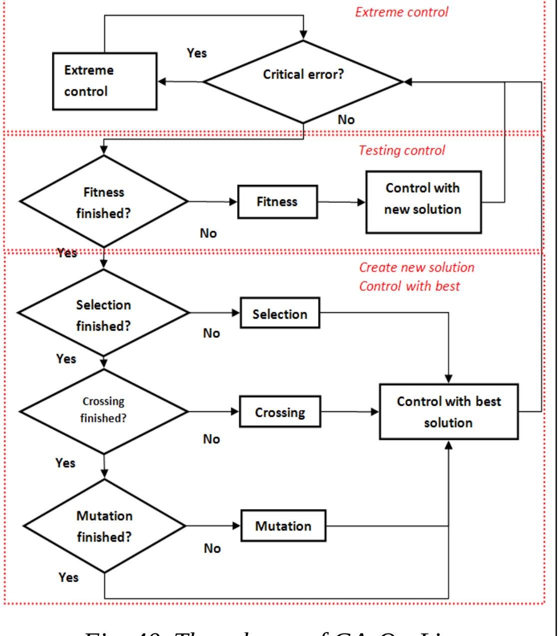


Fig. 40. The scheme of GA-On-Line (the best solution)

The best solution is choosing after each iteration that allows the GA to continue working and not losing control of the pendulum. The inclusion of extreme control is to increase time control errors up to a certain threshold. The PID gain range value is set by an expert based on CO dynamic behavior. During selection, crossover and mutation, CPU time processing solutions, and GA is calculated with the best solution $K_pK_iK_d$.

The convergence of the system GA is shown in Fig. 41. The GA advantage compared to other methods of extremum is that you do not need to calculate the undefined function derivative.

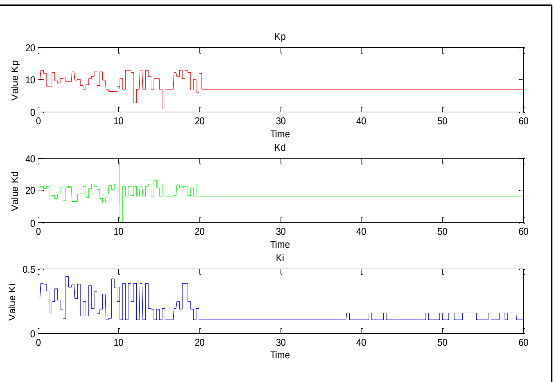


Fig. 41. The convergence of the PID gains in the robot GA-process

The resulting information can be used as a teaching signal for the approximation to a fuzzy neural network.

2. ***Quantum Computing Optimizer.*** We can design several FCs for various situations using SCO. However, which one to use in the new unforeseen situation? A QFI algorithm implemented in a QCO is able to select an appropriate signal for a current error from a set of FC outputs. Therefore, we can design a set of KB for all possible control situations or controller types, but we still need an algorithm for online switching between outputs of different FCs. Moreover, there are control situations when the operation of an intelligent control system based on SCO is impossible without additional operational information. Then, for these purposes, we have developed a QFI algorithm and a QCO to adjust this algorithm for a particular CO. Fig. 1 designates a QFI algorithm. The algorithm uses quantum mathematics formalism: the output gains of all FCs are converted to some kind of qubits, after that a tensor product creates their superposition. We will not need to dwell on it in detail, it is important that there is a interdependence between PID controller gains. This dependence can be built in the QFI algorithm initially as a design parameter. This relationship is given in the form of the correlation matrix. There are different ways to make this correlation.

One way is to use correlation between various control gains at the same time point. We call such correlation spatial. Correspondingly, we can take the values of one control gain (K_p for example) at different time points. This is a temporal correlation. The third main correlation is the mixture of the first two. This is a spatiotemporal correlation. In addition, we can introduce more complex correlations and consider internal and external correlations. A correlation matrix and a superposition form a set of states and their corresponding probability amplitudes.

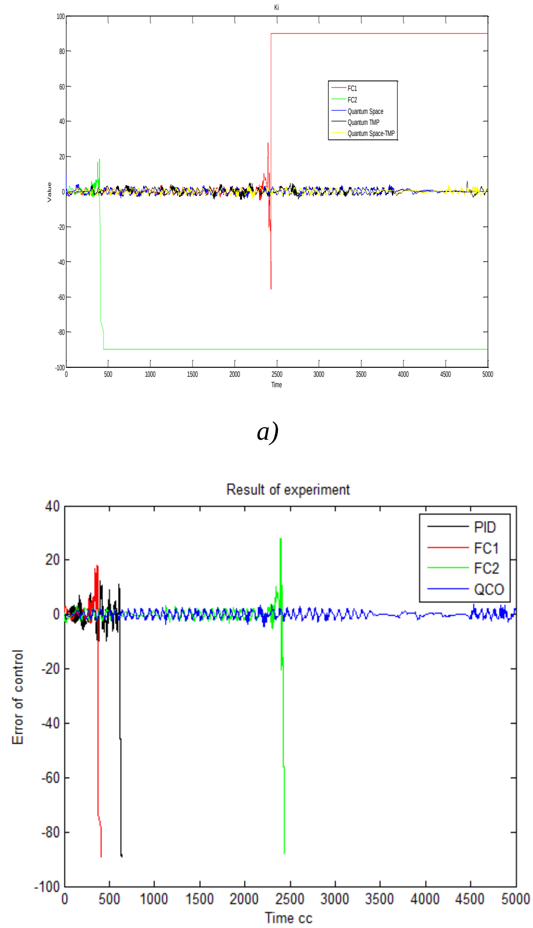
We use the integral probability function of an input signal to create a quantum state. It is assumed that the probability amplitudes reflect the degree of suitability of these coefficients in terms of control quality; the higher a probability amplitude, the better a value. It is assumed that this is due to the fact that the probability amplitudes are introduced at the conversation to a quantum bits stage based on a teaching signal, which is obtained in such way that is the best by the minimum control error criterion. Thus, we choose the optimal state – the state with the maximum probability amplitude. After that we covert qubits to the specific values of the PID gains. This was a brief overview of the developed technology.

The modern control theory has methods to create control systems for well-formalized and well-described control situations. However, control systems often face unforeseen situation. The QFI technology ensures the required level of robustness without changing the lower level of control, using only a software level. For experiments and modeling we use QFI with temporal correlation, between FC1 and FC2.

An experiment and a result. We have three situations of control. First situation represents a simple situation. We use uniform noise in a control channel, Gaussian noise in wheel friction and delay of control action 0.01 s and the third situation has delay of a control action equal to 0.03 s.

Simulation and experimental results are shown on Fig. 42.

PID controller and FCs do not reach the goal in an unpredicted situation. However, a quantum controller based on these imperfect FCs is successful in an unpredicted situation.



a)

b)

Fig. 42. A control error. An unpredicted situation: a) modeling; b) a physical model

Conclusion

The described ICS design technology based on SCO includes: multiple using GA to search for optimal control, FNN for approximation found by the GA optimal control signal and retrieval based on this “optimal” KB, as well as fine-tuning KB based on GA using information and entropic criteria. SCO allows: implementing the principle of designing optimal ICS with the highest level of reliability and controllability of complex CO under conditions of the initial information uncertainty; reducing the minimum number of sensors required to collect and transmit information, as in the control loop, and in the measurement system without losing accuracy and quality control.

The design of robust ICS based on this approach requires minimum initial information about the behavior of CO as well as of external perturbations.

The quantum FC performance is higher than the performance of FC implemented with SCO or with a classical control system based on a conventional PID controller.

The QFI strategy allows reaching the control goal even in unpredicted situations and demonstrates quantum supremacy of quantum search algorithm applications.

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Промышленная роботизированная интеллектуальная робастная система управления: применение технологий квантовых мягких вычислений и квантовой программной инженерии в неопределенных условиях управления

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В работе описана стратегия проектирования интеллектуальных систем управления на основе технологий квантовых и мягких вычислений. Представлен синергетический эффект квантовой самоорганизации робастной базы знаний, извлеченной из несовершенных баз знаний интеллектуального нечеткого регулятора. Разработанная технология повышает надежность интеллектуальных когнитивных систем управления в непредвиденных ситуациях управления, например, с различными типами взаимодействующих роботов.

Наглядные примеры продемонстрировали эффективное внедрение схемы квантового нечеткого логического вывода в качестве готового программируемого алгоритмического решения для систем управления нижнего исполнительного уровня, встроенных в стандартную плату, а также квантовое превосходство квантового интеллектуального управления классическими объектами управления, расширяя тезис Фейнмана–Манина.

Обсуждается корректная физическая интерпретация процесса управления самоорганизацией на квантовом уровне на основе квантовых информационно-термодинамических моделей обмена и извлечения квантовой (скрытой) ценной информации из/между классическими траекториями частиц в модели «рой взаимодействующих частиц».

Продемонстрирован новый информационный синергетический эффект: из двух ненадежных баз знаний нечеткого регулятора в режиме реального времени создается робастная база знаний квантового нечеткого регулятора. Этот эффект имеет чисто квантовую природу и использует скрытую квантовую информацию, извлеченную из классических состояний. Обсуждаются основные физические и информационно-термодинамические аспекты модели квантового интеллектуального управления классическими объектами управления.

Ключевые слова: квантовый нечеткий вывод, интеллектуальное управление в условиях неопределенности, робастность, квантовые алгоритмы, промышленный робот.

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