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Intelligent Robust Robotic Controllers: SW & HW Toolkit of Applied Quantum Soft Computing

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Abstract

A generalized design strategy of intelligent robust control systems based on quantum/soft computing technologies that enhance robustness of hybrid intelligent controllers by supplying a self-organizing capability is described. We stress our attention on the robustness features of intelligent control systems in unpredicted control situations with the simulation of Benchmark.

Keywords: Intelligent Control, Quantum algorithm, Self-Organization, Knowledge Base, Quantum Fuzzy Inference.

1 Introduction

For complex and ill-defined dynamic control objects that are not easily controlled by conventional control systems (such as P-$[I]$-D-controllers) – especially in the presence of fuzzy model parameters and different stochastic noises – the System of Systems Engineering methodology provides fuzzy controllers (FC) as one of alternative way of control systems design.

Soft computing methodologies, such as genetic algorithms (GA) and fuzzy neural networks (FNN) had expanded application areas of FC by adding optimization, learning and adaptation features.

But still now it is difficult to design optimal and robust intelligent control system, when its operational conditions have to evolve dramatically (aging, sensor failure and so on).

Such conditions could be predicted from one hand, but it is difficult to cover such situations by a single FC.

Using unconventional computational intelligence toolkit we propose a solution of such kind of generalization problems by introducing a *self-organization* design process of robust KB – FC that is supported by the *Quantum Fuzzy Inference* (QFI) based on quantum soft computing ideas [1–3].

2 Problem's Formulation

2.1 Main problem and toolkit

One of the main problems in modern FC design is how to design and introduce robust KBs into control system for increasing *self-learning, self-adaptation and self-organizing capabilities* that enhance robustness of developed FC in unpredicted control situations.

The *learning* and *adaptation* aspects of FC's have always the interesting topic in advanced control theory and system of systems engineering. Many learning schemes were based on the *back-propagation* (BP) algorithm and its modifications (see, for example, [1] and their references). Adaptation processes are based on iterative stochastic algorithms.

These ideas are successfully working if we perform our control task without a presence of ill-defined stochastic noises in environment or without a presence of unknown noises in sensors systems and control loop, and so on.

For more complicated control situations learning and adaptation methods based on BP-algorithms or iterative stochastic algorithms do not guarantee the required robustness and accuracy of control.

The solution of this problem based on Soft Computing Optimizer (SCO) was developed in [2]. For achieving of *self-organization* level in intelligent control system it is necessary to use QFI [3, 4]. The described *self-organizing* FC design method is based on special form of QFI that uses a few of partial KBs designed by SCO.

QFI uses the laws of quantum computing technologies [5] and explores three main unitary operations: (i) superposition; (ii) entanglement (quantum correlations); and (iii) interference. According to quantum gate computation, the logical union of a few KBs in one generalized space is realized with *superposition* operator; with *entanglement* operator (that can be equivalently described by different models of *quantum oracle* [6]) a search of a "successful" marked solution is formalized; and with *interference* operator we can extract "good" solutions with classical *measurement* operations [7].

2.2 Method of solution

The proposed QFI system consists of a few KB-FCs, each of which has prepared for appropriate conditions of control object and excitations by SCO [2]. QFI system is a new quantum control algorithm of self-organization block, which performs post processing of the results of fuzzy inference of each independent FC and produces in on-line the generalized control signal output [4].

In this case the output of QFI is an optimal robust control signal, which combines best features of each independent FC outputs. Therefore the operation area of such a control system can be expanded greatly as well as its robustness.

Robustness of control is the background for support the reliability of advanced control accuracy in uncertainty and information risk [5].

The simulation example of robust intelligent control based on QFI is introduced.

2.3 Main goal

The main technical purpose of QFI is to supply a self-organization capability for many (sometimes unpredicted) control situations based on a few KBs. QFI produces robust optimal control signal for the current control situation using a reducing procedure and compression of redundant information in KB's of individual FCs. Process of rejection and compression of redundant information in KB's uses the laws of quantum information theory [5 – 7].

Decreasing of redundant information in KB-FC increases the robustness of control without loss of important control quality as reliability of control accuracy. As a result, a few KB-FC with QFI can be adapted to unexpected change of external environments and to uncertainty in initial information.

We introduce main ideas of quantum computation and quantum information theory [6] applied in developed QFI methods. *Quantum Fuzzy Inference* ideas are introduced. Robustness of new types of *self-organizing intelligent control systems* is demonstrated.

3 SCO-structure based on soft computing

3.1 KB of FC creation

SCO uses the chain of GAs (GA_1, GA_2, GA_3) and approximates measured or simulated data (TS) about the modeled system with desired accuracy or using real robot for it. GA_1 solves optimization problem connected with the optimal choice of number of membership functions and their shapes. GA_2 searches optimal KB with given level of rules activation. Introduction of activation level of rules allows us to sort fuzzy rules in accordance with value information and design robust KB. GA_3 refines KB by using a few criteria.

Figure 2 shows the flow chart of SCO operations on macro level and combination of several stages.

Stage 1: *Fuzzy Inference System* (FIS) *Selection.* The user makes the selection of fuzzy inference model with the featuring of the following initial parameters: Number of input and output variables; Type of fuzzy inference model (Mamdani, Sugeno, Tsukamoto, etc.); Preliminary type of MFs.

Stage 2: *Creation of linguistic values.* By using the information (that was obtained on Stage 1), GA_1 optimizes membership functions number and their shapes, approximating teaching signal (TS), obtained from the in-out tables, or from dynamic response of control object (real or simulated in Matlab).

Stage 3: *Creation rules.* At this stage we use the rule rating al-

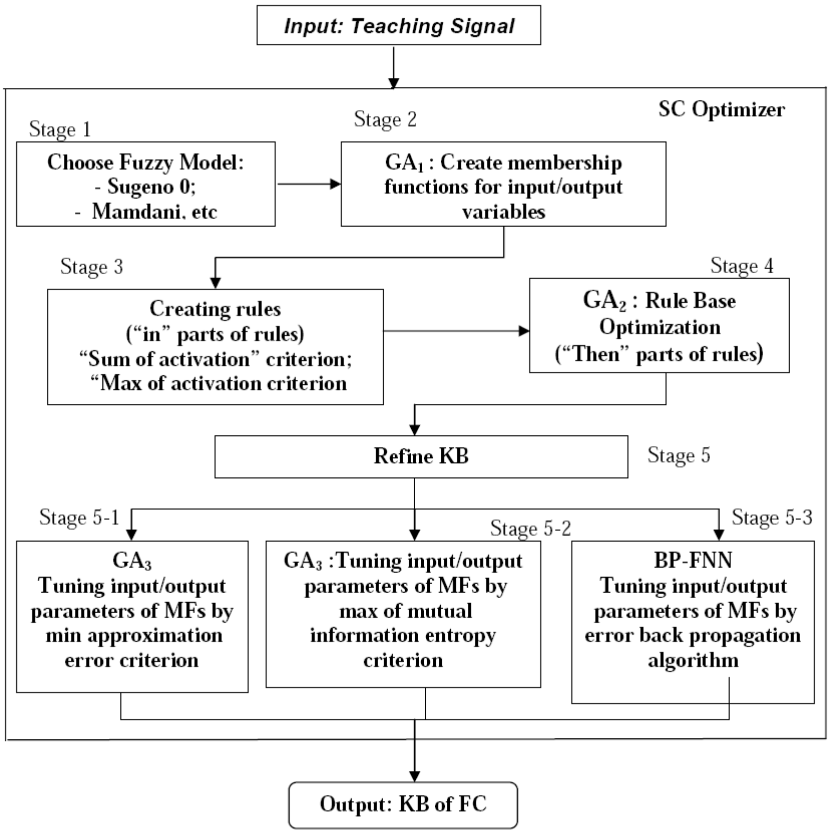


Figure 1. Flow chart of SC Optimizer

gorithm for selection of certain number of selected rules prior to the selection of the index of the output membership function corresponding to the rules. For this case two criteria are selected based on a rule's activation parameter called as a "manual threshold level" (TL). This parameter is given by a user (or it can be introduced automatically).

Stage 4: *Rule base optimization*. GA_2 optimizes the rule base obtained on the Stage 3, using the fuzzy model obtained on Stage 1, optimal linguistic variables, obtained on Stage 2, and the same TS as it was used on Stage 1. Rule base optimization can be performed by using mathematical model, or by using distance connection to real control object.

Stage 5: *Refine KB*. On this stage, the structure of KB is already specified and close to global optimum. In order to reach the optimal structure, a few methods can be used. First method is based on GA_3 with fitness function as minimum of approximation error, and in this case KB refining is similar to classical derivative based optimization procedures (like error back propagation (BP) algorithm for FNN tuning). Second method is also based on GA_3 with fitness function as maximum of mutual information entropy. Third method is realized as pure error back propagation (BP) algorithm. BP algorithm may provide further improvement of output after genetic optimization. As output results of the Stages 3, 4 and 5, we have a set of KB corresponding to chosen KB optimization criteria.

3.2 Remote rule base optimization

Remote KB optimization is performed on the fourth stage of designing FC (Fig. 1). The implementation of the physical environment connection intends to use additional equipment for the data transfer, such as radio channel, Bluetooth, WiFi or a cable connection, such as USB. Exchange of information between the management system and the SCO intended to form a KB (Fig. 2).

The control system reads the sensors and sends data to a computer for further processing. By taking input values, SCO evaluates previous decision (KB-FC) and performs fuzzy inference to check the following

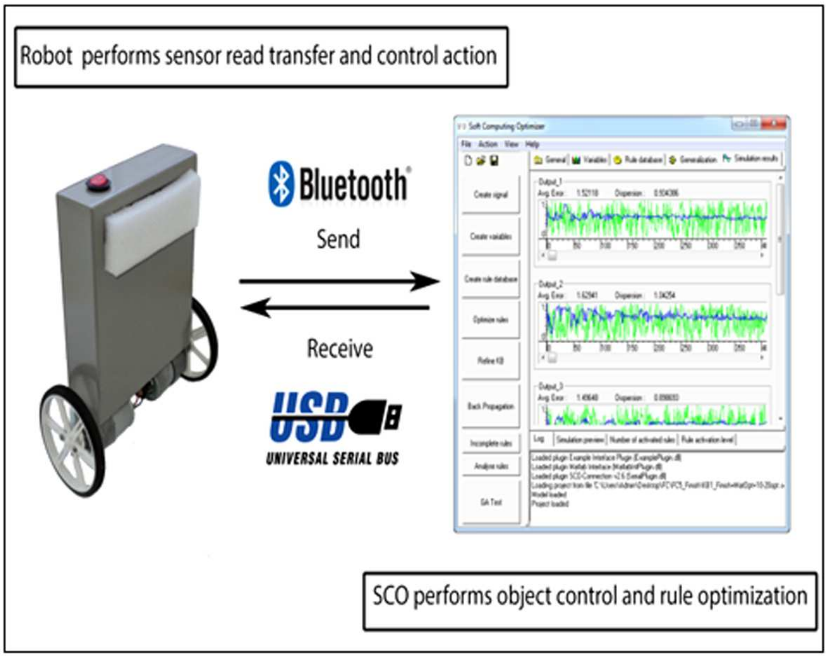


Figure 2. Remote rule base optimization scheme

solutions (KB-FC). The result of the fuzzy inference is sent to the remote device. Thereafter, the control system by processing the input values generates control action.

Synchronization of SCO and control systems is based on the remote device (robot). To this end, a special program (firmware) is developed.

Connection profile uses the serial port. Transmission rate in this case is 115,200 bits / sec. During operation, floats in symbolic form are passing via COM-port. Connection to SCO uses designed plug-in. Before establishing a connection to the SCO, COM port number and the check time of one solution (the number of cycles of the system to test solution) are selected.

4 QFI-structure based on quantum computing

For design of QFI based on a few KBs it is needed to apply the additional operations to partial KBs outputs that draw and aggregate the valuable information from different KBs. Soft computing tool does not contain corresponding necessary operations [8].

The necessary unitary reversible operations are called as *superposition*, *entanglement* (quantum correlation) and *interference* that physically are operators of quantum computing in information processing.

We introduce briefly the particularities of quantum computing and quantum information theory that are used in the quantum block QFI (Fig. 3) supporting a self-organizing capability of FC in robust intelligent control system (ICS).

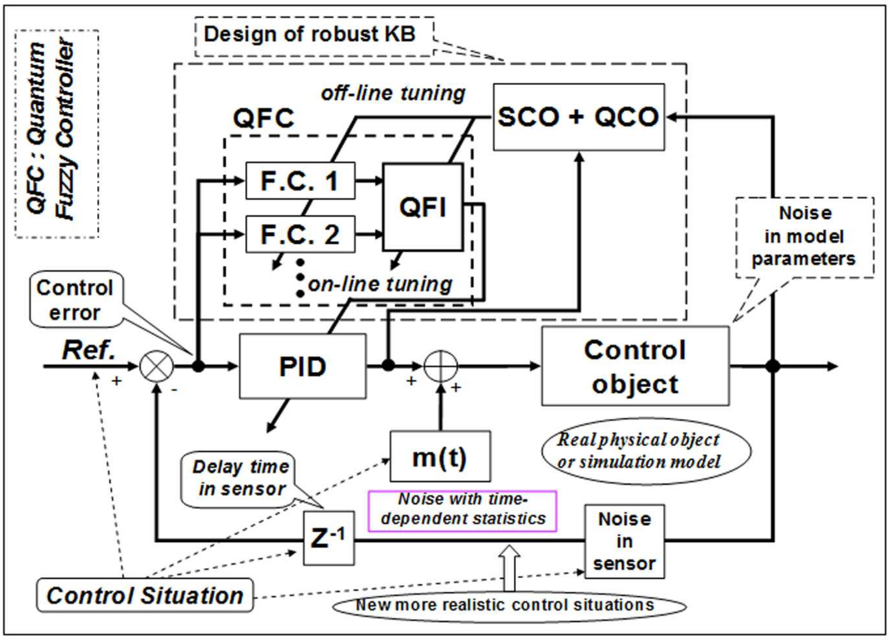


Figure 3. *Structure of robust* ICS *based on* QFI

4.1 Quantum computing

In Hilbert space the superposition of classical states $\left(c_1^{(1)}|0\rangle + c_2^{(1)}|1\rangle\right)$ called quantum bit (qubit) means that "*False*" and "*True*" are jointed in one state with different probability amplitudes, $c_i^1,\ i = 1, 2,\ \left(c_1^1\right)^2 + \left(c_1^1\right)^2 = 1$. If the Hadamard transform $H = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$ is independently applied to different classical states, then a tensor product of superposition states is the result:

$$|\psi\rangle = H^{\otimes n}|False\rangle = \frac{1}{\sqrt{2^n}} \otimes_{i=1}^{n} \left(|False\rangle + |True\rangle\right). \qquad (1)$$

The fundamental result of quantum computation stays that all of the computation can be embedded in a circuit, the nodes of which are the universal gates.

These gates offer an expansion of unitary operator U that evolves the system in order to perform some computation. Thus, naturally two problems are discussed: (i) Given a set of functional points $S = \{(x, y)\}$ find the operator U such that $y = U \cdot x$; (ii) Given a problem, find the quantum circuit that solves it. Algorithms for solving these problems may be implemented in a hardware quantum gate or in software as computer programs running on a classical computer.

It is shown that in quantum computing the construction of a universal quantum simulator based on classical effective simulation is possible [3, 6, 7].

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

- preparation of the initial state $|\psi_{out}\rangle$ (classical or quantum);
- 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 $|\psi_{out}\rangle$.

Hence, a quantum gate approach can be used in a global optimization of KB structures of ICSs that are based on quantum computing, on a quantum genetic search and quantum learning algorithms [8].

4.2 Quantum information resources in QFI algorithm

Figure 4 shows the algorithm for coding, searching and extracting the valuable information from two KBs of fuzzy PID controllers designed by SCO.

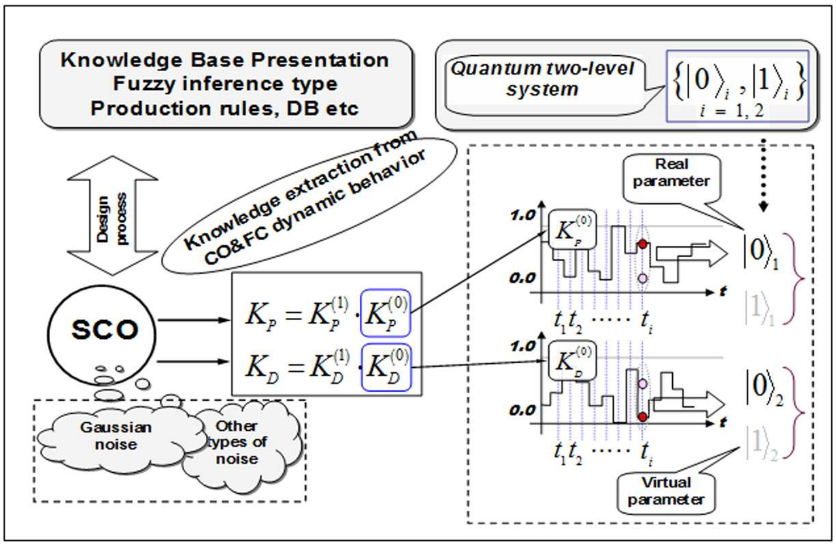


Figure 4. *Example of information extraction in* QFI

Thus, in the quantum algorithm for QFI (Fig. 5) the following actions are realized [5]:

- The results of fuzzy inference are processed for each independent FC;

- Based on the methods of quantum information theory, valuable quantum information hidden in independent (individual) knowledge bases is extracted;
- In on-line, the generalized output robust control signal is designed in all sets of knowledge bases of the fuzzy controller.
- In this case, the output signal of QFI in on-line is an optimal signal of control of the variation of the gains of the PID controller, which involves the necessary (best) qualitative characteristics of the output control signals of each of the fuzzy controllers, thus implementing the self-organization principle.

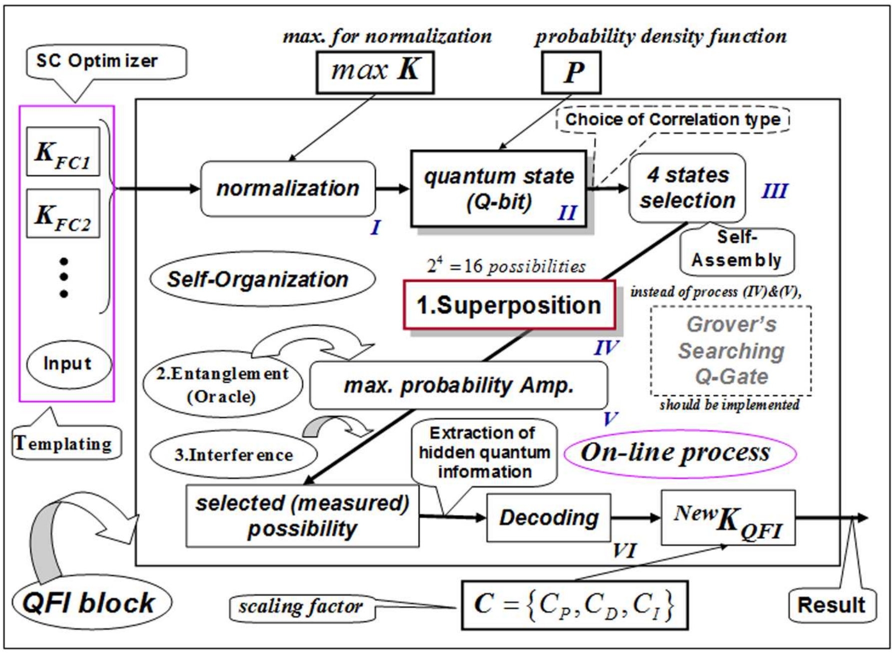


Figure 5. *The structure of* QFI *gate*

Therefore, the domain of efficient functioning of the structure of the intelligent control system can be essentially extended by including robustness, which is a very important characteristic of control quality.

The robustness of the control signal is the background for maintaining the reliability and accuracy of control under uncertainty conditions of information or a weakly formalized description of functioning conditions and/or control goals.

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

Optimal drawing process of valuable information from a few KBs that are designed by soft computing is based on the following four facts from quantum information theory [4]: (i) effective quantum data compression; (ii) splitting of classical and quantum parts of information in quantum state; (iii) total correlations in quantum state are "mixture" of classical and quantum correlations; and (iv) exiting of hidden (locking) classical correlation in quantum state [6, 9].

This quantum control algorithm uses these four Facts from quantum information theory: (i) compression of classical information by coding in computational basis $\{|0\rangle, |1\rangle\}$ and forming the quantum correlation between different computational bases (Fact 1); (ii) separating and splitting total information and correlations on "classical" and "quantum" parts using Hadamard transform (Facts 2 and 3); (iii) extract unlocking information and residual redundant information by measuring the classical correlation in quantum state (Fact 4) using criteria of maximal corresponding amplitude probability.

These facts are the informational resources of QFI background. Using these facts it is possible to extract an additional amount of quantum value information from smart KBs produced by SCO for design a *wise* control using compression and rejection procedures of the redundant information in a classical control signal.

Below we discuss the application of this quantum control algorithm in QFI structure.

4.3 Remote quantum base optimization

As the adjustable parameter scaling factor is used in remote quantum base optimization. Scaling factor is used in the final step of forming the gain of PID (Fig. 5).

During operation, floats in symbolic form are passed via COM-port. The control system reads the sensors and sends them to a computer for further processing. By taking the input values, the GA evaluates the previous decision, and carries a quantum fuzzy inference to check the following solutions. The result of the fuzzy inference is sent to the remote device. Thereafter, the control system by processing the input values generates control action. Connection to QFI is developed through a plug-in.

Before establishing a connection to the SCO, COM port number and the check time of one solution (the number of cycles of the system to test solution) are selected (Fig. 6).

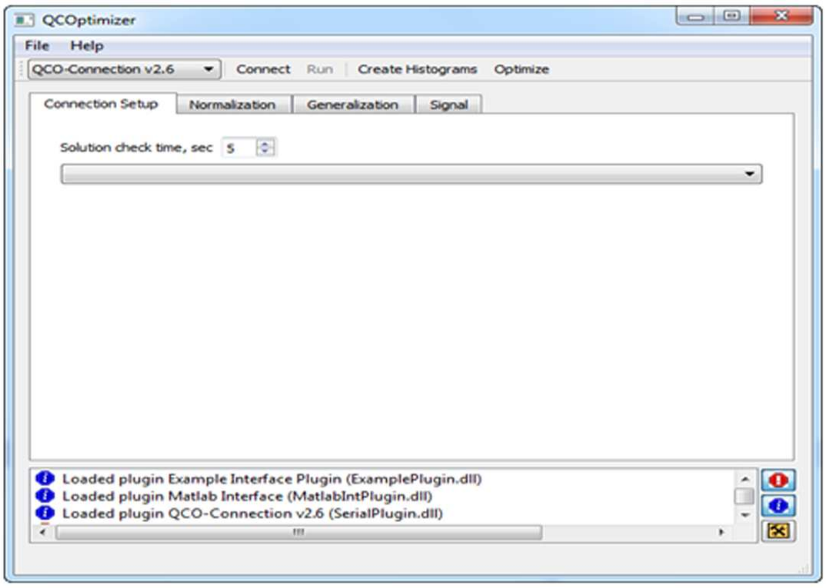


Figure 6. *Remote connection plug-in for QCOptimizer*

5 KB-self-organization of FC's based on QFI

5.1 Robust FC design toolkit

The kernel of the abovementioned FC design toolkit is a so-called SCO implementing advanced soft computing ideas. SCO is considered as a new flexible tool for design of optimal structure and robust KBs of FC based on a chain of genetic algorithms (GAs) with information-thermodynamic criteria for KB optimization and advanced error back-propagation algorithm for KB refinement [2]. Input to SCO can be some measured or simulated data (called as 'teaching signal" (TS)) about the modelling system. For TS design (or for GA fitness evaluation) we used stochastic simulation system based on the control object model. More detailed description of SCO is given in [1, 2]. Below we discuss the application of this algorithm in QFI structure.

Figure 3 illustrates as an example the structure and main ideas of self-organized control system consisting of two FC's coupling in one QFI chain that supplies a self-organizing capability. According to the described above algorithm the input to the QFI gate is considered according to (1) as a superposed quantum state $K_1(t) \otimes K_2(t)$, where $K_{1,2}(t)$ are the outputs from fuzzy controllers FC1 and FC2 designed by SCO (see Fig. 4) for the given control task in different control situations (for example, in the presence of different stochastic noises).

The algorithm of superposition calculation is presented in Fig. 7 and described in details in [4, 5].

We discuss for simplicity the situation in which an arbitrary amount of correlation is unlocked with a one-way message. Let us consider the communication process between two KBs as communication between two players A and B (see Figs 4 and 7) and let $d = 2^n$. According to the law of quantum mechanics, initially we must prepare a quantum state description by density matrix ρ from two classical states (KB_1 and KB_2).

The initial state ρ is shared between subsystems held by A (KB_1)

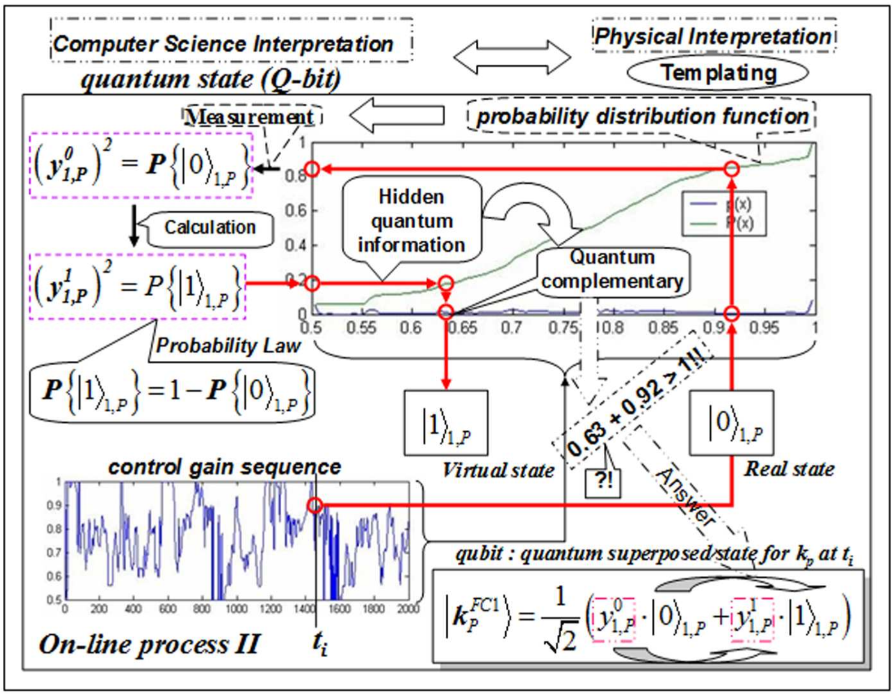


Figure 7. The algorithm of superposition calculation

and B (KB_2), with respective dimensions d,

$$\rho = \frac{1}{2d} \sum_{k=0}^{d-1} \sum_{t=0}^{1} \left(|k\rangle \langle k| \otimes |t\rangle \langle t| \right)_A \otimes \left(U_t |k\rangle \langle k| U_t^{\dagger} \right)_B . \tag{2}$$

Here $U_0 = I$ and U_1 change the computational basis to a conjugate basis $|\langle i \mid U_1 |k\rangle| = 1\big/\sqrt{d} \quad \forall\, i, k$.

In this case, B chooses $|k\rangle$ randomly from d states in two possible random bases, while A has complete knowledge on his state. The state (2) can arise from the following scenario. A picks a random ρ'-bit string k and sends $B\,|k\rangle$ or $H^{\otimes n}\,|k\rangle$ depending on whether the random bit $t = 0$ or 1. A can send t to B to unlock the correlation later. Experimentally, Hadamard transform, H and measurement on single qubits are sufficient to prepare the state (2), and the latter extracts the unlocked correlation in ρ'. The initial correlation is small, i.e. $I_{Cl}^{(l)}(\rho) = \frac{1}{2}\log d$. The final amount of information after the complete measurement M_A in one-way communication is ad hoc, $I_{Cl}(\rho') = I_{Cl}^{(l)}(\rho) = \log d + 1$, i.e., the amount of *accessible information increases*. This phenomenon is impossible classically.

However, states exhibiting this behaviour *need not to be entangled* and the corresponding communication can be organized using Hadamard transformation [9]. Therefore, using the Hadamard transformation and a new type of quantum correlation as the communication between a few KB's it is possible to increase initial information by unconventional quantum correlation (as the quantum cognitive process of a value hidden information extraction in on-line, see, e.g. Fig. 4).

In the present report we consider a simplified case of QFI, when with the Hadamard transformation there is organized an unlocked correlation in superposition of two KBs; instead of the difficultly defined entanglement operation an equivalent quantum oracle is modeled that can estimate an "*intelligent state*" with the maximum of amplitude probability in corresponding superposition of classical states (minimum entropy principle relative to extracted quantum knowledge [5]).

Interference operator extracts this maximum of amplitude probability with a classical measurement.

Figure 8 shows the structure of Quantum Computing Optimizer of robust KB-FC based on QFI [4].

The usage of the described QFI model to control non-linear dynamical systems with local and global instabilities is described below.

6 Benchmark's simulation

It is demonstrated that FCs prepared to maintain control object in the prescribed conditions often fail to control when such conditions are dramatically changed. We propose the solution of such kind of problems by introducing a quantum generalization of strategies in fuzzy inference in on-line from a set of pre-defined fuzzy controllers by new

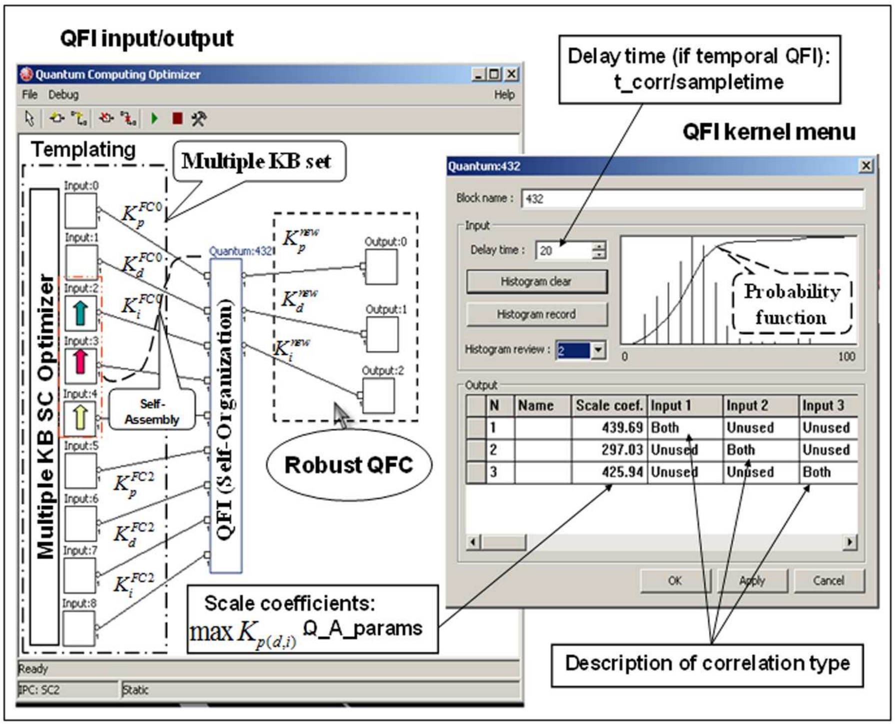


Figure 8. QFI-*process by using* QC Optimizer (QFI *kernel*)

QFI based systems. The latter is a new quantum algorithm in quantum computation without entanglement. Two Benchmarks are considered: robust control of locally and globally unstable control objects.

6.1 Benchmark 1: Globally unstable control object simulation

"Cart – pole" control object is a non-linear dissipative system. This is a typical task of control theory. The effective solution of this task demonstrates quality of control system. Task of control is the stability of inverted pendulum in vertical position. The motion of the dynamic system “cart – pole” is described by the following equations

$$\ddot{\theta} = \frac{g\sin\theta + \cos\theta\left(\frac{u+\xi(t)+a_1\dot{z}+a_3z-ml\dot{\theta}^2\sin\theta}{m_c+m}\right) - k\dot{\theta}}{l\left(\frac{4}{3} - \frac{m\cos^2\theta}{m_c+m}\right)} \tag{3}$$

$$\ddot{z} = \frac{u+\xi(t)-a_1\dot{z}-a_2z+ml(\dot{\theta}^2\sin\theta-\ddot{\theta}\cos\theta)}{m_c+m},$$

where θ is the pendulum deviation angle (degrees); z is the movement of the cart (m); g is the acceleration of gravity (9.8 m/s^2); m_c is the pendulum mass (kg); l is the pendulum half-length (m); $\xi(t)$ is the stochastic excitation; and u is the control force acting on the cart (N). The equations for the entropy production rate in the control object and the PID controller have the following form, respectively:

$$\frac{d}{dt}S_\theta = \frac{k\dot{\theta}^2 + \frac{ml\dot{\theta}^3\sin 2\theta}{m_c+m}}{l(\frac{4}{3} - \frac{m\cos^2\theta}{m_c+m})};\ \frac{d}{dt}S_z = a_1\dot{z}^2;\ \frac{d}{dt}S_u = k_d\dot{e}^2 \tag{4}$$

The following parameter values are determined: $m_c = 1$; $m = 0.1$; $l = 0.54k = 0.4$; $a_1 = 0.1$; $a_2 = 5$; and the initial position $\left[\theta_0; \dot{\theta}_0; z_0; \dot{z}_0\right] = [10; 0.1; 0; 0]$ (the value of the pendulum deviation angle is given in degrees); the constraint on the control force is $-0.5 < u < 5.0$.

The specific feature of control problem for the given control object (3) is the application of one fuzzy PID controller for controlling the movement of the cart (with one degree of freedom), while the control object has two degrees of freedom.

The control goal is that the pendulum deviation angle (second generalized coordinate) reaches the given value via the implicit control using the other generalized coordinate and corresponding essentially nonlinear cross-connections with the cart movement coordinate (effect of energy transmission between the generalized coordinates).

In the case of the similar initial learning conditions, the SCO with soft computing is used to design KB_1 of FC_1 for the generalized criterion of minimal mean square error:

$$\int_{t_0}^{t_{end}} \theta^2(t)\,dt + \int_{t_0}^{t_{end}} \dot{\theta}^2(t)\,dt$$

and KB_2 for FC_2 for the generalized criterion of minimal absolute error of the pendulum position:

$$\int_{t_0}^{t_{end}} \mid \theta\left(\tau\right) \mid d\tau + \int_{t_0}^{t_{end}} \left| \dot{\theta}\left(\tau\right) \right| d\tau.$$

Thus we consider the solution of the vector (multi-objective) optimization problem based on the decomposition of the KB. The Gaussian noise was used as the random signal for designing KB_1, and Rayleigh noise was used for forming KB_2 (see Fig. 9, learning situations (**S1**, **S2**), respectively).

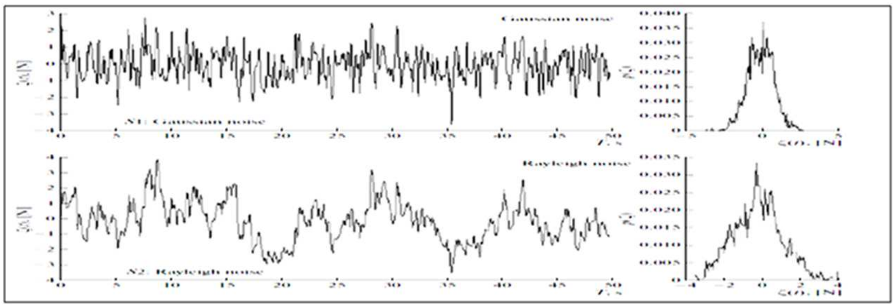


Figure 9. Random noise used in situations (**S1**, **S2**)

Physically the first criterion is equivalent to the total energy of the overturned pendulum and the second criterion characterizes the precision of the dynamic behavior of the control object.

Figure 10 shows KB_1 and KB_2 with the corresponding activated numbers of rules equal to 22 and 33 for a total number of rules of 729.

Two contingency control situations (**S3**, **S4**) were simulated; in one of them (**S3**) the new noise $\xi\left(t\right)$ was introduced, the random signal with uniform one dimensional distribution, the control error signal delay (0.03), and the noise signal in the position sensor of the pendulum (noise amplification coefficient 0.015).

Figure 11 shows the example of operation of the quantum FC for formation of the robust control signal using the proportional gain in contingency control situation **S3**. In this case, the output signals of

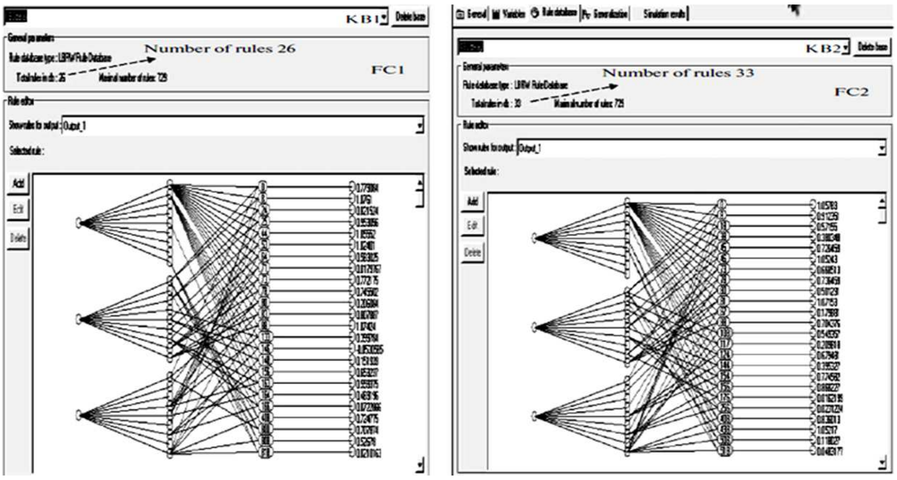


Figure 10. Form of KB_1 and KB_2 with corresponding activated production rules

KB_1 and KB_2 in the form of the response on the new control error in situation **S3** are received in the quantum FC. The output of the block of quantum FC is the new signal for on line control of the factor k_p.

Thus, the blocks of KB_1 and KB_2, and quantum FC in Fig. 3 form the block of KB self-organization in the contingency control situation.

Figure 12 shows the dynamic behavior of the studied system "cart – pole" and the control laws of the self-organized quantum controller (QFI), FC_1 and FC_2.

Remark. The following notation is used in Fig. 12 and below: $x = \theta$ is the angle of pendulum deviation from the given position; z is the cart position; the quantum FC is based on the spatial correlation.

The results of simulation (Fig. 12) demonstrate that the dynamic control object in contingency control situations (**S3**) for the control of FC_1 (FC_2) loses stability, and for the control of quantum FC the control system possesses the property of robustness and achieving the control goal is guaranteed. According to the results of simulation (Fig. 12), the required amount of control for the given criteria in contingency control situations (**S3**) for the control of FC_1 and FC_2 also is not achieved,

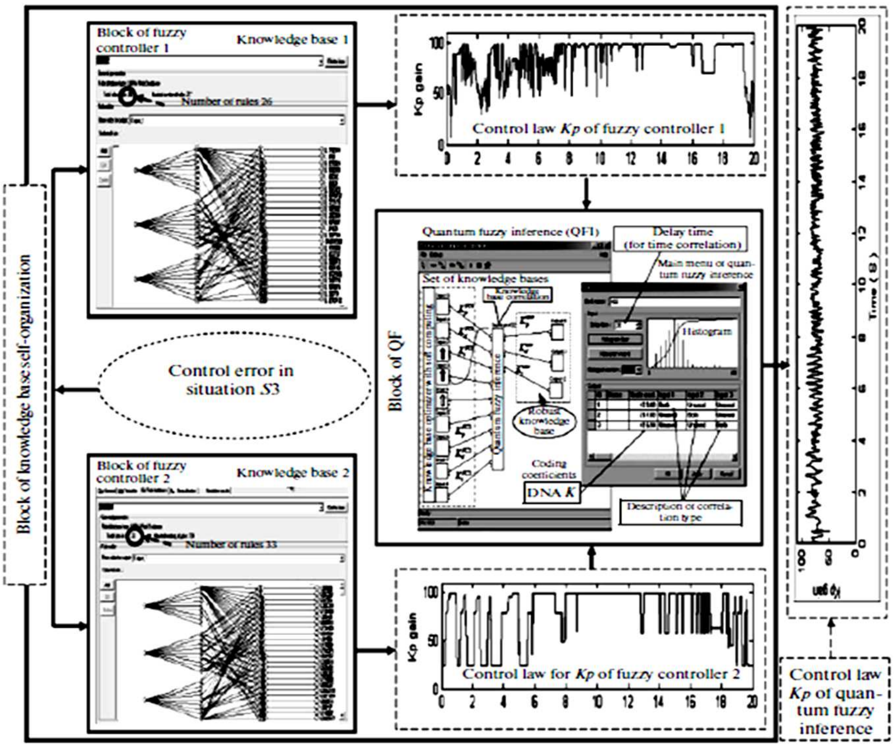


Figure 11. Example of operation of the block of KB self-organization based on QFI

while in the case of control of the quantum FC the control system possesses the required amount of control. This yields that two non robust fuzzy controllers can be used to design in on line the robust fuzzy controller using quantum self-organization; the KB of this robust FC satisfies both quality criteria.

Therefore, the decomposition of the solution to the above multi-objective optimization problem for the robust KB in the contingency control situation into partial solutions to optimization sub-problems physically can be performed in on line in the form of separate responses of the corresponding individual KBs optimized with different fixed cost functions and control situations.

The aggregation of the obtained partial solutions in the form of the new robust KB is performed based on the quantum FC containing the mechanism of formation of the quantum correlation between the obtained partial solutions.

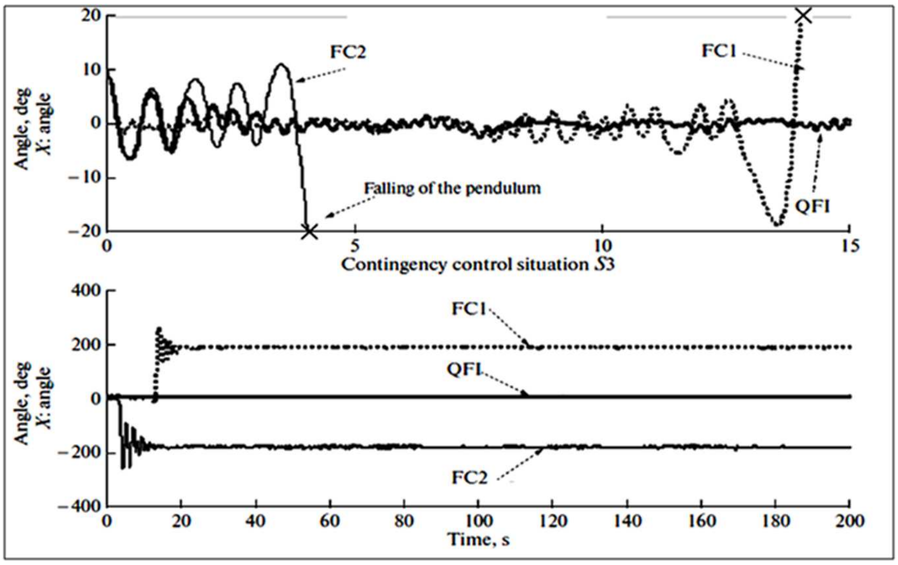


Figure 12. Dynamic motion of pole in situation **S3**

As a result, only responses of the finite number of individual KBs containing limiting admissible control laws in the given contingency situations are used.

The control laws of variation of the gains of the fuzzy PID controller formed by the new robust KB have a simpler physical realization, and as a result they possess better characteristics of individual control cost function for the contingency control situation.

For experimental testing a physical model of robot (Fig. 13) is used.

Three situations of control are tested.

The first situation images simple situation.

The second situation uses uniform noise in control channel, Gaus-

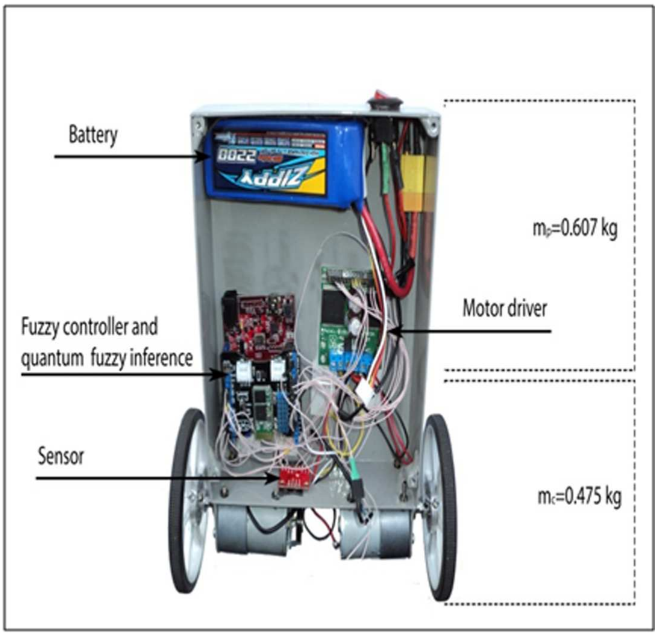


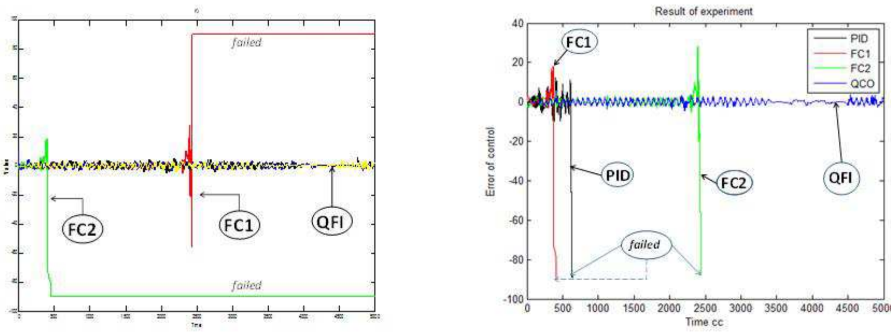
Figure 13. Mobile robot configuration

sian noise in wheel friction and delay of control action – 0.01 s. And the third situation has delay of control action equal to 0.03 s. Simulation and experimental results (for the complex situation 3) are shown in Fig. 14.

PID controller as FC_1 and FC_2 do not reach the goal in unpredicted situation.

But quantum FC based on these fuzzy controllers, are successful in unpredicted situation. For experiments and modeling we use QFI with temporal correlation, between FC_1 and FC_2.

Thus, the output signal of the quantum FC represents the on line optimal control signal for variation of the gains of the fuzzy PID controller which includes the necessary (best) qualitative characteristics of output control signals of each of the fuzzy controllers with priority and dominating component among the control quality criteria. Therefore the generalized self-organization principle [5, 8, 10 – 13] is realized.



(a) (b)

Figure 14. Control error. Unpredicted situation: (a) modeling; (b) experiment on physical model

6.2 Benchmark 2: Remote rule base optimization

To compare method of remote rule optimization on the real control object with method using Matlab simulation for optimization we created 6 KB-FC.

	TS Source	Optimization method	Rules count
FC1	Math. model	Math. modelling	125
FC2	CO (GA-PID)	Math. modelling	125
FC3	Math. model	Remote connection	125
FC4	CO (GA-PID)	Remote connection	125
FC5	Math. model	Math. modeling + Remote connection	125
FC6	CO (GA-PID)	Remote connection + Math. modeling	125

Experiment and modeling were performed in two control situations.

The first situation (S1) is typical for the control system (the initial angle equals to 1). The goal is to maintain the pendulum in equilibrium (0° angle of deflection). It should be noted that KB optimization is held in this control situation.

The second situation is unexpected (S2). The initial angle equals to 5°. This situation characterizes the perturbation caused by external influences on CO.

Figure 15 shows the comparison of integrals of squared error for all regarded regulators in a typical situation of control:

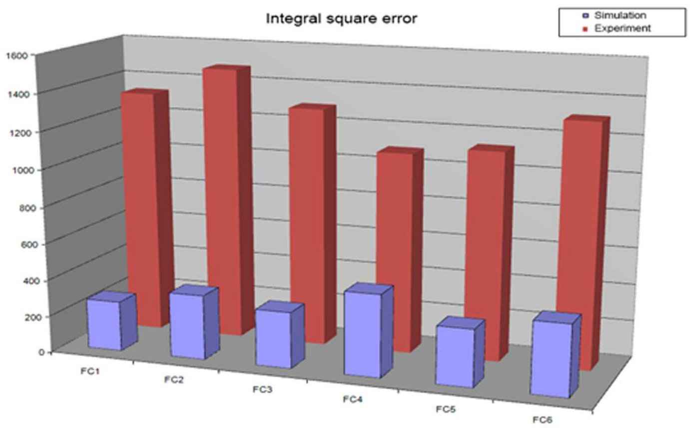


Figure 15. Integral square error. Typical situation: Simulation and experiment

The lower is integral square error level, the better controller works. Consider the results of simulation and experiment in unpredicted situation of control:

Figure 16 shows the comparison of integrals of squared error for all regarded regulators in an unpredicted situation of control.

6.3 Benchmark 3: Remote quantum base optimization

Let's compare the PID controller, fuzzy controllers FC_1 and FC_4, and QFI controllers based on different correlations: Quantum-Space (Q-S), Quantum-Time (Q-T), Quantum-Space-Time (Q-ST). These QFI controllers are optimized using remote connection.

Mathematical modeling and physical experiments took place in two control situations:

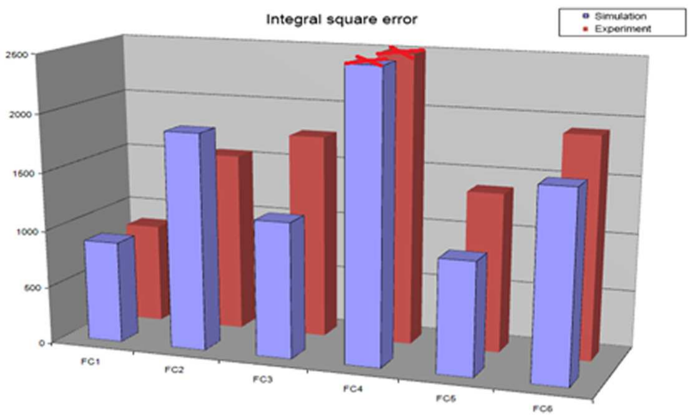


Figure 16. Integral square error. Unpredicted situation: Simulation and experiment

- in the first (typical) situation (S1), the delay of control is standard as 0.015 sec;
- in the second, unpredicted situation (S2), the delay of the control is as 0.035 sec.

From Figs 17 and 18 it can be seen that KB optimization using a remote connection with quantum optimizer can improve the quality of control in the typical and unpredicted situations.

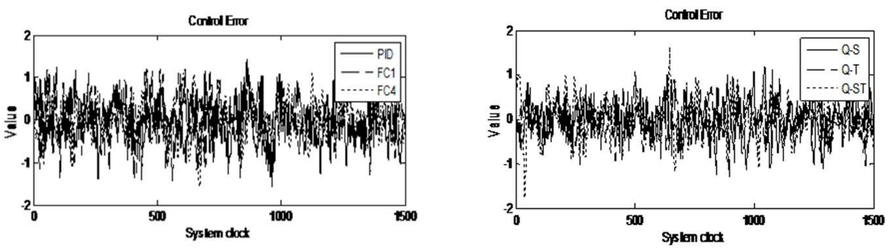


Figure 17. Control error. Typical situation of control (Experiment)

Related works. Quantum computing approaching in robot path planning, emotion design, navigation, learning, decision making was

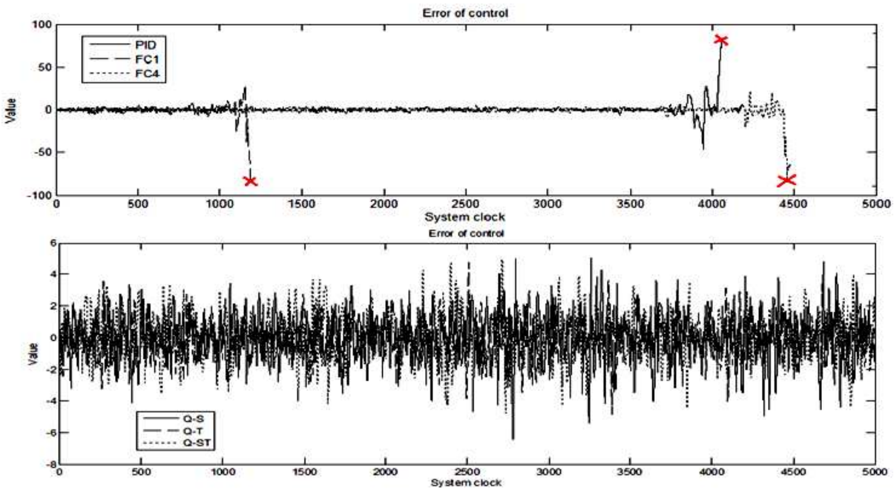


Figure 18. Control error. Unpredicted situation of control (Experiment)

applied also in [14 – 28] etc. Our approach is based on quantum self-organization of knowledge bases using responses of fuzzy controllers on unpredicted situations in on line.

7 Conclusions

The described approach opens new prospects for application of the model of quantum FC as the particular variant of the quantum self-organization algorithm in multi-objective control problems for the control object with weakly formalized structure and large dimensionality of the phase space of control parameters, application of experimental data in the form of the learning signal without development the mathematical model of the control object. These facts present a great advantage which is manifested as the possibility of design of control with required robustness in on line.

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