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Self-Organized Intelligent Robust Control Based on Quantum Fuzzy Inference

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1. Introduction

This Chapter describes a generalized design strategy of intelligent robust control systems based on quantum/soft computing technologies that enhance robustness of hybrid intelligent fuzzy controllers by supplying a self-organizing capability. Main ideas of self-organization processes are discussed that are the background for robust knowledge base (KB) design. Principles and physical model examples of self-organization are described. Main quantum operators and general structure of quantum control algorithm of self-organization are introduced. It is demonstrated that fuzzy controllers (FC) prepared to maintain control object (CO) in the prescribed conditions are often fail to control when such a 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 FCs by new *Quantum Fuzzy Inference* (QFI) based systems. The latter is a new quantum algorithm (QA) in quantum computing without entanglement. A new structure of intelligent control system (ICS) with a quantum KB self-organization based on QFI is suggested. Robustness of control is the background for support the reliability of advanced control accuracy in uncertainty environments. We stress our attention on the robustness features of ICS's with the effective simulation of Benchmarks.

1.1 Method of solution

Proposed QFI system consists of a few KB of FC (KB-FCs), each of which has prepared for appropriate conditions of CO and excitations by Soft Computing Optimizer (SCO). 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. In this case the output of QFI is an optimal robust control signal, which includes best features of the each independent FC outputs. Therefore the operation area of such a control system can be expanded greatly as well as its robustness.

1.2 Main goal

In this Chapter we give a brief introduction on soft computing tools for designing independent FC and then we will provide QFI methodology of quantum KB self-organization in unforeseen situations. The simulation example of robust intelligent control

based on QFI is introduced. The role of self-organized KB design based on QFI in the solution of System of Systems Engineering problems is also discussed.

2. Problem's formulation

Main problem 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. 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. 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 SCO of KB was developed (Litvintseva et al., 2006).
For achieving of *self-organization* level in intelligent control system it is necessary to use QFI (Litvintseva et al., 2007).
The described *self-organizing* FC design method is based on special form of QFI that uses a few of partial KBs designed by SCO. In particularity, QFI uses the laws of quantum computing 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*) a search of "successful" marked solution is formalized; and with *interference* operator we can extract "good" solutions together with classical *measurement* operations. Let us discuss briefly the main principles of self-organization that are used in the knowledge base self-organization of robust ICS.

3. Principles and physical model examples of self-organization

The theory of self-organization, learning and adaptation has grown out of a variety of disciplines, including quantum mechanics, thermodynamics, cybernetics, control theory and computer modeling. The present section reviews its most important definitions, principles, model descriptions and engineering concepts of self-organization processes that can be used in design of robust ICS's.

3.1 Definitions and main properties of self-organization processes

Self-organization is defined in general form as following: *The spontaneous emergence of large-scale spatial, temporal, or spatiotemporal order in a system of locally interacting, relatively simple components.* Self-organization is a bottom-up process where complex organization emerges at multiple levels from the interaction of lower-level entities. The final product is the result of nonlinear interactions rather than planning and design, and is not known a priori. Contrast this with the standard, top-down engineering design paradigm where planning precedes implementation, and the desired final system is known by design. Self-organization can be defined as the spontaneous creation of a globally coherent pattern out of

local interactions. Because of its distributed character, this organization tends to be robust, resisting perturbations. The dynamics of a self-organizing system is typically nonlinear, because of circular or feedback relations between the components. Positive feedback leads to an explosive growth, which ends when all components have been absorbed into the new configuration, leaving the system in a stable, negative feedback state. Nonlinear systems have in general several stable states, and this number tends to increase (bifurcate) as an increasing input of energy pushes the system farther from its thermodynamic equilibrium. To adapt to a changing environment, the system needs a variety of stable states that is large enough to react to all perturbations but not so large as to make its evolution uncontrollably chaotic. The most adequate states are selected according to their fitness, either directly by the environment, or by subsystems that have adapted to the environment at an earlier stage.

Formally, the basic mechanism underlying self-organization is the (often noise-driven) variation which explores different regions in the system's state space until it enters an *attractor*. This precludes further variation outside the attractor, and thus restricts the freedom of the system's components to behave independently. This is equivalent to the increase of coherence, or *decrease* of statistical *entropy*, that defines *self-organization*. The most obvious change that has taken place in systems is the *emergence* of *global* organization. Initially the elements of the system (spins or molecules) were only interacting *locally*. This locality of interactions follows from the basic continuity of all physical processes: for any influence to pass from one region to another it must first pass through all intermediate regions.

In the self-organized state, on the other hand, all segments of the system are *strongly correlated*. This is most clear in the example of the magnet: in the magnetized state, all spins, however far apart, point in the same direction. *Correlation* is a useful measure to study the transition from the disordered to the ordered state. Locality implies that neighboring configurations are strongly correlated, but that this correlation diminishes as the distance between configurations increases. The *correlation length* can be defined as the maximum distance over which there is a significant correlation. When we consider a highly organized system, we usually imagine some external or internal *agent* (controller) that is responsible for guiding, directing or controlling that organization. The controller is a physically distinct subsystem that exerts its influence over the rest of the system. In this case, we may say that control is *centralized*. In self-organizing systems, on the other hand, "control" of the organization is typically *distributed* over the whole of the system. All parts contribute evenly to the resulting arrangement.

A general characteristic of self-organizing systems is as following: they are *robust* or *resilient*. This means that they are relatively insensitive to perturbations or errors, and have a strong capacity to restore themselves, unlike most human designed systems. *One reason* for this fault-tolerance is the *redundant*, *distributed* organization: the non-damaged regions can usually make up for the damaged ones. *Another reason* for this intrinsic robustness is that self-organization thrives on *randomness*, fluctuations or "noise". A certain amount of random perturbations will facilitate rather than hinder self-organization. A *third reason* for resilience is the stabilizing effect of *feedback* loops. Many self-organizational processes begin with the amplification (through positive feedback) of initial random fluctuations. This breaks the symmetry of the initial state, but often in unpredictable but operationally equivalent ways. That is, the job gets done, but hostile forces will have difficulty predicting precisely how it gets done.

3.2 Principles of self-organization

A system can cope with an unpredictable environment autonomously using different but closely related approaches:

- *Adaptation* (learning, evolution). The system changes its behavior to cope with the change.
- *Anticipation* (cognition). The system predicts a change to cope with, and adjusts its behavior accordingly. This is a special case of adaptation, where the system does not require experiencing a situation before responding to it.
- *Robustness.* A system is robust if it continues to function in the face of perturbations. This can be achieved with modularity, degeneracy, distributed robustness, or redundancy. Successful self-organizing systems will use combinations of these approaches to maintain their integrity in a changing and unexpected environment.
  - *Adaptation* will enable the system to modify itself to "fit" better within the environment.
  - *Robustness* will allow the system to withstand changes without losing its function or purpose, and thus allowing it to adapt.
  - *Anticipation* will prepare the system for changes before these occur, adapting the system without it being perturbed.

Let us consider the peculiarities of common parts in self-organization models: (i) Models of self-organizations on macro-level are used the information from micro-level that support thermodynamic relations (second law of thermodynamics: increasing and decreasing of entropy on micro- and macro-levels, correspondingly) of dynamic evolution; (ii) Self-organization processes are used transport of the information on/to macro- and from micro-levels in different hidden forms; (iii) Final states of self-organized structure have minimum of entropy production; (iv) In natural self-organization processes are don't planning types of correlation before the evolution (Nature given the type of corresponding correlation through genetic coding of templates in self-assembly); (v) Coordination control for design of self-organization structure is used; (vi) Random searching process for self-organization structure design is applied; (vii) Natural models are biologically inspired evolution dynamic models and are used current classical information for decision-making (but don't have toolkit for extraction and exchanging of hidden quantum information from dynamic behavior of control object).

3.3 Quantum control algorithm of self-organization processes

In man-made self-organization *types of correlations* and *control of self-organization* are developed before the design of the searching structure. Thus the future design algorithm of self-organization must include these common peculiarities of bio-inspired and man-made processes: *quantum hidden correlations* and *information transport*.

Figure 1 shows the structure of a new *quantum control algorithm of self-organization* that includes the above mentioned properties.

Remark. The developed quantum control algorithm includes three possibilities: (i) from the simplest living organism composition in response to external stimuli of bacterial and neuronal self-organization; and (ii) according to correlation information stored in the DNA; (iii) from quantum hidden correlations and information transport used in quantum dots.

Quantum control algorithm of self-organization design in intelligent control systems based on QFI-model is described in (Litvintseva et al., 2009). Below we will describe the Level 1

(see, Fig. 1) based on QFI model as the background of robust KB design information technology. QFI model is described in details (Litvintseva et al., 2007) and used here as toolkit.

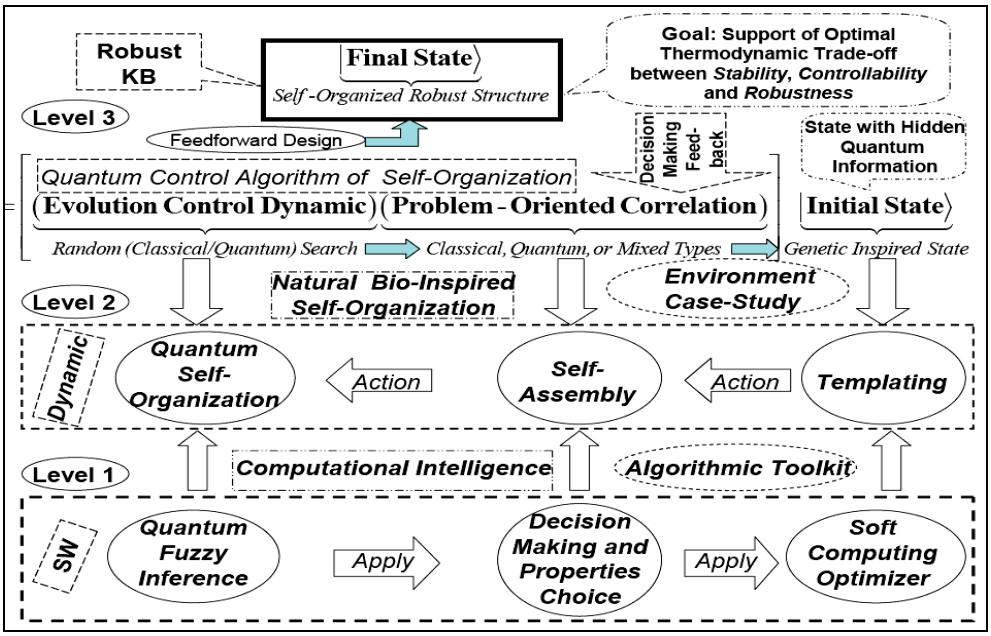


Fig. 1. General structure of quantum control algorithm of self-organization

Analysis of self-organization models gives us the following results. Models of self-organization are included natural *quantum* effects and based on the following *information-thermodynamic* concepts: (i) macro- and micro-level interactions with information exchange (in ABM micro-level is the communication space where the inter-agent messages are exchange and is explained by increased entropy on a micro-level); (ii) communication and information transport on micro-level ("quantum mirage" in quantum corrals); (iii) different types of quantum spin correlation that design different structure in self-organization (quantum dot); (iv) coordination control (swam-bot and snake-bot).

Natural evolution processes are based on the following steps: (i) templating; (iii) self-assembling; and (iii) self-organization.

According quantum computing theory in general form every QA includes the following unitary quantum operators: (i) superposition; (ii) entanglement (quantum oracle); (iii) interference. Measurement is the fourth classical operator. [It is irreversible operator and is used for measurement of computation results].

Quantum control algorithm of self-organization that developed below is based on QFI models. QFI includes these concepts of self-organization and has realized by corresponding quantum operators.

Structure of QFI that realize the self-organization process is developed. QFI is one of possible realization of quantum control algorithm of self-organization that includes all of these features: (i) superposition; (ii) selection of quantum correlation types; (iii) information

transport and quantum oracle; and (iv) interference. With *superposition* is realized *templating* operation, and based on macro- and micro-level interactions with information exchange of active agents. *Selection* of quantum correlation type organize *self-assembling* using power source of communication and information transport on micro-level. In this case the type of correlation defines the level of *robustness* in designed KB of FC. *Quantum oracle* calculates intelligent quantum state that includes the most important (value) information transport for *coordination* control. *Interference* is used for extraction the results of coordination control and design in on-line robust KB.

The developed QA of self-organization is applied to design of robust KB of FC in unpredicted control situations.

Main operations of developed QA and concrete examples of QFI applications are described.

The goal of quantum control algorithm of self-organization in Fig. 1 is the support of optimal *thermodynamic trade-off* between *stability*, *controllability* and *robustness* of control object behavior using robust self-organized KB of ICS.

Q. *Why with thermodynamics approach we can organize trade-off between stability, controllability and robustness?*

Let us consider the answer on this question.

3.4 Thermodynamics trade-off between stability, controllability, and robustness

Consider a dynamic control object given by the equation

$$\frac{dq}{dt} = \varphi\big(q, S(t), t, u, \xi(t)\big), \quad u = f\left(q, q_d, t\right), \tag{1}$$

where q is the vector of generalized coordinates describing the dynamics of the control object; S is the generalized entropy of dynamic system (1); u is the control force (the output of the actuator of the automatic control system); $q_d(t)$ is reference signal, $\xi(t)$ is random disturbance and t is the time. The necessary and sufficient conditions of asymptotic stability of dynamic system (1) with $\xi(t) \equiv 0$ are determined by the physical constraints on the form of the Lyapunov function, which possesses two important properties represented by the following conditions:

i. This is a strictly positive function of generalized coordinates, i.e., $V > 0$;
ii. The complete derivative in time of the Lyapunov function is a non-positive function,

$$\frac{dV}{dt} \le 0 .$$

In general case the Lagrangian dynamic system (1) is not lossless with corresponding outputs.

By conditions (i) and (ii), as the generalized Lyapunov function, we take the function

$$V = \frac{1}{2}\sum_{i=1}^{n} q_i^2 + \frac{1}{2}S^2 , \tag{2}$$

where $S = S_{cob} - S_c$ is the production of entropy in the open system "*control object* + *controller*"; $S_{cob} = \Psi\left(q, \dot{q}, t\right)$ is the production of entropy in the control object; and $S_c = \Upsilon\left(\dot{e}, t\right)$ is the production of entropy in the controller (actuator of the automatic control system). It is

possible to introduce the entropy characteristics in Eqs. (1) and (2) because of the scalar property of entropy as a function of time, $S(t)$.

Remark. It is worth noting that the presence of entropy production in (2) as a parameter (for example, entropy production term in dissipative process in Eq. (1)) reflects the dynamics of the behavior of the control object and results in a new class of substantially nonlinear dynamic automatic control systems. The choice of the minimum entropy production both in the control object and in the fuzzy PID controller as a fitness function in the genetic algorithm allows one to obtain feasible robust control laws for the gains in the fuzzy PID controller. The entropy production of a dynamic system is characterized uniquely by the parameters of the nonlinear dynamic automatic control system, which results in determination of an optimal selective trajectory from the set of possible trajectories in optimization problems.

Thus, the first condition is fulfilled automatically. Assume that the second condition $\frac{dV}{dt} \le 0$ holds. In this case, the complete derivative of the Lyapunov function (2) has the form

$$\frac{dV}{dt} = \sum_i q_i \dot{q}_i + S\dot{S} = \sum_i q_i \varphi_i(q, S, t, u) + (S_{cob} - S_c)(\dot{S}_{cob} - \dot{S}_c)$$

Taking into account (1) and the notation introduced above, we have

$$\underbrace{\frac{dV}{dt}}_{\text{Stability}} = \underbrace{\sum_i q_i \varphi_i(q, (\Psi - \Upsilon), t, u)}_{\text{Controllability}} + \underbrace{(\Psi - \Upsilon)(\dot{\Psi} - \dot{\Upsilon})}_{\text{Robustness}} \le 0 \tag{3}$$

Relation (3) relates the stability, controllability, and robustness properties.

Remark. It was introduced the new physical measure of control quality (3) to complex non-linear controlled objects described as non-linear dissipative models. This physical measure of control quality is based on the physical law of minimum entropy production rate in ICS and in dynamic behavior of complex control object. The problem of the minimum entropy production rate is *equivalent* with the associated problem of the maximum released mechanical work as the optimal solutions of corresponding Hamilton-Jacobi-Bellman equations. It has shown that the variational fixed-end problem of the *maximum work* W is equivalent to the variational fixed-end problem of the *minimum entropy production*. In this case both optimal solutions are equivalent for the dynamic control of complex systems and the principle of minimum of entropy production guarantee the maximal released mechanical work with intelligent operations. This new physical measure of control quality we using as fitness function of GA in optimal control system design. Such state corresponds to the minimum of system entropy.

The introduction of physical criteria (the minimum entropy production rate) can guarantee the stability and robustness of control. This method differs from aforesaid design method in that a new *intelligent global feedback* in control system is introduced. The interrelation between the stability of control object (the Lyapunov function) and controllability (the entropy production rate) is used. The basic peculiarity of the given method is the necessity of model investigation for CO and the calculation of entropy production rate through the parameters of the developed model. The integration of joint systems of equations (the

equations of mechanical model motion and the equations of entropy production rate) enable to use the result as the fitness function in GA.

Remark. The concept of an energy-based hybrid controller can be viewed from (3) also as a feedback control technique that exploits the coupling between a physical dynamical system and an energy-based controller to efficiently remove energy from the physical system. According to (3) we have

$$\sum_i q_i \varphi_i\left(q,(\Psi-\Upsilon),t,u\right)+(\Psi-\Upsilon)\left(\dot{\Psi}-\dot{\Upsilon}\right)\le 0 \text{ , or}$$

$$\sum_i q_i \varphi_i\left(q,(\Psi-\Upsilon),t,u\right)\le(\Psi-\Upsilon)\left(\dot{\Upsilon}-\dot{\Psi}\right). \tag{4}$$

Therefore, we have different possibilities for support inequalities in (4) as following:

$$\text{(i)} \sum_i q_i\dot{q}_i<0,(\Psi>\Upsilon),\left(\dot{\Upsilon}>\dot{\Psi}\right), S\dot{S}>0\,;$$

$$\text{(ii)} \sum_i q_i\dot{q}_i<0,(\Psi<\Upsilon),\left(\dot{\Upsilon}<\dot{\Psi}\right), S\dot{S}>0\,;$$

$$\text{(iii)} \sum_i q_i\dot{q}_i<0,(\Psi<\Upsilon);\left(\dot{\Upsilon}>\dot{\Psi}\right), S\dot{S}<0, \sum_i q_i\dot{q}_i<S\dot{S} \text{ , etc}$$

and its combinations, that means thermodynamically stabilizing compensator can be constructed. These inequalities specifically, if a dissipative or lossless plant is at high energy level, and a lossless feedback controller at a low energy level is attached to it, then energy will generally tends to flow from the plant into the controller, decreasing the plant energy and increasing the controller energy. Emulated energy, and not physical energy, is accumulated by the controller. Conversely, if the attached controller is at a high energy level and a plant is at a low energy level, then energy can flow from the controller to the plant, since a controller can generate real, physical energy to effect the required energy flow. Hence, if and when the controller states coincide with a high emulated energy level, then it is possible reset these states to remove the emulated energy so that the emulated energy is not returned to the CO.

In this case, the overall closed-loop system consisting of the plant and the controller possesses discontinuous flows since it combines logical switching with continuous dynamics, leading to impulsive differential equations. Every time the emulated energy of the controller reaches its maximum, the states of the controller reset in such a way that the controller's emulated energy becomes zero.

Alternatively, the controller states can be made reset every time the emulated energy is equal to the actual energy of the plant, enforcing the second law of thermodynamics that ensures that the energy flows from the more energetic system (the plant) to the less energetic system (the controller). The proof of asymptotic stability of the closed-loop system in this case requires the non-trivial extension of the hybrid invariance principle, which in turn is a very recent extension of the classical *Barbashin-Krasovskii* invariant set theorem. The subtlety here is that the resetting set is not a closed set and as such a new transversality condition involving higher-order Lie derivatives is needed.

Main goal of robust intelligent control is support of optimal *trade-off* between stability, controllability and robustness with thermodynamic relation as (3) or (4) as

thermodynamically stabilizing compensator. The resetting set is thus defined to be the set of all points in the closed-loop state space that correspond to decreasing controller emulated energy. By resetting the controller states, the plant energy can never increase after the first resetting event. Furthermore, if the closed-loop system total energy is conserved between resetting events, then a decrease in plant energy is accompanied by a corresponding increase in emulated energy. Hence, this approach allows the plant energy to flow to the controller, where it increases the emulated energy but does not allow the emulated energy to flow back to the plant after the first resetting event.

This energy dissipating hybrid controller effectively enforces a one-way energy transfer between the control object and the controller after the first resetting event. For practical implementation, knowledge of controller and object outputs is sufficient to determine whether or not the closed-loop state vector is in the resetting set. Since the energy-based hybrid controller architecture involves the exchange of energy with conservation laws describing transfer, accumulation, and dissipation of energy between the controller and the plant, we can construct a modified hybrid controller that guarantees that the closed-loop system is consistent with basic thermodynamic principles after the first resetting event.

The entropy of the closed-loop system strictly increases between resetting events after the first resetting event, which is consistent with thermodynamic principles. This is not surprising since in this case the closed-loop system is *adiabatically isolated* (i.e., the system does not exchange energy (heat) with the environment) and the total energy of the closed-loop system is conserved between resetting events. Alternatively, the entropy of the closed-loop system strictly decreases across resetting events since the total energy strictly decreases at each resetting instant, and hence, energy is not conserved across resetting events.

Entropy production rate is a continuously differentiable function that defines the resetting set as its zero level set. Thus the resetting set is motivated by thermodynamic principles and guarantees that the energy of the closed-loop system is always flowing from regions of higher to lower energies after the first resetting event, which is in accordance with the second law of thermodynamics. This guarantees the existence of entropy function for the closed-loop system that satisfies the Clausius-type inequality between resetting events. Hence, it is reset the compensator states in order to ensure that the second law of thermodynamics is not violated. Furthermore, in this case, the hybrid controller with resetting set is a thermodynamically stabilizing compensator. Analogous thermodynamically stabilizing compensators can be constructed for lossless dynamical systems.

Equation (3) joint in analytic form different measures of control quality such as *stability, controllability*, and *robustness* supporting the required level of reliability and accuracy. As particular case Eq. (3) includes the entropic principle of robustness. Consequently, the interrelation between the Lyapunov stability and robustness described by Eq. (3) is the main physical law for designing automatic control systems. This law provides the background for an applied technique of designing KBs of robust intelligent control systems (with different levels of intelligence) with the use of soft computing.

In concluding this section, we formulate the following conclusions:

1. The introduced physical law of intelligent control (3) provides a background of design of robust KB's of ICS's (with different levels of intelligence) based on soft computing.
2. The technique of soft computing gives the opportunity to develop a universal approximator in the form of a fuzzy automatic control system, which elicits information

from the data of simulation of the dynamic behavior of the control object and the actuator of the automatic control system.

3. The application of soft computing guarantees the purposeful design of the corresponding robustness level by an optimal design of the total number of production rules and types of membership functions in the KB.

The main components and their interrelations in the information design technology are based on new types of (soft and quantum) computing. The key point of this information design technology is the use of the method of eliciting objective knowledge about the control process irrespective of the subjective experience of experts and the design of objective KB's of a FC, which is principal component of a robust ICS.

The output result of application of this information design technology is a robust KB of the FC that allows the ICS to operate under various types of information uncertainty. Self-organized ICS based on soft computing technology can supports thermodynamic trade-off in interrelations between stability, controllability and robustness (Litvintseva et al., 2006).

Remark. Unfortunately, soft computing approach also has bounded possibilities for global optimization while multi-objective GA can work on fixed space of searching solutions. It means that robustness of control can be guaranteed on similar unpredicted control situations. Also search space of GA choice expert. It means that exist the possibility that searching solution is not included in search space. (It is very difficult find black cat in dark room if you know that cat is absent in this room.) The support of optimal *thermodynamic trade-off* between *stability*, *controllability* and *robustness* in self-organization processes (see, Fig. 1) with (3) or (4) can be realized using a new quantum control algorithm of self-organization in KB of robust FC based on quantum computing operations (that absent in soft computing toolkit).

Let us consider the main self-organization idea and the corresponding structure of quantum control algorithm as QFI that can realize the self-organization process.

4. QFI-structure and knowledge base self-organization based on quantum computing

General physical approach to the different bio-inspired and man-made model's description of self-organization principles from quantum computing viewpoint and quantum control algorithm of self-organization design are described. Particular case of this approach (based on early developed quantum swarm model) was introduced (see, in details (Litvintseva et al., 2009)). Types of quantum operators as superposition, entanglement and interference in different model's evolution of self-organization processes are applied from quantum computing viewpoint. The physical interpretation of self-organization control process on quantum level is discussed based on the information-thermodynamic models of the exchange and extraction of quantum (hidden) value information from/between classical particle's trajectories in particle swarm. New types of quantum correlations (as behavior control coordinator with quantum computation by communication) and information transport (value information) between particle swarm trajectories (communication through a quantum link) are introduced.

We will show below that the structure of developed QFI model includes necessary self-organization properties and realizes a self-organization process as a new QA. In particular case in intelligent control system (ICS) structure, QFI system is a QA block, which performs post-processing in on-line of the results of fuzzy inference of each independent FC and

produces the generalized control signal output. In this case the on-line output of QFI is an optimal robust control signal, which combines best features of the each independent FC outputs (self-organization principle).
Thus QFI is one of the possible realizations of a general quantum control algorithm of the self-organization processes.

4.1 Quantum Fuzzy Inference process based on quantum computing

From computer science viewpoint the QA structure of QFI model (as a particular case of the general quantum control algorithm of self-organization) must includes following necessary QA features: *superposition* preparation; *selection of quantum correlation* types; *quantum oracle* (black box model) application and *transportation* of extracted information (dynamic evolution of "*intelligent control state*" with minimum entropy); a *quantum correlation* over a classical correlation as power source of computing; applications of an *interference* operator for the answer extraction; *quantum parallel massive* computation; *amplitude amplification* of searching solution; effective quantum solution of classical *algorithmically unsolved* problems.
In this section we will show that we can use ideas of mathematical formalism of quantum mechanics for discovery new control algorithms that can be calculated on classical computers.
Let us consider main ideas of our QFI algorithm.
First of all, we must be able to construct normalized states $|0\rangle$ (for example, it can be called as "*True*") and $|1\rangle$ (that can be called as "*False*") for inputs to our QFI algorithm. In Hilbert space the superposition of classical states $(\alpha_0|0\rangle + \alpha_1|1\rangle)$ called a quantum bit (qubit) means that "*True*" and "*False*" are joined in one quantum state with different probability amplitudes $\alpha_k, k = 0,1$. If P is a probability of a state, then $|\alpha_k|^2 = P$ or $\alpha_k = \sqrt{P}$.
The probabilities governed by the amplitudes α_k must sum to unity. This necessary constraint is expressed as the unitary condition $\sum_k |\alpha_k|^2 = 1$. To create a superposition from a single state, the Hadamard transform H is used. H denotes the fundamental unitary matrix:

$$H = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}.$$

If the Hadamard operator H is applied to classical state $|0\rangle$ we receive the following result:

$$H \otimes |0\rangle \equiv \frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}\begin{pmatrix} 1 \\ 0 \end{pmatrix} = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 \\ 1 \end{pmatrix} = \frac{1}{\sqrt{2}}\left(\begin{pmatrix} 1 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix}\right) = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle).$$

Remark. The state $|0\rangle$ in a vector form is represented as a vector $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$ and state $|1\rangle$ is represented as a vector $\begin{pmatrix} 0 \\ 1 \end{pmatrix}$. So, a superposition of two classical states giving a quantum state represented as follows:

$$|\psi\rangle = \frac{1}{\sqrt{2}}\left(\sqrt{P(|0\rangle)}|0\rangle + \sqrt{1 - P(|0\rangle)}|1\rangle\right) = quantum\ bit\ .$$

If the Hadamard operator H is independently applied to different classical states then a tensor product of superposition states is the result:

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

The fundamental result of quantum computation says that all of the computation can be embedded in a circuit, which nodes 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: (1) Given a set of functional points $S = \{(x, y)\}$ find the operator U such that $y = U \cdot x$; (2) Given a problem, fined 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. Hence, a quantum gate approach can be used in a global optimization of KB structures of ICS's that are based on quantum computing, on a quantum genetic search and quantum learning algorithms.
A general structure of QFI block is shown on Figure 2.
In particularity, Figure 2 shows the structure of QFI algorithm for coding, searching and extracting the value information from the outputs of a few of independent fuzzy controllers with different knowledge bases (FC-KBs).
Inputs to QFI are control signals

$$K^i = \{k_p^i(t), k_D^i(t), k_I^i(t)\},$$

where index i means a number of KB (or FC) and t is a current temporal point.
Remark. In advanced control theory, control signal $K^i = \{k_p^i(t), k_D^i(t), k_I^i(t)\}$ is called as *a PID gain coefficient schedule*. We will call it as a *control laws vector*.
These inputs are the outputs from fuzzy controllers (FC1, FC2, …,FCn) designed by SC Optimizer (SCO) tools for the given control task in different control situations (for example, in the presence of different stochastic noises). Output of QFI block is a new, redesigned (self-organized), control signal. The robust laws designed by the model of QFI are determined in a learning mode based on the output responses of individual KB's (with a fixed set of production rules) of corresponding FC's (see below Fig. 2) to the current unpredicted control situation in the form signals for controlling coefficient gains schedule of the PID controller and implement the adaptation process in online.
This effect is achieved only by the use of the laws of quantum information theory in the developed structure of QFI (see above the description of four facts from quantum information theory).
From the point of view of quantum information theory, the structure of the quantum algorithm in QFI (Level 3, Fig. 1) plays the role of a quantum filter simultaneously. The KB's consist of logical production rules, which, based on a given control error, form the laws of the coefficient gains schedule in the employed fuzzy PID controllers.
The QA in this case allows one to extract the necessary valuable information from the responses of two (or more) KB's to an unpredicted control situation by eliminating additional redundant information in the laws of the coefficient gains schedule of the controllers employed.

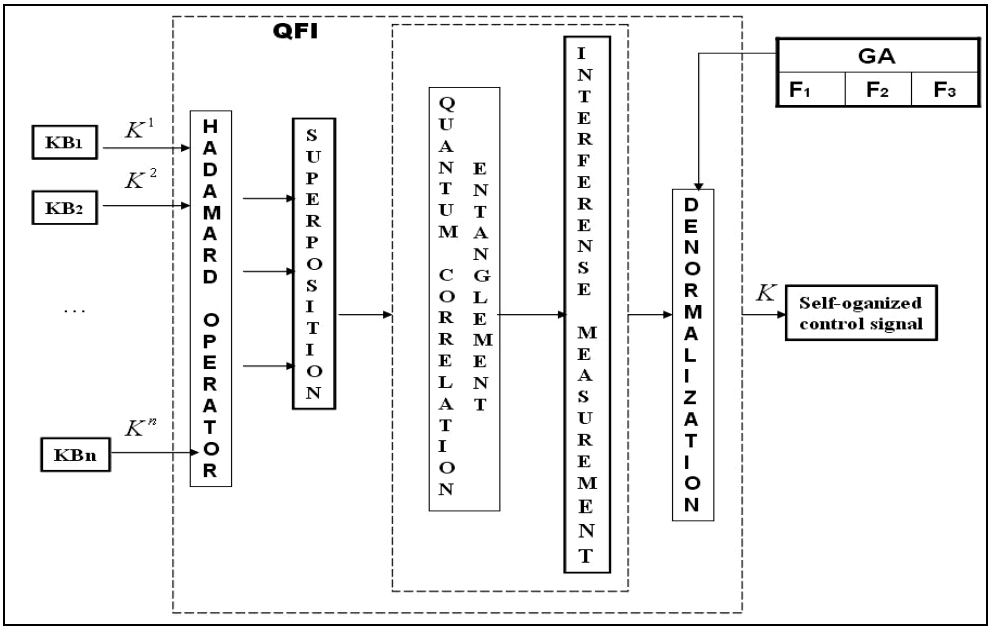


Fig. 2. Quantum Fuzzy Inference (QFI) block

4.2 Requirements to QFI-model design and its features in quantum algorithm control of self-organization

4.2.1 Main proposals and features of QFI model

Main *proposals* and *features* of the developed swarm QFI-model in the solution of intelligent control problems are as following:

A. *Main proposals*

1. The digital value's set of control signals produced by responses of FC outputs are considered as swarm particles along of classical control trajectories with individual marked intelligent agents;
2. Communication between particle swarm trajectories through a quantum link is introduced;
3. Intelligent agents are used different types of quantum correlations (as behavior control coordinator with quantum computation by communication) and information transport (value information);
4. The (hidden) quantum value information extracted from *classical* states of control signal classical trajectories (with minimum entropy in "intelligent states" of designed robust control signals).

B. *Features*

1. Developed QFI model is based on *thermodynamic* and *information-theoretic* measures of intelligent agent interactions in communication space between macro- and micro-levels (the entanglement-assisted correlations in an active system represented by a collection of intelligent agents);
2. From computer science viewpoint, QA of QFI model plays the role of the information-algorithmic and SW-platform support for design of self-organization process;

3. Physically, QFI supports optimally a new developed *thermodynamic trade-off* of control performance (between stability, controllability and robustness) in self-organization KB process.

From quantum information theory viewpoint, QFI reduces the redundant information in classical control signals using four facts (Litvintseva et al., 2007) from quantum information for data compression in quantum information processing: 1) efficient quantum data compression; 2) coupling (separation) of information in the quantum state in the form of classical and quantum components; 3) amount of total, classical, and quantum correlation; and 4) hidden (observable) classical correlation in the quantum state.

We are developed the gate structure of QFI model with self-organization KB properties that includes all of these QA features (see, below Fig. 3) based on abovementioned proposals and general structure on Fig. 2.

Let us discuss the following question.

Q. *What is a difference between our approach and Natural (or man-made) models of self-organization?*

A. *Main differences* and *features* are as followings:

- In our approach a self-organization process is described as a *logical algorithmic* process of value information *extraction* from hidden layers (*possibilities*) in classical control laws using quantum decision-making logic of QFI-models based on main facts of quantum information, quantum computing and QA's theories (Level 3, Fig. 1);
- Structure of QFI includes all of natural elements of self-organization (templating, self-assembly, and self-organization structure) with corresponding quantum operators (superposition of initial states, selection of quantum correlation types and classes, quantum oracles, interference, and measurements) (Level 2, Fig. 1);
- QFI is a new quantum search algorithm (belonging to so called *QPB*-class) that can solve classical algorithmically unsolved problems (Level 1, Fig. 1);
- In QFI the self-organization principle is realized using the on-line responses in a dynamic behavior of classical FC's on new control errors in unpredicted control situations for the design of robust intelligent control (see Fig. 2);
- Model of QFI supports the thermodynamic interrelations between *stability*, *controllability* and *robustness* for design of self-organization processes (Goal description level on Fig. 1).

Specific features of QFI applications in design of robust *KB*. Let us stress the fundamentally important specific feature of operation of the QA (in the QFI model) in the design process of robust laws for the coefficient gain schedules of fuzzy PID controllers based on the individual KB that designed on SCO with soft computing (Level 1, Fig. 1).

4.2.2 Quantum information resources in QFI algorithm

In this section we introduce briefly the particularities of quantum computing and quantum information theory that are used in the quantum block – QFI (see, Fig. 1) supporting a self-organizing capability of FC in robust ICS. According to described above algorithm the input to the QFI gate is considered according Fig. 2 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, below Fig. 3) for the given control task in different control situations (for example, in the presence of different stochastic noises).

4.2.3 Quantum hidden information extraction in QFI

Using the four facts from quantum information theory QFI extracts the hidden quantum value information from classical KB1 and KB2 (see, Figure 3).

In this case between KB1 and KB2 (from quantum information theory of viewpoint) we organize a communication channel using quantum correlations that is impossible in classical communication theory. The algorithm of superposition calculation is presented below and described in details in (Litvintseva et al., 2007).

We discuss for simplicity the situation in which an arbitrary amount of correlation is unlocked with a one-way message.

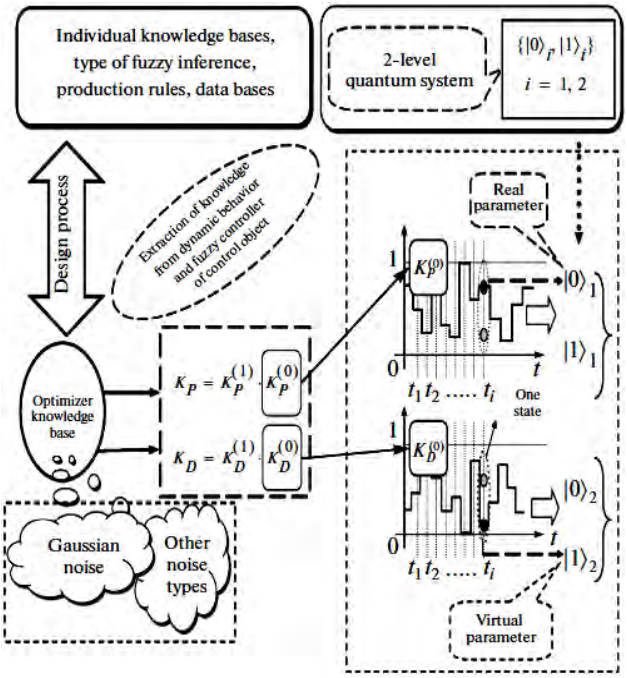
Let us consider the communication process between two KBs as communication between two players A and B (see, Figs 2 and 3) and let $d = 2^n$. According to the law of quantum mechanics, initially we must prepare a quantum state description by density matrix ρ from two classical states (KB1 and KB2). The initial state ρ is shared between subsystems held by A (KB1) and B (KB2), with respective dimensions d,

$$\rho = \frac{1}{2d}\sum_{k=0}^{d-1}\sum_{t=0}^{1}\left(|k\rangle\langle k| \otimes |t\rangle\langle t|\right)_A \otimes \left(U_t|k\rangle\langle k|U_t^\dagger\right)_B . \tag{5}$$

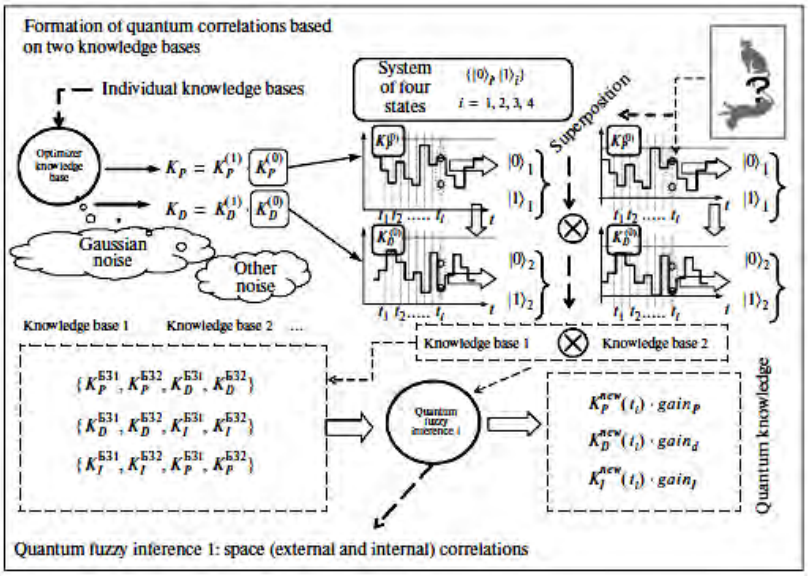
Here $U_0 = I$ and U_1 changes the computational basis to a conjugate basis $\left|\langle i|U_1|k\rangle\right| = 1/\sqrt{d} \quad \forall\, i,k$.

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 (5) can arise from 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. Player A can send t to player B to unlock the correlation later. Experimentally, Hadamard transform, H and measurement on single qubits are sufficient to prepare the state (2), and later extract 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 increase*.

This phenomenon is *impossible* classically. However, states exhibiting this behaviour *need not be entangled* and corresponding communication can be organized using Hadamard transform. 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. 3,b).In present section we consider a simplified case of QFI when with the Hadamard transform is organized an unlocked correlation in superposition of two KB's; instead of the difficult defined entanglement operation an equivalent quantum oracle is modelled that can estimates an "*intelligent state*" with the maximum of amplitude probability in corresponding superposition of classical states (minimum entropy principle relative to extracted quantum knowledge (Litvintseva et al., 2009)). Interference operator extracts this maximum of amplitude probability with a classical measurement.



(a)



(b)

Fig. 3. (a, b). Example of information extraction in QFI

Figure 4 shows the algorithm for coding, searching and extracting the value information from KB's of fuzzy PID controllers designed by SCO and QCO (quantum computing optimizer).

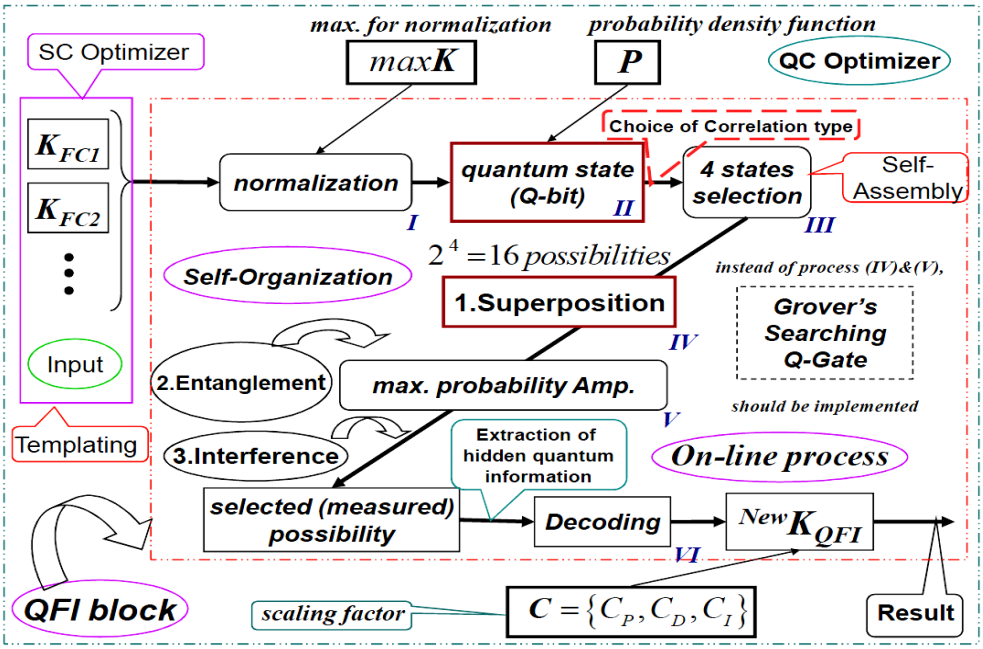


Fig. 4. The structure of QFI gate

Optimal drawing process of value information from a few KBs that are designed by soft computing is based on following four facts from quantum information theory (Litvintseva et al., 2007): (*i*) the effective quantum data compression; (*ii*) the splitting of classical and quantum parts of information in quantum state; (*iii*) the total correlations in quantum state are "mixture" of classical and quantum correlations; and (*iv*) the exiting of hidden (locking) classical correlation in quantum state.

This quantum control algorithm uses these four Facts from quantum information theory in following way: (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.

5. Structures of robust ICS and information design technology of quantum KB self-organization

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 BP-algorithm for KB refinement. 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 use stochastic simulation system based on the control object model. More detail description of SCO is given in (Litvintseva et al., 2006).

Figure 5 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. CO may be represented in physical form or in the form of mathematical model. We will use a mathematical model of CO described in Matlab-Simulink 7.1 (some results are obtained by using Matlab-Simulink 6.5). The kernel of the abovementioned FC design tools is a so-called SC Optimizer (SCO) implementing advanced soft computing ideas.

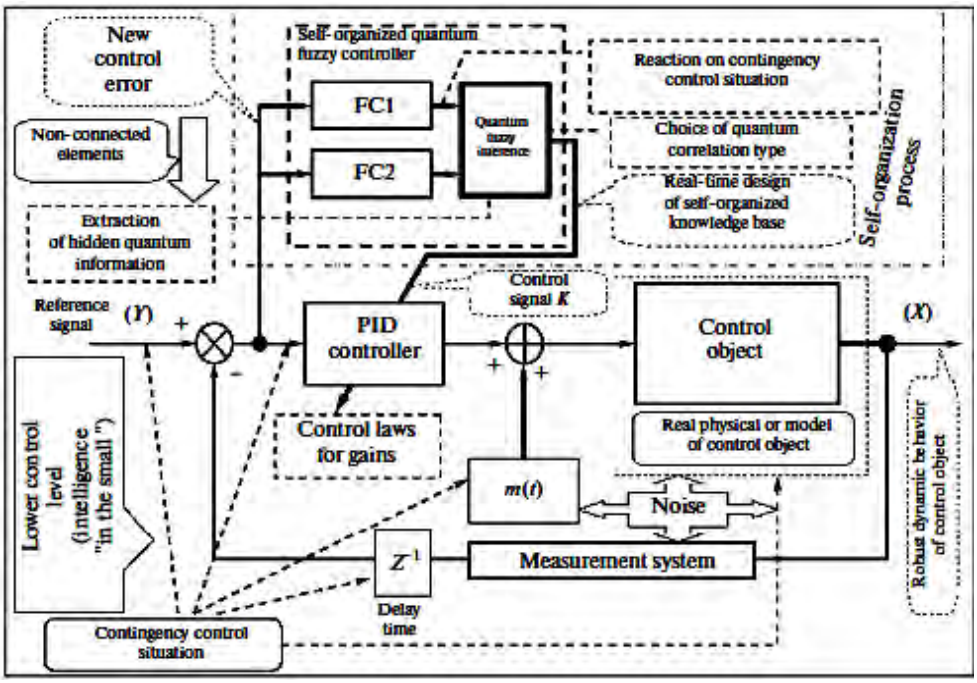


Fig. 5. Structure of robust ICS based on QFI

Figure 6 shows the structural diagram of the information technology and design stages of the objective KB for robust ICS's based on new types of computational intelligence.

Remark. Unconventional computational intelligence: *Soft and quantum computing technologies*. Soft computing and quantum computing are new types of unconventional computational intelligence (details see in http://www.qcoptimizer.com/). Technology of soft computing is

based on GA, fuzzy neural network, and fuzzy logic inference. Quantum computational intelligence is used quantum search algorithm, quantum neural network, and QFI. These algorithms are includes three main operators. In GA selection, crossover, and mutation operators are used. In quantum search algorithm superposition, entanglement, and interference are used.

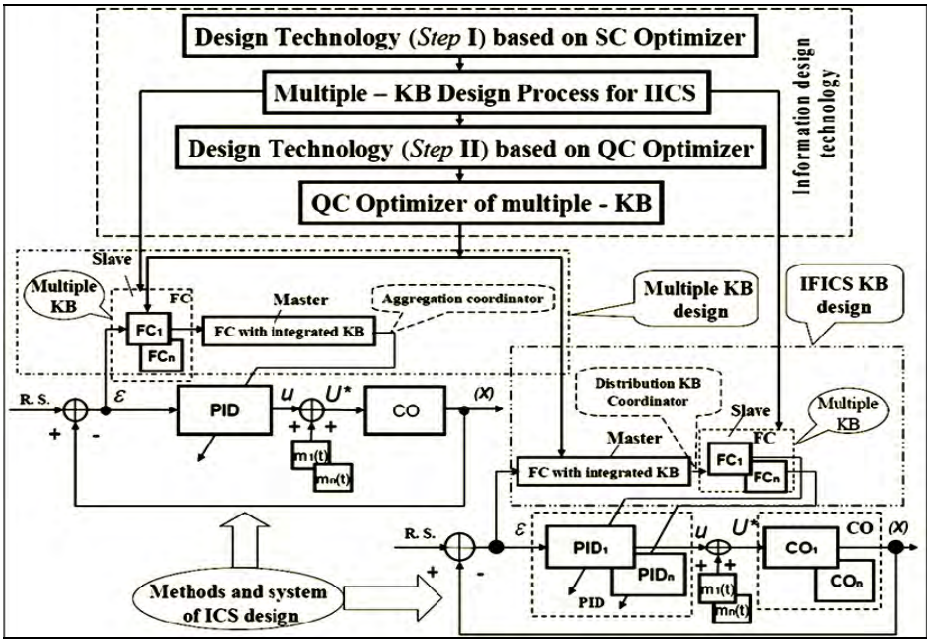


Fig. 6. Structure of robust KB information technology design for integrated fuzzy ICS (IFICS) (R.S. – reference signal) Information design technology includes two steps: 1) step 1 based on SCO with soft computing; and 2) step 2 based on SCO with quantum computing.

Main problem in this technology is the design of robust KB of FC that can include the self-organization of knowledge in unpredicted control situations. The background of this design processes is KB optimizer based on quantum/soft computing. Concrete industrial Benchmarks (as 'cart - pole' system, robotic unicycle, robotic motorcycle, mobile robot for service use, semi-active car suspension system etc.) are tested successfully with the developed design technology. In particular case, the role of Kansei engineering in System of System Engineering is demonstrated. An application of developed toolkit in design of "*Hu-Machine* technology" based on Kansei Engineering is demonstrated for emotion generating enterprise (purpose of enterprise).

We illustrate the efficiency of application of QFI by a particular example. Positive applied results of classical computational technologies (as soft computing) together with quantum computing technology created a new alternative approach – applications of quantum computational intelligence technology to optimization of control processes in classical CO (physical analogy of inverse method investigation "*quantum control system – classical* CO").

We will discuss also the main goal and properties of quantum control design algorithm of self-organization robust KB in ICS. Benchmarks of robust intelligent control in unpredicted situation are introduced.

Therefore the operation area of such a control system can be expanded greatly as well as its robustness. Robustness of control signal is the background for support the reliability of control accuracy in uncertainty environments. The effectiveness of the developed QFI model is illustrated for important case - the application to design of robust control system in unpredicted control situations.

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 a 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. 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.

Let us discuss in detail the design process of robust KB in unpredicted situations.

6. KB self-organization quantum algorithm of FC's based on QFI

We use real value of a current input control signal to design normalized state $|0\rangle$. To define probability amplitude α_0 we will use simulation results of controlled object behavior in teaching conditions. In this case by using control signal values, we can construct histograms of control signals and then taking integral we can receive probability distribution function and calculate $\alpha_0 = \sqrt{P_0}$. Then we can find $\alpha_1 = \sqrt{1 - P_0}$. After that it is possible to define state $|1\rangle$ as shown on Fig. 7 below.

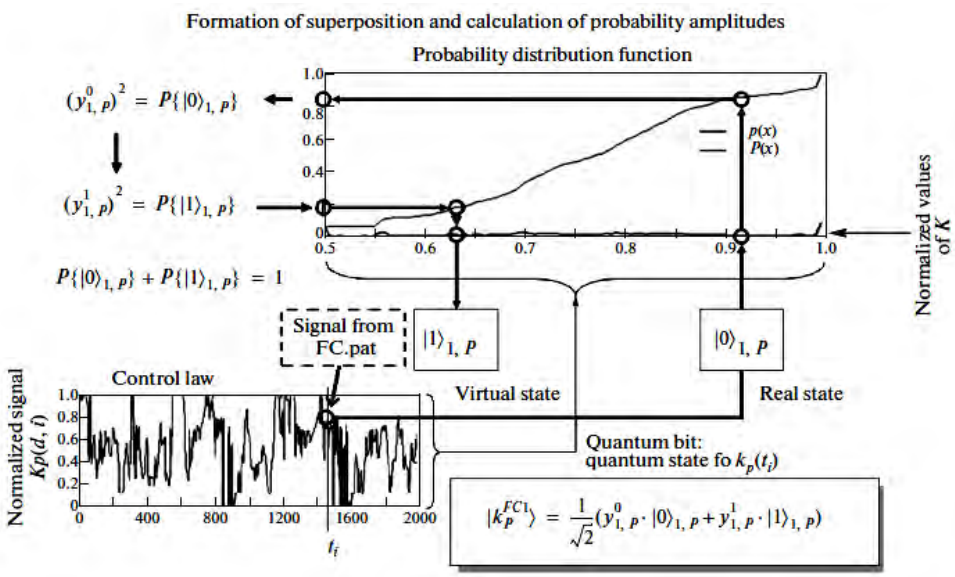


Fig. 7. Example of control signal and corresponding probability distribution function

For QA design of QFI it is needed to apply the additional operations to partial KBs outputs that drawing and aggregate the value information from different KBs. Soft computing tool does not contain corresponding necessary operations**.** The necessary unitary reversible operations are called *superposition*, *entanglement* (quantum correlation) and *interference* that physically are operators of quantum computing.

Consider main steps of developed QFI process that is considered as a QA.

Step 1. Coding

- Preparation of all normalized states $|0\rangle$ and $|1\rangle$ for current values of control signal $\{k_P^i(t), k_D^i(t), k_I^i(t)\}$ (index i means a number of KB) with respect to the chosen knowledge bases and corresponding probability distributions, including:
- (a) calculation of probability amplitudes α_0, α_1 of states $|0\rangle$ and $|1\rangle$ from histograms;
- (b) by using α_1 calculation of normalized value of state $|1\rangle$.

Step 2. *Choose quantum correlation type for preparation of entangled state.* In the Table **1** investigated types of quantum correlations are shown. Take, for example, the following quantum correlation type:

$$\{k_P^1(t), k_D^1(t), k_P^2(t), k_D^2(t)\} \to k_P^{new}(t),$$

where 1 and 2 are indexes of KB.

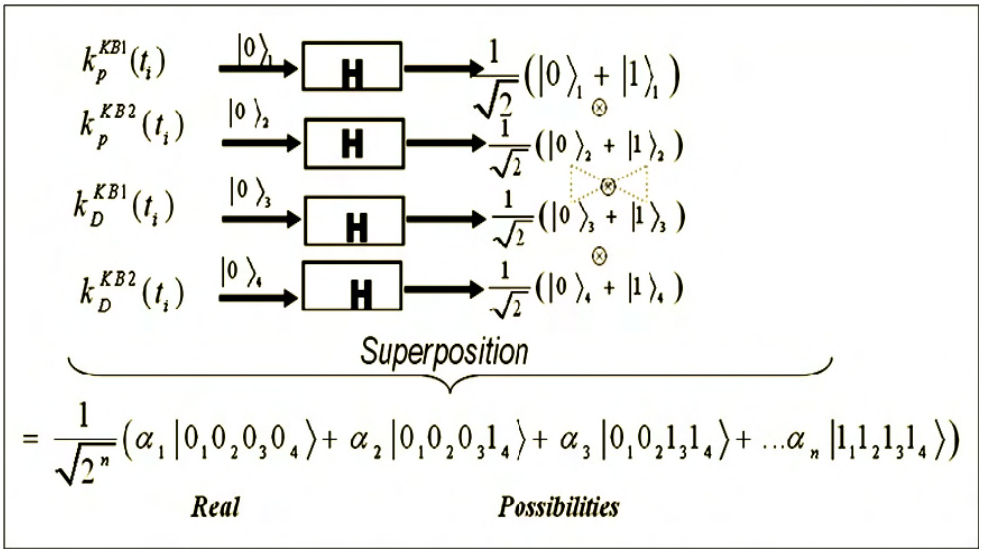
Then a quantum state $|a_1 a_2 a_3 a_4\rangle = |k_P^1(t)\, k_D^1(t)\, k_P^2(t)\, k_D^2(t)\rangle$ is considered as correlated (entangled) state

1. QFI based on spatial correlations	$k_P^{KB1,KB2}(t_i) k_D^{KB1,KB2}(t_i) \to k_P^{new}(t_i) \cdot gain_P$ $k_D^{KB1,KB2}(t_i) k_I^{KB1,KB2} \to k_D^{new}(t_i) \cdot gain_D$ $k_I^{KB1,KB2}(t_i) k_P^{KB1,KB2}(t_i) \to k_I^{new}(t_i) \cdot gain_I$
2. QFI based on temporal correlations	$k_P^{KB1,KB2}(t_i) k_P^{KB1,KB2}(t_i - \Delta t) \to k_P^{new}(t_i) \cdot gain_P$ $k_D^{KB1,KB2}(t_i) k_D^{KB1,KB2}(t_i - \Delta t) \to k_D^{new}(t_i) \cdot gain_D$ $k_I^{KB1,KB2}(t_i) k_I^{KB1,KB2}(t_i - \Delta t) \to k_I^{new}(t_i) \cdot gain_I$
3. QFI based on spatio-temporal correlations	$k_P^{KB1}(t_i) k_D^{KB1}(t_i - \Delta t) k_P^{KB2}(t_i - \Delta t) k_D^{KB2}(t_i) \to k_P^{new}(t_i) \cdot gain_P$ $k_D^{KB1}(t_i) k_I^{KB1}(t_i - \Delta t) k_D^{KB2}(t_i - \Delta t) k_I^{KB2}(t_i) \to k_D^{new}(t_i) \cdot gain_D$ $k_I^{KB1}(t_i) k_P^{KB1}(t_i - \Delta t) k_I^{KB2}(t_i - \Delta t) k_P^{KB2}(t_i) \to k_I^{new}(t_i) \cdot gain_I$

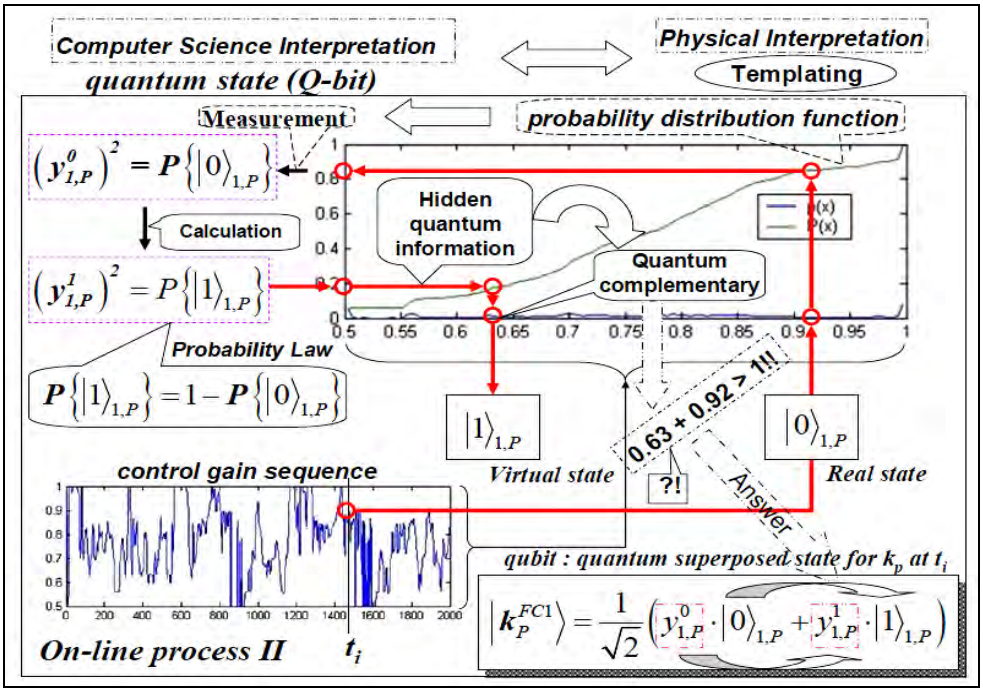
Table 1. Types of quantum correlations

Step 3. *Superposition and entanglement.* According to the chosen quantum correlation type construct superposition of entangled states as shown on general Fig. 8,a,b, where **H** is the Hadamard transform operator.

Step 4. Interference and measurement



(a)



(b)

Fig. 8. The algorithm of superposition calculation

- Choose a quantum state $|a_1 a_2 a_3 a_4\rangle$ with maximum amplitude of probability $|\alpha_k|^2$

Step 5. *Decoding*

- Calculate normalized output as a norm of the chosen quantum state vector as follows

$$k_P^{new}(t) = \frac{1}{\sqrt{2^n}}\sqrt{\langle a_1 ... a_n | a_1 ... a_n \rangle} = \frac{1}{\sqrt{2^n}}\sqrt{\sum_{i=1}^{n}(a_i)^2}$$

Step 6. Denormalization

- Calculate final (denormalized) output result as follows:

$$k_P^{output} = k_P^{new}(t)\cdot gain_p, k_D^{output} = k_D^{new}(t)\cdot gain_D, k_I^{output} = k_I^{new}(t)\cdot gain_I.$$

Step 6a. Find robust QFI scaling gains $\{gain_P, gain_D, gain_I\}$ based on GA and a chosen fitness function.

In proposed QFI we investigated the proposed types of quantum QFI correlations shown in Table 1 where the correlations are given with 2KB, but in general case a few of KBs may be; t_i is a current temporal point and Δt is a correlation parameter. Let us discuss the particularities of quantum computing that are used in the quantum block QFI (Fig. 4) supporting a self-organizing capability of a fuzzy controller. Optimal drawing process of value information from a few of KBs as abovementioned is based on the following four facts from quantum information theory:

- the effective quantum data compression (*Fact*1);
- the splitting of classical and quantum parts of information in quantum state (Fact 2);
- the total correlations in quantum state are "mixture" of classical and quantum correlations (*Fact* 3); and
- existing of hidden (locking) classical correlation in quantum state using criteria of maximal corresponding probability amplitude (*Fact* 4).

These facts are the informational resources of QFI background. Using these facts it is possible to extract the value information from KB1 and KB2. In this case between KB1 and KB2 (from quantum information theory point of view) we organize a communication channel using quantum correlations that is impossible in classical communication. In QFI algorithm with the Hadamard transform an unlocked correlation in superposition of states is organized. The entanglement operation is modelled as a quantum oracle that can estimate a maximum of amplitude probability in corresponding superposition of entangled states. Interference operator extracts this maximum of amplitudes probability with a classical measurement.

Thus from two FC-KBs (produced by SCO for design a smart control) we can produce a wise control by using compression and rejection procedures of the redundant information in a classical control signal. This completes the particularities of quantum computing and quantum information theory that are used in the quantum block supporting a self-organizing capability of FC.

7. Robust FC design toolkit: SC and QC Optimizers for quantum controller's design

To realize QFI process we developed new tools called "QC Optimizer" that are the next generation of SCO tools.

7.1 QC Optimizer Toolkit

QC Optimizer Toolkit is based on Quantum & Soft Computing and includes the following:

- Soft computing and stochastic fuzzy simulation with information-thermodynamic criteria for robust KBs design in the case of a few teaching control situations;
- QFI-Model and its application to a self-organization process based on two or more KBs for robust control in the case of unpredicted control situations.

Internal structure of QC Optimizer is shown on Figs 9 and 10.

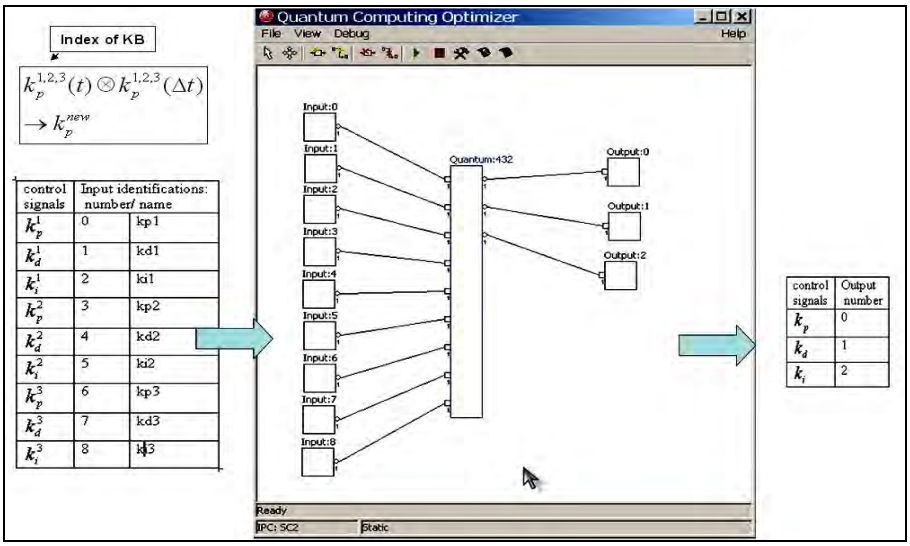


Fig. 9. First internal layer of QC Optimizer

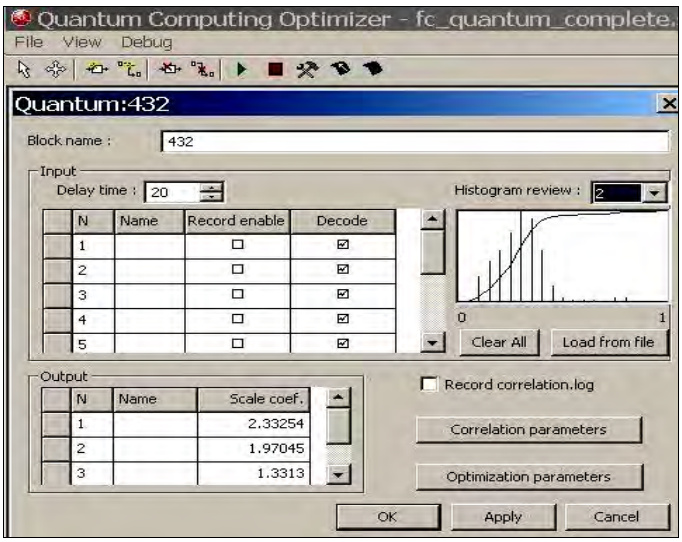


Fig. 10. Second internal layer of QC Optimizer

Remark. On Fig. 9, the first internal layer of QC Optimizer is shown (inputs/output). On Fig. 10, the quantum block realizing QFI process based on three KB is described. On the Fig. 10, "delay time = 20 (sec)" corresponds to the parameter "Δt" given in temporal quantum correlations description (see, Table 1); the knob named "correlation parameters" call other block (see, Fig. 10) where a chosen type of quantum correlations (Table 1) is described.
On Fig. 11 description of temporal quantum correlations is shown. Here "kp1_r" means state $|0\rangle$ for $k_p(t)$ of FC1 (or KB1); "kp1_r_t" means state $|0\rangle$ for $k_p(t+\Delta t)$ of FC1 (or KB1); "kp1_v" means state $|1\rangle$ for $k_p(t)$ of FC1 (or KB1); "kp1_v_t" means state $|1\rangle$ for $k_p(t+\Delta t)$ of FC1 (or KB1); and so on for other FC2 (KB2) and FC3(KB3).

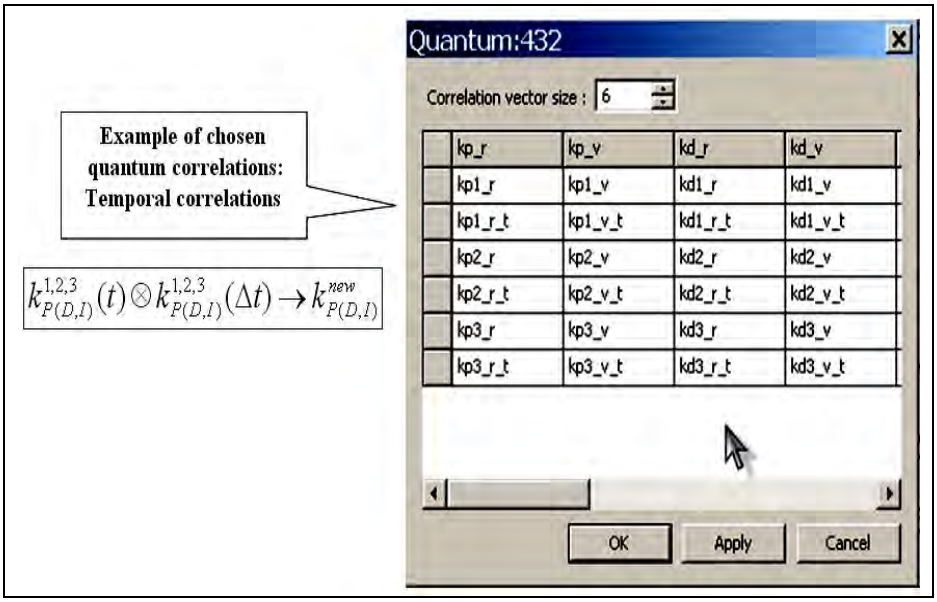


Fig. 11. Internal structure of "correlation parameters" block

7.2 Design of intelligent robust control systems for complex dynamic systems capable to work in unpredicted control situations

Describe now key points of Quantum & Soft Computing Application in Control Engineering according to Fig. 6 as follows:

- PID Gain coefficient schedule (control laws) is described in the form of a Knowledge Base (KB) of a Fuzzy Inference System (realized in a Fuzzy Controller (FC));
- Genetic Algorithm (GA) with complicated Fitness Function is used for KB-FC forming;
- KB-FC tuning is based on Fuzzy Neural Networks using error BP-algorithm;
- Optimization of KB-FC is based on *SC optimizer tools* (Step 1 technology);
- Quantum control algorithm of self-organization is developed based on the QFI-model;
- QFI-model realized for the KB self-organization to a new unpredicted control situation is based on *QC optimizer tools* (Step 2 technology).

In this Chapter we are introduced briefly the particularities of quantum computing and quantum information theory that are used in the quantum block – QFI (see, Fig. 12) supporting a self-organizing capability of FC in robust ICS.

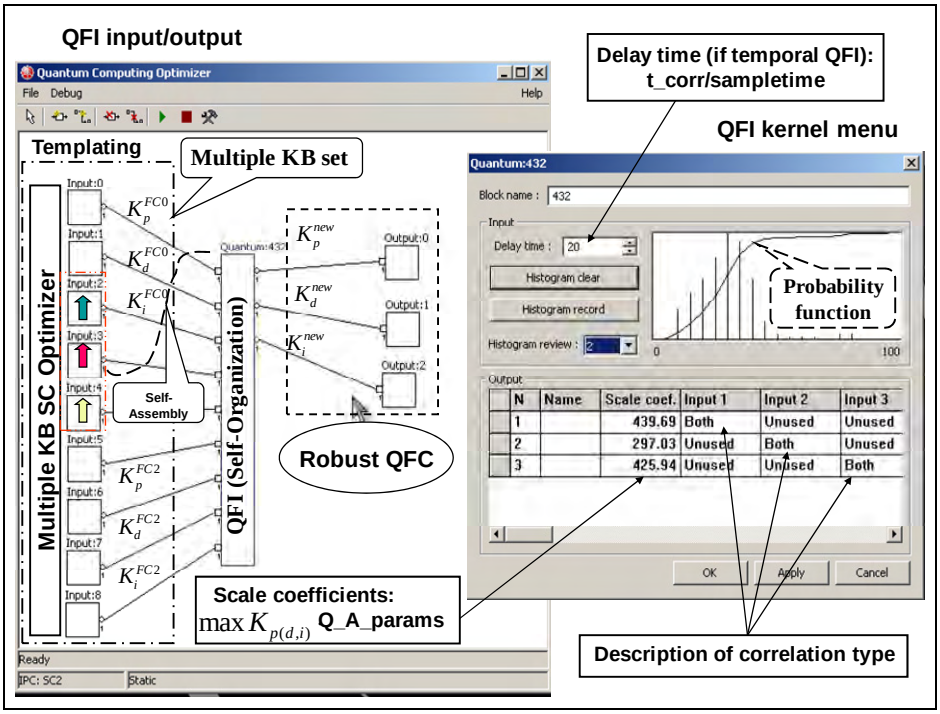


Fig. 12. QFI-process by using QC Optimizer (QFI kernel)

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 supported by the *Quantum Fuzzy Inference* (QFI) based on Quantum Soft Computing ideas.

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. 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.

At the second stage of design with application of the QFI model, we do not need yet to form new production rules. It is sufficient only to receive in on-line the response of production rules in the employed FC to the current unpredicted control situation in the form of the output control signals of the coefficient gains schedule in the fuzzy PID controller. In this

case, to provide the operation of the QFI model, the knowledge of particular production rules fired in the KB is not required, which gives a big advantage, which is expressed the form of an opportunity of designing control processes with the required robustness level in on-line.

Note that the achievement of the required robustness level in an unpredicted control situation essentially depends in a number of cases on the quality and quantity of the employed individual KB's.

Thus, the QA in the QFI model is a physical prototype of production rules, implements a virtual robust KB for a fuzzy PID controller in a program way (for the current unpredicted control situation), and is a problem-independent toolkit. The presented facts give an opportunity to use experimental data of the teaching signal without designing a mathematical model of the CO. This approach offers the challenge of QFI using in problems of CO with weakly formalized (ill-defined) structure and a large dimension of the phase space of controlled parameters.

In present Chapter we are described these features. The dominant role of self-organization in robust KB design of intelligent FC for unpredicted control situations is discussed.

8. Benchmark simulation

Robustness of new types of self-organizing intelligent control systems is demonstrated.

8.1 Control object's model simulation

Consider the following model of control object as nonlinear oscillator:

$$\ddot{x} + \left[2\beta + a\dot{x}^2 + k_1 x^2 - 1\right]\dot{x} + kx = \xi(t) + u(t); \quad \frac{dS_x}{dt} = \left[2\beta + a\dot{x}^2 + k_1 x^2 - 1\right]\dot{x} \cdot \dot{x}, \tag{6}$$

where $\xi(t)$ is a stochastic excitation with an appropriate probability density function; $u(t)$ is a control force; and S_x is an entropy production of control object x. The system, described by Eq.(6) have essentially nonlinear dissipative components and appears different types of behaviour: if $\beta = 0.5$ (other parameters, for example, $\alpha = 0.3; k_1 = 0.2; k = 5$), then dynamic system motion is asymptotically stable; if $\beta = -1$ (other parameters is the same as above), then the motion is locally unstable.

Consider an excited motion of the given dynamic system under hybrid fuzzy PID-control. Let the system be disturbed by a Rayleigh (non Gaussian) noise. The stochastic simulation of random excitations with appropriate probability density functions is based on nonlinear forming filters methodology is developed. In modelling we are considered with developed toolkit (see, Fig. 12) different unforeseen control situations and compared control performances of FC1, FC2, and self-organized control system based on QFI with two FC's. The stochastic simulation of random excitations with appropriate probability density functions is based on nonlinear forming filters methodology developed in (Litvintseva et al., 2006).

FC1 *design*: The following model parameters: $\beta = 0.5; \alpha = 0.3; k_1 = 0.2; k = 5$ and initial conditions [2.5] [0.1] are considered. Reference signal is: $x_{ref} = 0$. K-gains ranging area is [0, 10]. By using SC Optimizer and teaching signal (TS) obtained by the stochastic simulation system with GA or from experimental data, we design KB of FC 1, which optimally approximate the given TS (from the chosen fitness function point of view).

FC2 *design*: The following *new* model parameters: $\beta = -1; \alpha = 0.3; k_1 = 0.2; k = 5$ are used. Initial conditions are the same: [2.5] [0.1]. *New* reference signal is as following: $x_{ref} = -1$; K-gains ranging area is [0, 10].
In modelling we are considered with developed toolkit different unforeseen control situations and compared control performances of FC1, FC2, and self-organized control system based on QFI with two FC's.
In Table 2 four different control situations are described.

Environment 1: Rayleigh noise; Ref signal = 0; Model parameters: $\beta = 0.5; \alpha = 0.3;$ $k_1 = 0.2; k = 5$	*Environment 2:* Rayleigh noise; Ref signal = -1; Model parameters : $\beta = -1; \alpha = 0.3;$ $k_1 = 0.2; k = 5$
Environment 3: Gaussian noise; Ref signal = -0.5; Model parameters: $\beta = -1; \alpha = 0.3;$ $k_1 = 0.2; k = 5$	*Environment 4:* Gaussian noise; Ref signal = +0.5; Model parameters: $\beta = -1; \alpha = 0.3;$ $k_1 = 0.2; k = 5$

Table 2. Learning and unpredicted control situation types

CO may be represented in physical form or in the form of mathematical model. We will use a mathematical model of CO described in Matlab-Simulink 7.1 (some results are obtained by using Matlab-Simulink 6.5). The kernel of the abovementioned FC design tools is a so-called SC Optimizer (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 BP-algorithm for KB refinement. Input to SCO can be some measured or simulated data (called as 'teaching signal" (TS)) about the modelling system. For TS design we use stochastic simulation system based on the CO model and GA. More detail description of SCO is given below. The output signal of QFI is provided by new laws of the coefficient gains schedule of the PID controllers (see, in details Fig. 2 in what follows).

8.2 Result analysis of simulation

For *Environments* 2 and 4 (see, Table 1), Figs 13 -15 show the response comparison of FC1, FC2 and QFI-self-organized control system. *Environment* 2 for FC1 is an unpredicted control situation. Figure 9 shows responses of FC's on unpredicted control situation: a *dramatically new* parameter $\beta = -0.1$ (R1 *situation*) in the model of the CO as (3) and with the similar as above Rayleigh external noise. *Environment* 4 and R1 situation are presented also unpredicted control situations for both designed FC1 & FC2.

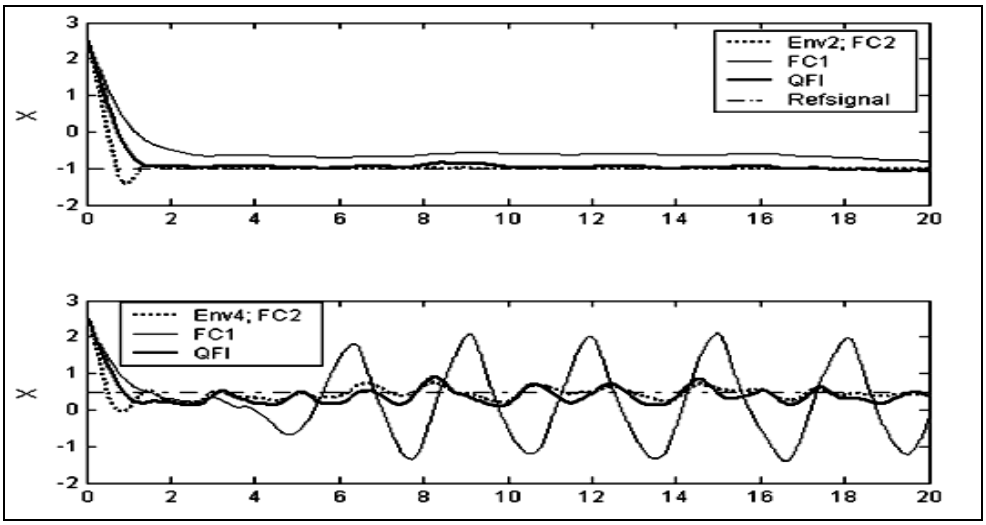


Fig. 13. Motion under different types of control

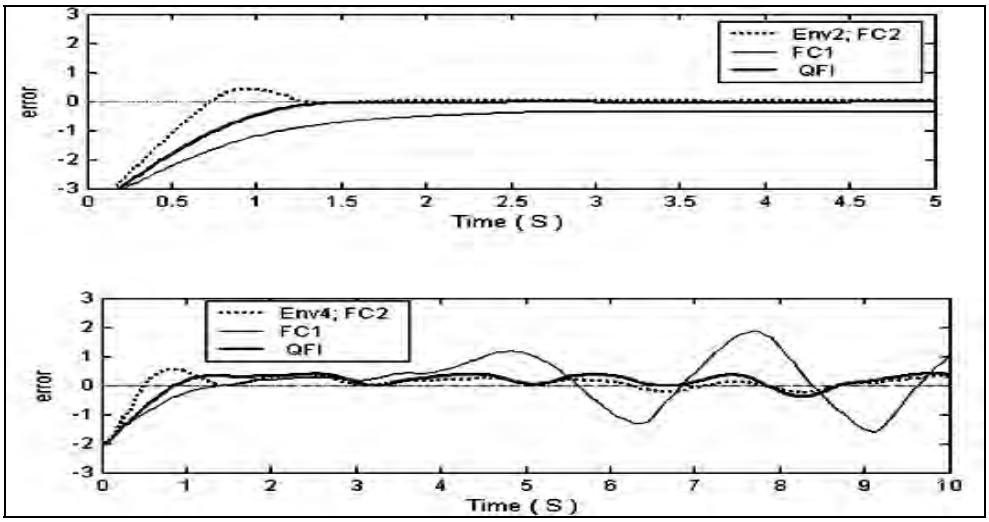


Fig. 14. Control error in different types of control

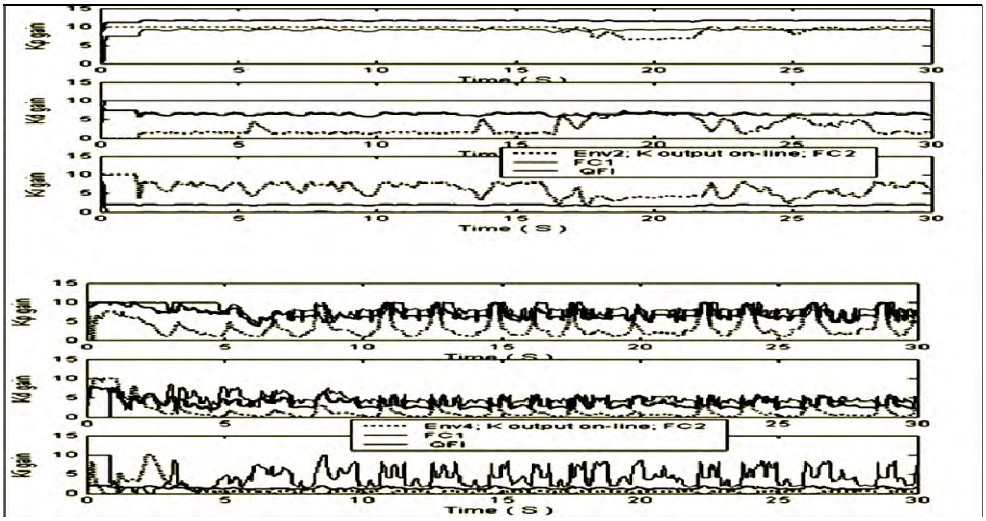


Fig. 15. Control laws in different types of environments

Figure 16 shows responses of FCs on unpredicted control situation: a dramatically new parameter $\beta = -0.1$ (R1 unpredicted situation) in the model of the CO (6) and with the similar as above Rayleigh external noise.

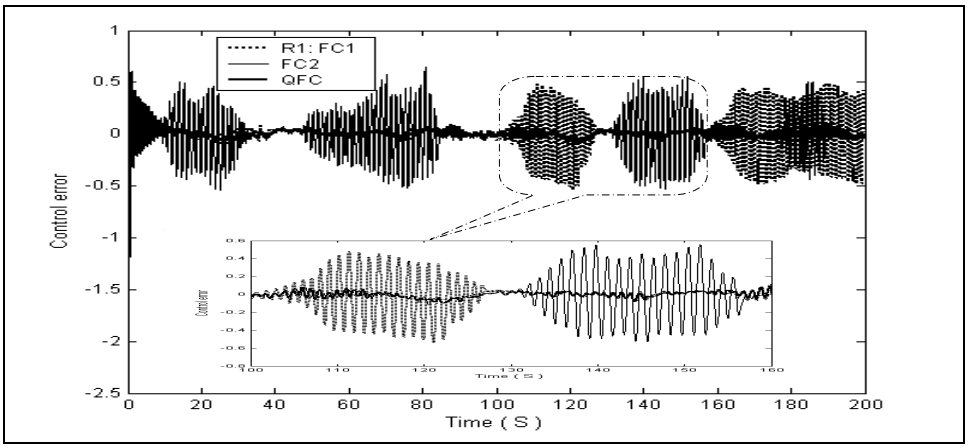


Fig. 16. Control error in unpredicted control situation

Figure 17 shows the example of operation of the quantum fuzzy controller for formation of the robust control signal using the proportional gain in contingency control situation S3.
In this case, the output signals of knowledge bases 1 and 2 in the form of the response on the new control error in situation **S3** are received in the block of the quantum FC. The output of the block of quantum FC is the new signal for real time control of the factor k_p. Thus, the blocks of KB's 1, 2, and quantum FC in Fig. 17 form the block of self-organization of the knowledge base with new synergetic effect in the contingency control situation.

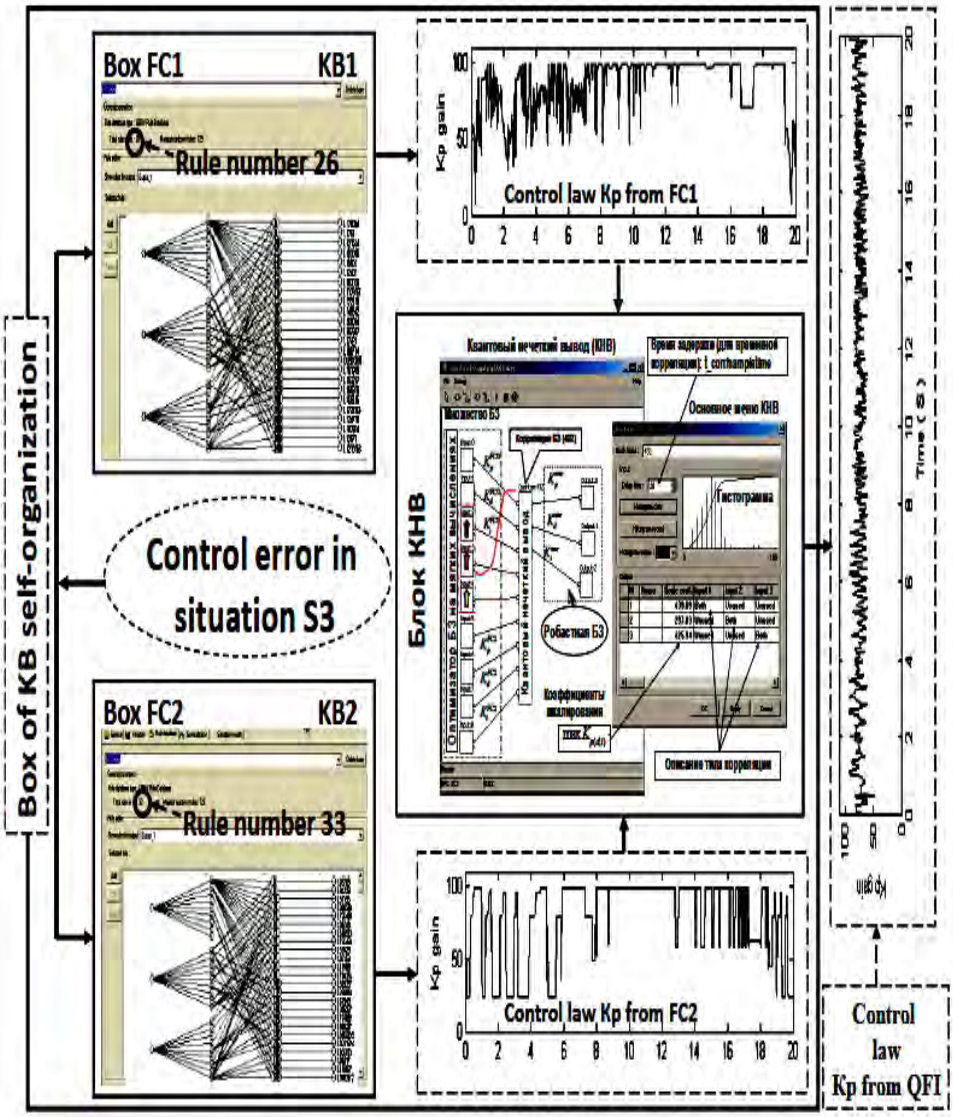
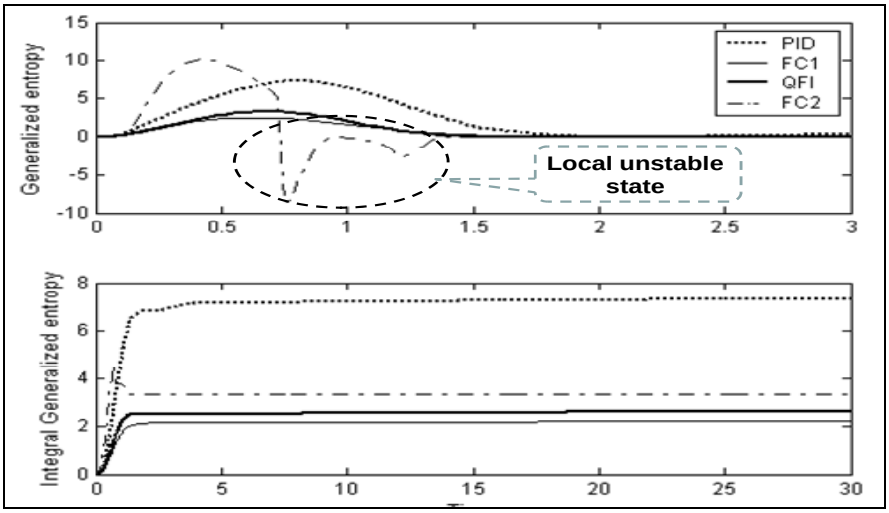


Fig. 17. Example of operation of the block of self-organization of the knowledge base based on quantum fuzzy inference

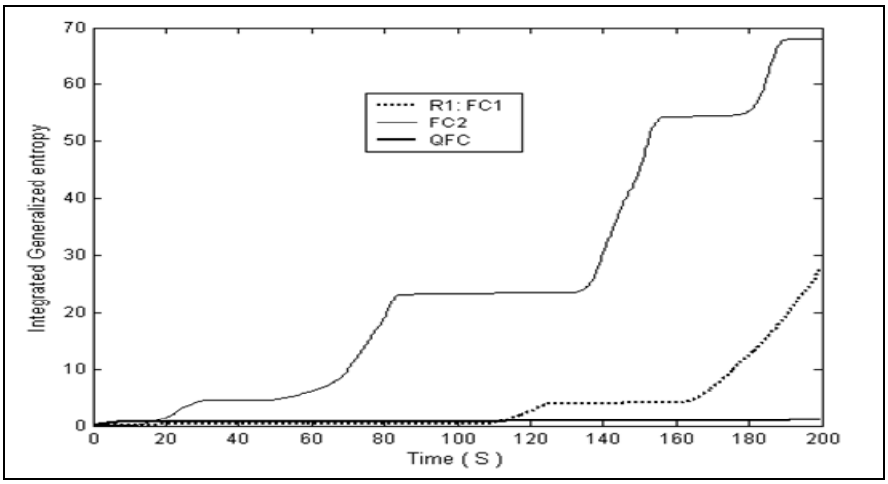
Figure 18 presents the values of generalized entropies of the system "CO + FC" calculated in accordance with (6).

The necessary relations between the qualitative and quantitative definitions of the Lyapunov stability, controllability, and robustness of control processes of a given controlled object are correctly established. Before the achievement of the control goal (the reference control signal equal (–1) in this case) the process of self-learning the FC and extraction of

valuable information from the results of reactions of the two FC's to an unpredicted control situation in on-line with the help of quantum correlation is implemented. Since quantum correlation contains information about the current values of the corresponding gains, the self-organizing FC uses for achievement of the control goal the advantage of performance of the FC2 and the aperiodic character of the dynamic behavior of the FC1.



(a)



(b)

Fig. 18. The dynamic behavior of the generalized entropies of the system (CO + FC): (a) temporal generalized entropy; (b) the accumulated value of the generalized entropy

As a consequence, improved control quality is ensured (Karatkevich et al., 2011).

Figure 19 demonstrate the final results of control law of coefficient gains simulation for intelligent PID-controller.

Simulation results show that with QFI it is possible from two non-robust KB's outputs to design the optimal robust control signal with simple wise control laws of PID coefficient gain schedule in unpredicted control situations. The latter is despite the fact that in Environments 2 & 4 (see, below Table) FC1 and in R1 situation both FC1 & FC2 lose robustness.

Physically, it is the employment demonstration of the minimum entropy principle relative to extracted quantum knowledge. As to the viewpoint of quantum game theory we have *Parrondo'* paradox: from two classical KBs - that are not winners in different unforeseen environments - with QFI toolkit we can design one winner as a wise control signal using quantum strategy of decision making (without entanglement) (Ulyanov & Mishin, 2011).

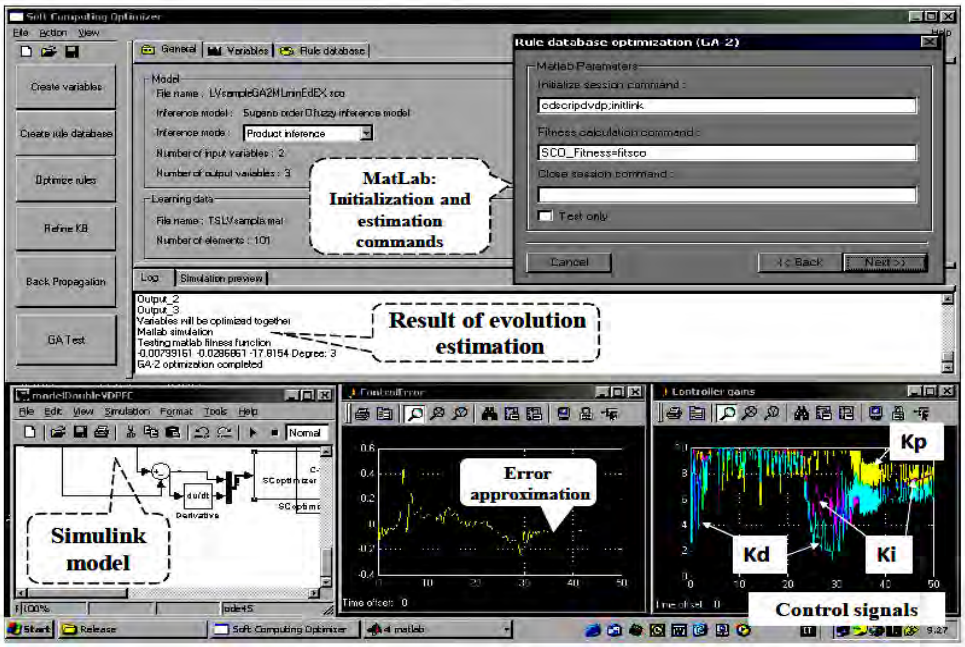


Fig. 19. Simulation results of coefficient gains for intelligent PID-controller

This synergetic quantum effect of knowledge self-organization in robust control was described also on other examples of unstable control systems (details of technology description, see in Web site: http://www.qcoptimizer.com/).

Other examples are described in (Oppenheim, 2008 and Smith & Yard, 2008) later.

9. Conclusions

1. QFI block enhances robustness of FCs using a self-organizing capability and hidden quantum knowledge.
2. SCO allows us to model different versions of KBs of FC that guarantee robustness for fixed control environments.

3. Designed FC based on QFI achieves the prescribed control objectives in many unpredicted control situations.
4. Using SCO and QFI we can design *wise control* of essentially non-linear stable and, especially of unstable dynamic systems in the presence of information uncertainty about external excitations and in presence of dramatically changing control goal, model parameters, and emergency.
5. QFI based FC requires minimum of initial information about external environments and internal structures of a control object adopted a computing speed-up and the power of quantum control algorithm in KB-self-organization.

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