QUANTUM SOFTWARE ENGINEERING SUPREMACY PT 2. APPLICATION OF QUANTUM COMPUTING OPTIMIZER

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ABSTRACT

*Dynamic systems not easily controlled by traditional control systems such as P- [I]-D-controllers in the case of complex, essentially non-linear and ill-defined structures of control objects, and especially in a presence of different stochastic noises and unpredicted control situations. A new approach to the intelligent robust control system design for complex unstable dynamic systems capable to control even in the case of unpredicted control situations described. The approach founded on the new ideas of soft and quantum computing applied to the design of robust Knowledge Bases of hybrid fuzzy PID controllers. For knowledge bases designof robust fuzzy controller, the new program toolkit called Quantum Computing Optimizer (*QCOptKB™*) developed. Simulation results of control performance for two benchmarks(3DoF robot manipulator and cart-pole system) described.*

KEYWORDS

Intelligent control system; quantum knowledge base optimization; soft computing technology; quantum search algorithms, quantum fuzzy inference; Benchmarks.

1. INTRODUCTION

It is impossible to control complex unstable dynamic systems especially in the case of unpredicted control situations by using classical control methods. Traditionally control systems such as P- [I]-D-controllers in the case of complex, essentially non-linear and ill-defined structures of controlled objects and in a presence of different stochastic noises are not robust. A general problem of intelligent PID-controllers design was considered in [1-5]. To improve robustness and control quality of traditional intelligent control systems design we have proposed a new approach based on soft and quantum computing [6-8].

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 quantum fuzzy inference (QFI) models based on main facts of quantum information, quantum computing and quantum algorithm's (QA's) theories [8,9]. The quantum operators, such as superposition, entanglement and interference, give rise to the quantum logic used in quantum computing. Moreover, the usefulness of these quantum operators gives rise to the new viewpoint on control and quantum knowledge base (KB) self-organization algorithms.

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A significant increase in robustness when using these types of computational intelligence allows us to say that the creation of an effective robust and adaptive control system for robotic devices requires an additional software and algorithmic support platform in the form of sophisticated toolkit based on soft and quantum computing (***Quantum computational intelligence toolkit***). Specialists in the design and development of various robots rely on an intelligent software platform for the application of computational intelligence technologies. This approach allows unifying the process of IT intellectualization of the created hybrid industrial service and special purpose robots.

In thisPart 2 of article we are focused the attention on the fact that the application of quantum computing in the design process of intelligent control systems significantly increases the reliability of hybrid intelligent controllers by introducing knowledge self-organization capability. The basic principles of creating robust KB described. The paper demonstrates an experiment, the results of which make it clear that the effectiveness of a fuzzy controller (FC) is significantly reduced in case of emergency situations. We propose an approach that allows to solve a similar problem by introducing a quantum generalization of strategies in fuzzy inference in on-line from a set of predefined FC's by QFI as new quantum search algorithm. We consider a new structure of intelligent control system with a quantum KB self-organization based on QFI. We especially focus on ***robustness of control*** because it is the background for support the reliability of advanced control accuracy in uncertainty environments. The main goal of this work is to provide a brief description of soft computing tools for designing independent FC, then we will provide the QFI methodology of quantum KB self-organization in unforeseen situations. Quantum supremacy of classical intelligent control system design in unexpected control situations demonstrated.

In particular case, in this article we consider the application of Quantum Computing Optimizer of KB (QCOptKB™ toolkit) to smart control systems design for two benchmarks: cart-pole's control system and 3DoF robotic manipulator's control system based on QFIalgorithm.

2. QUANTUM PID CONTROLLERS DESIGN BASED ON A QUANTUM FUZZYINFERENCE ALGORITHM

In this section we consider a new method of robust PID controller design based on a quantum fuzzy inference algorithm.

On the Figure1 the general structure of a control system with a quantum PID controller in the presence of external stochastic noise, sensor's time delay and noise in sensor system is shown.

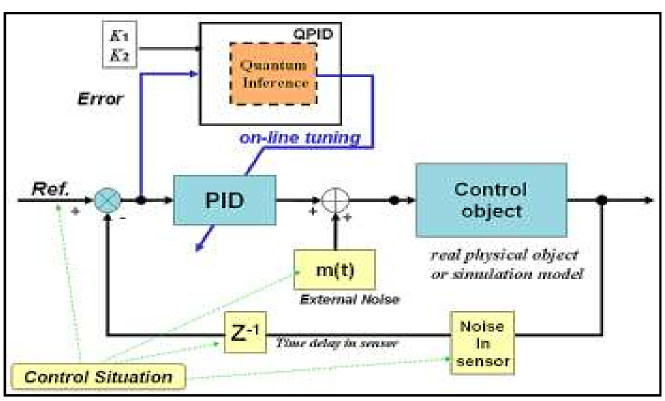


Figure 1. General structure of QPID based on two K-gains of classical PID and quantum inference

Consider main ideas of *Quantum Fuzzy Inference algorithm based on two PID gains*. We have the following computing steps. We will call it as a QI algorithm.

First of all, we must choose two teaching control conditions. Then for these two teaching conditions we will design two PID-gains: K_1 and K_2. For this aim we use PID tuning based on the genetic algorithm (GA) and obtain two PID-gains: $K_1 = \left[k_P^1\ k_D^1\ k_I^1\right]$ and $K_2 = \left[k_P^2\ k_D^2\ k_I^2\right]$.

By using artificial stochastic noise disturb obtained K-gains as follows:

$$K_{1,2}(t) = \begin{bmatrix} k_P + G_P \cdot \xi(t) \\ k_D + G_D \cdot \xi(t) \\ k_I + G_I \cdot \xi(t)] \end{bmatrix}, \text{where} \xi(t) - \textit{stochastic} \text{ noise with amplitude 1}$$

and G_P, G_D, G_I are increasing/decreasing coefficients that can be chosen manually.

In two teaching conditions, simulate control object motion with the new disturbed *K*-gains and design two probability distributions of *K*- signals for design of states $|0\rangle$ and $|1\rangle$ in QFI.

Realize quantum inference process with the following steps [3–5].

Step 1:*Coding*.

The preparation of all normalized states $|0\rangle$ and $|1\rangle$ for current values of disturbed control signals K_1 and K_2 including acalculation of probability amplitudes α_0, α_1 of states $|0\rangle$ and $|1\rangle$ from histograms;

Step 2: The entangled states preparation

Consider the following quantum correlation (spatial):

$$\begin{gathered} e_1 e_2 k_P^{1,2} k_D^{1,2} \to k_P^{new} \cdot gain_P; \\ \dot{e}_1\ \dot{e}_2\ k_D^{1,2} k_I^{1,2} \to k_D^{new} \cdot gain_D; \\ Ie_1\ Ie_2\ k_I^{1,2} k_P^{1,2} \to k_I^{new} \cdot gain_I; \end{gathered}$$

where $e, \dot{e}, Ie$ are control error, derivative and integral of control error and $gain_{P(D,I)}$ are QI scaling factors that can be obtained by GA.

So, a quantum state $|a_1 a_2 a_3 a_4 a_5 a_6\rangle = |e_1 e_2 k_P^1(t)\, k_D^1(t)\, k_P^2(t)\ k_D^2(t)\rangle$ is considered as the *entangled state.*

Step 3: The superposition of entangled states.

According to the chosen quantum correlation type construct superposition of entangled states.

Step 4: Theinterference and measurement.

Choose a quantum state $|a_1 a_2 a_3 a_4 a_5 a_6\rangle = |e_1(t) e_2(t) k_P^1(t)\, k_D^1(t)\, k_P^2(t)\ k_D^2(t)\rangle$ with maximum amplitude of probability $A = \sqrt{P_{e_1}} \cdot \sqrt{P_{e_2}} \cdot \sqrt{P_{k_P^1}} \cdot \sqrt{P_{k_D^1}} \cdot \sqrt{P_{k_P^2}} \cdot \sqrt{P_{k_D^2}}$. Choose subvector $|k_P^1(t)\, k_D^1(t)\, k_P^2(t)\ k_D^2(t)\rangle$.

Step 5: *Decoding*.

Calculate normalized output as a norm of subvector of the chosen quantum state as follows:

$$k_P^{new}(t) = \frac{1}{\sqrt{2^{n-2}}}\sqrt{\langle a_3 \ldots a_n | a_3 \ldots a_n \rangle} = \frac{1}{\sqrt{2^{n-2}}}\sqrt{\sum_{i=3}^{n}(a_i)^2}.$$

Step 6: Denormalization.

Calculate final (denormalized) output result as follows:

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

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

Let us consider simulation results of one control object benchmark and investigate robustness and self-organization properties of proposed QPID controller based on developed QI algorithm.

2.1 Quantum PID based smart control design: the example of benchmark simulation results

The typical control object benchmark for testing control system capabilities is a so called “cart-pole system”.The geometrical model of this control object is shown on Figure2.

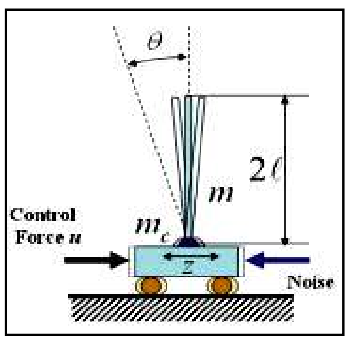


Figure2. Geometrical model of cart-pole system

The inverted pendulum (called also a pole) problem control is described by second-order differential equations for calculating the force to be used for moving the cart:

$$\ddot{\theta} = \frac{g\sin\theta + \cos\theta\left(\dfrac{+(u+\xi(t)) + \{+a_1\dot{z} + a_2 z\} - ml\dot{\theta}^2\sin\theta}{m_c + m}\right) - k\dot{\theta}}{l\left(\dfrac{4}{3} - \dfrac{m\cos^2\theta}{m_c + m}\right)},$$

$$\ddot{z} = \frac{u + \xi(t) + \{-a_1\dot{z} - a_2 z\} + ml(\dot{\theta}^2\sin\theta - \ddot{\theta}\cos\theta)}{m_c + m},$$

where z and θ are generalized coordinate; g is the acceleration due to gravity (usually $9.8\ m/\sec^2$), m_c is the mass of the cart, m is the mass of inverted pendulum (called also as a pole), l is the half-length of the pendulum, k and a_1 are friction coefficients in z and θ correspondingly, a_2 is a spring force in cart , $\xi(t)$ is external stochastic noise and u is the applied control force in Newton's.PID controller is connected with a cart. In this case for the pole stabilization ($\theta = 0$) we introduce a new reference signal for z as follows: z_{ref} (a reference signal for z) is a projection on axis z of the center of gravity of the pole. It must be 0 for stabilization the pole motion.

We can represent z_{ref} as follows: $z_{ref} = -w \cdot l \cdot \sin\theta$, where w is some scaling parameter. If $\theta \to 0; z_{ref} \to 0$. We also introduce limitations on the center of gravity projection: $\left|z_{ref}\right| \le 1$ and on applied control force: $\lfloor u \rfloor \le 5\,(N)$.

Teaching conditions for PID tuning. In Table 1 model parameters for the chosen control object are described.

Table 1. Cart-Pole System: Model Parameters

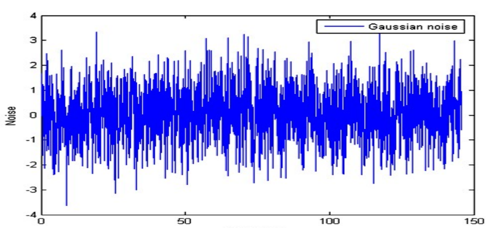
m_C [kg]	m [kg]	l [m]	Damping in q, k	Damping in z, a2	Spring force coefficient in dz,a1
1.0	0.1	0.5	0.4	0.1	5.0

We also take the following Cart-Pole initial conditions:

The pole angle θ = [10 ; 0.1] in degrees; cart position z =[0; 0] in m.

<u>*Constraints*</u>:Cart position: -1.0 <z < 1.0 [m]; Control Force: -5.0 <u < 5.0 [N].Sensor's delay time = 0.001 sec.

We will use two stochastic external noises (shown on Figure3) for two teaching conditions with different probability distribution density functions: Gaussian noise (symmetric probability distribution density function) and Rayleign noise (with nonsymmetrical probability distribution density function).



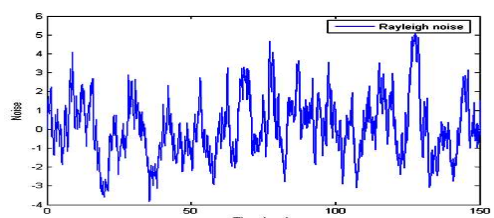


Figure3. External stochastic noises in teaching control situations.

According to description of QI algorithm above at first stage let us find for two teaching conditions two K-gains K_1 and K_2 by using GA.

PID tuning based on GA. Search space for PID gains K = [100 100 100] is defined from preliminary simulations with PID control. We will use the following Fitness Function (y) for GA tuning:

$$y = -\sum_t \theta^2 - \sum_t \dot{\theta}^2$$

In *Matlab*, fitness function is represented as follows:

$$y = -sum(\text{simoutX}(:,1).\hat{}\,2) / \text{Norm} - sum(\text{simoutX}(:,2).\hat{}\,2) / \text{Norm}$$

where simoutX(:,1) is a vector of angle values; simoutX(:,2) is a vector of angular velocity values and Norm is a length of these vectors.

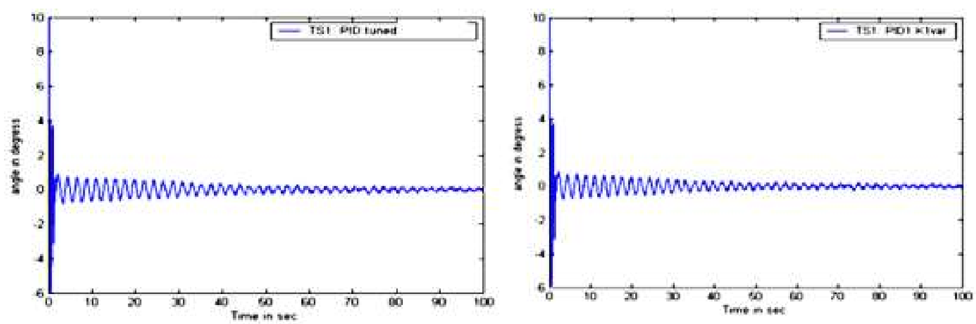
Teaching conditions 1 *with Gaussian noise* (named as TS1). As result of GA tuning we obtained the following K_1 = [82.7 13.6 9.4]. We will call PID with K_1 as PID1.

Teaching conditions 2 *with Rayleigh noise* (named as TS2). As result of GA tuning we obtained K_2 = [92.2 14.9 7.84]. We will call PID with K_2 as PID2.

Now consider the motion of our control object under disturbed *K*-gains as shown below (Figure 4).

1. TS1 control situation

$$K_1(t) = \begin{bmatrix} k_p + gain_p \cdot \xi(t) \\ k_d + gain_d \cdot \xi(t) \\ k_i + gain_i \cdot \xi(t)] \end{bmatrix} = \begin{bmatrix} 82.7 + 20 \cdot \xi(t) \\ 13.6 + 10 \cdot \xi(t) \\ 9.4 + 5 \cdot \xi(t)] \end{bmatrix}$$,where $\xi(t) - G$aussian noise with amplitude 1.



(a) Pole motion with constant K **(b) Pole motion with variable K**

Figure4. Teaching conditions 1: Pole motion with constant and disturbed K-gains of PID1

Simulation results show that the pole motion is stable in both cases. On Figure 5 the disturbed K-gains of PID1 (called as *control laws*) are shown.

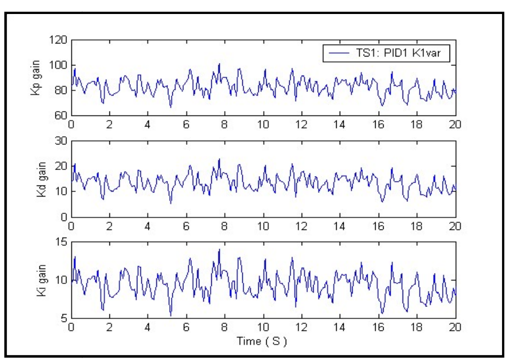
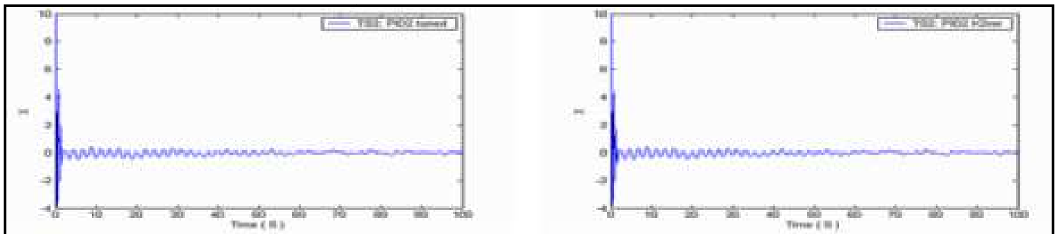


Figure5. Teaching conditions 1: Control laws

Remark. On the Figure6 and all others below we will denote pole angle θ as *x*.

2. TS2 control situation

$$K_2(t) = \begin{bmatrix} k_p + gain_p \cdot \xi(t) \\ k_d + gain_d \cdot \xi(t) \\ k_i + gain_i \cdot \xi(t)] \end{bmatrix} = \begin{bmatrix} 92.2 + 20 \cdot \xi(t) \\ 14.9 + 10 \cdot \xi(t) \\ 7.84 + 5 \cdot \xi(t)] \end{bmatrix}$$, where $\xi(t)$ – gaussian noise with amplitude 1.



(a) Pole motion with constant K (b) Pole motion with variable K

Figure6. Teaching conditions 2: Pole motion with constant and disturbed K-gains of PID2

In this case also simulation results show that the pole motion is stable in both cases (Figure7).

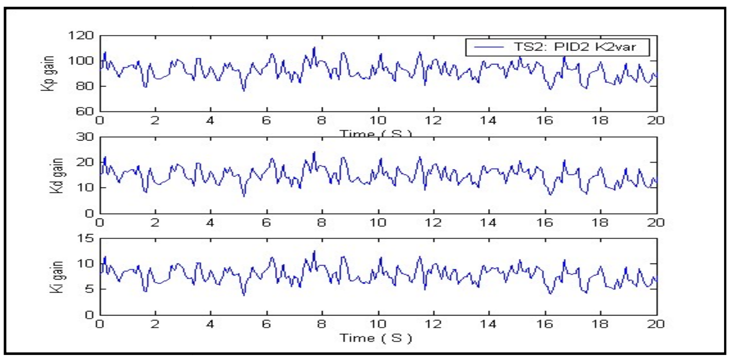


Figure7. Teaching conditions 2: Control laws

Conclusion: simulation results show that the pole motion is stable in both cases. It means that we can use disturbed *K*-values for further calculations.

2.2.QPID controller based on new type of computing

We developed special tools for Quantum Fuzzy and Quantum PID inference based on QC optimizer.

QC optimizer tools allow to control as physical system and mathematical model of control object as shown on the Figure8.

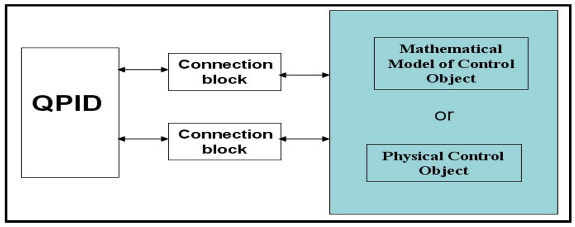


Figure8. QPID controller connected with control object

We will work with mathematical model of control object represented in Matlab/Simulink version 6.5. Control loop with QPID is shown on Figure9.

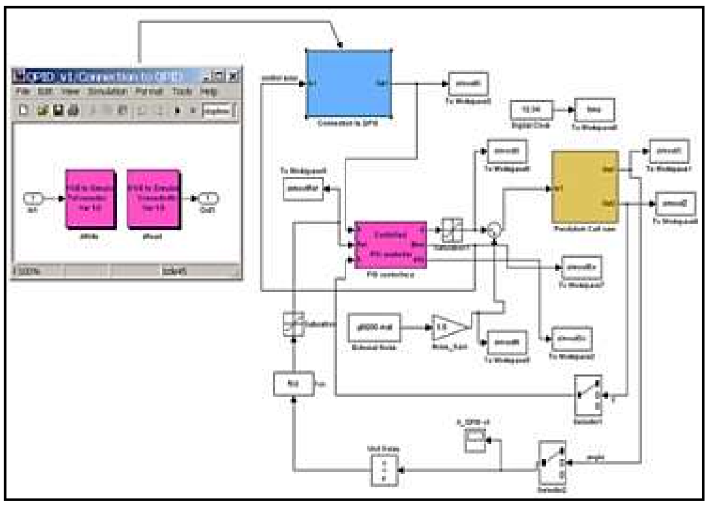


Figure9. Matlab/Simulink model of control object with control loop based on QPID

Calculations corresponding to Quantum Inference based (QI) on two *K*-gains are realized in the block QPID by QC Optimizer tools.

2.3.QPID in terms of QC optimizer toolkit

On Figures10-11,the internal structure of QPID in terms of our tools is shown.

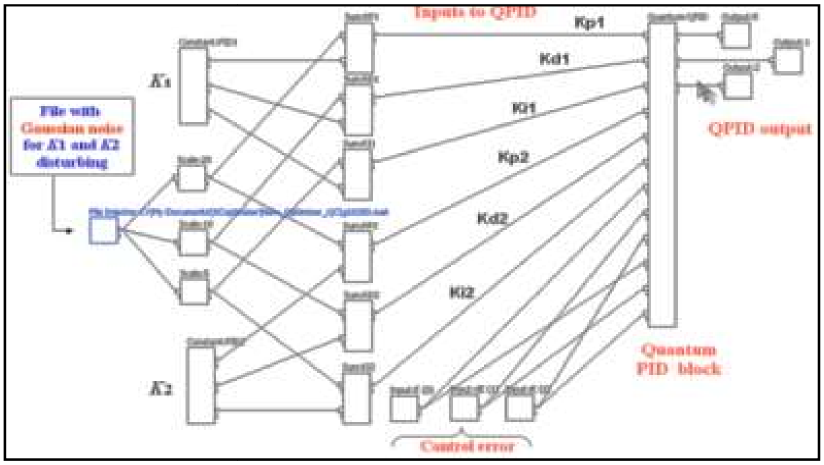


Figure10. QPID structure in terms of QC Optimizer tools

On Figure11 internal structure of QPID block is shown. In this block the following items are described:

- names of input variables $k^{1,2}_{P(D,I)}$, where indexes 1,2 denotes PID1 and PID2 (or K_1 and K_2; names of output variables $k_{P(D,I)}$;

- histograms for each input variable representing probability distribution of the given input;

- QI scaling coefficients for calculation output values (that is founded by GA for teaching conditions and then used for all control situations);

- a knob«correlation parameters» is used for chosen type of quantum correlation description.

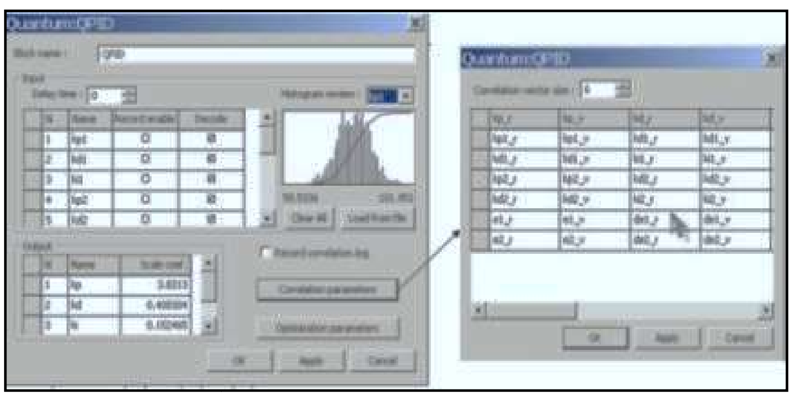


Figure11. QPID structure. Internal layer

For example, as follows spatial quantum correlations:

$$e_1 e_2 k_P^{1,2} k_D^{1,2} \rightarrow k_P^{new};$$
$$\dot{e}_1\ \dot{e}_2\ k_D^{1,2} k_I^{1,2} \rightarrow k_D^{new};$$
$$Ie_1\ Ie_2\ k_I^{1,2} k_P^{1,2} \rightarrow k_I^{new}.$$

By using GA and chosen quantum correlation we obtained the following QI scaling coefficients: Q_A_params = 2.4200 0.3320 0.1000.

Now investigate robustness properties of designed QPID based on QI with *spatial correlations* in different control situations.

2.4. Investigation of self-organization capability of Quantum PID Control based on two PID controllers (or two K-gains)

We will consider the following controllers:PID1 controller with constant gains K_1= [82.7 13.6 9.4];PID2 controller with constant gains K_2 = [92.2 14.9 7.84];QPID controller based on quantum inference with K_1andK_2.

Consider now behavior of our control object in teaching and modeled unpredicted control situations and investigate robustness property of designed controllers.

Investigation of different types of quantum correlations: *Spatial correlations*.

TS1: Comparison of QPID, PID1 and PID2 control performances (Figures 12-13).

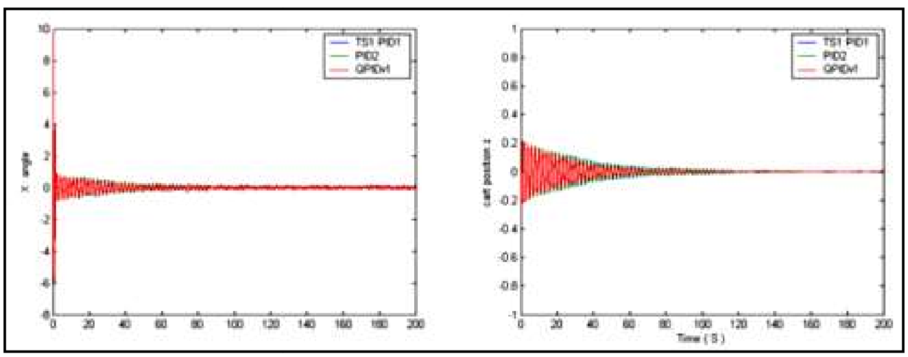


Figure12. Pole motion (left) and cart motion (right) comparison

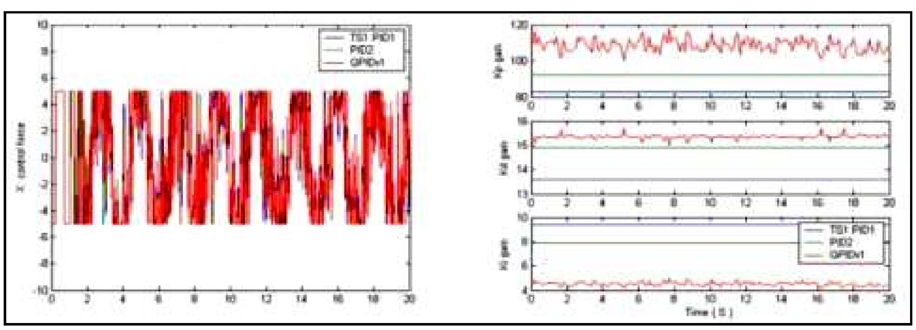


Figure 13. Control force and control laws

Conclusion: all controllers are successful to balance the Pole in TS1 situation.

TS2: Comparison of QPID, PID1 and PID2 control performances.

On Figures 14-15, behavior of Cart-Pole system in teaching conditions TS2 is shown.

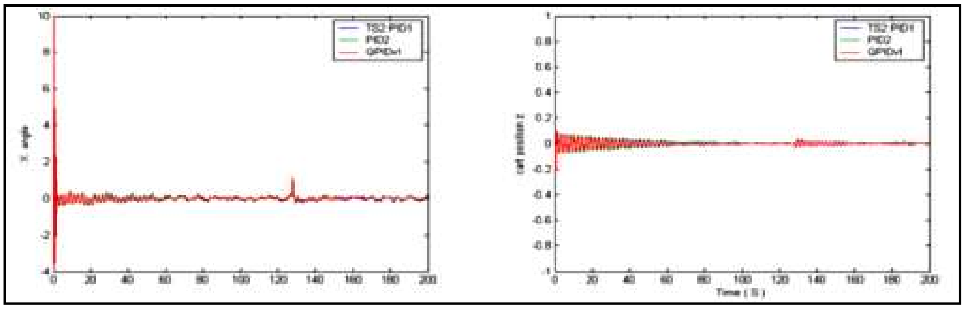


Figure 14. Pole motion (left) and cart motion (right) comparison in TS2 situation

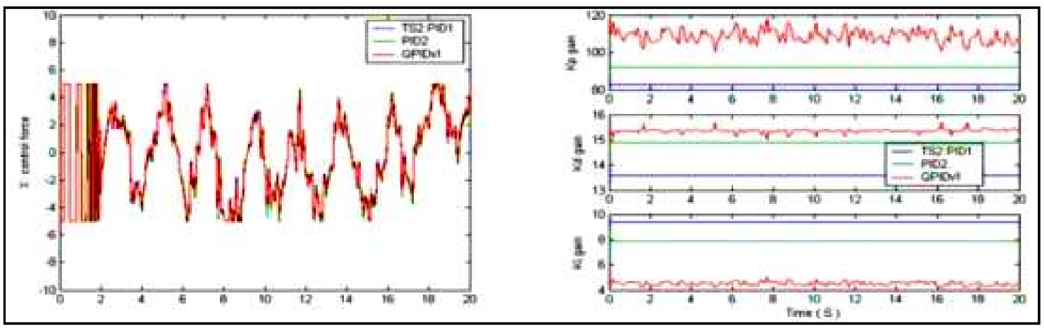


Figure 15. Control force and control laws in TS2 situation

Conclusion: all controllers are successful to balance the Pole in TS2situation.

2.4.1. Investigation of robustness and self-organization capability of control system based on the QI algorithm

In the Table 2 modeled unpredicted control situations (Class 1) are shown.

Let us investigate a robustness property of the proposed QPID model in the new control environment (Table 2).

Table 2. Class 1 of modeled unpredicted control situations

New 1 control situation	**New 2 control situation**	**New 3 control situation**
(in plots below - legend S1) External noise: *Rayleigh* (TS2 teaching noise); New sensor's time delay = 0.005 sec; Internal sensor noise: Gaussian noise with amplitude = 0.015; TS model parameters	(in legend S1a) External noise: *Rayleigh* (TS2 teaching noise); New sensor's time delay = 0.005 sec; Internal sensor noise: Gaussian noise with amplitude = 0.015; *New model parameter a*2=8	(in legend S1b) External noise: *Rayleigh* (TS2 teaching noise); Sensor's time delay = 0.001 sec; Internal sensor noise: Gaussian noise with amplitude = 0.01; *New model parameter a*2=6

New 1control situation (Figures 16-17).

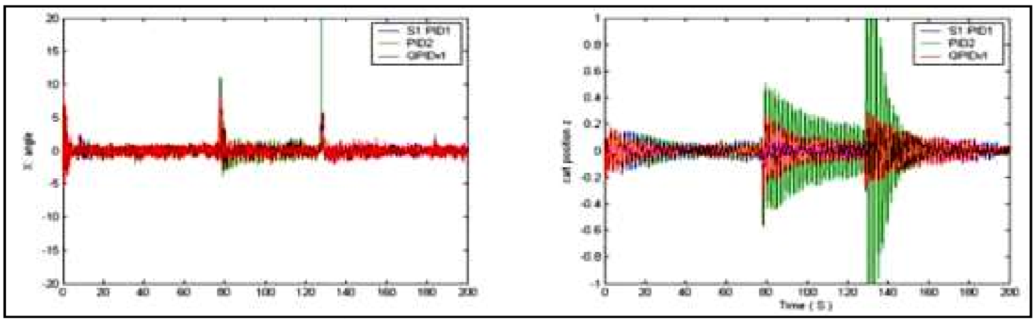
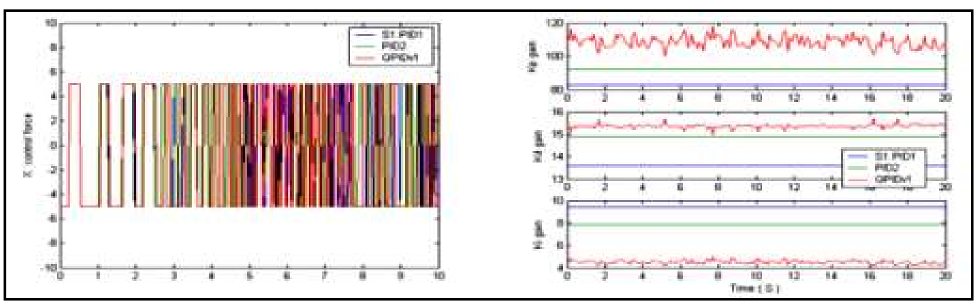


Figure 16. Pole motion (left) and cart motion (right) comparison in New 1 situation



Fugure 17. Control force and control laws in New 1 situation

Conclusion: QPID and PID1 controllers are successful to balance the Pole in New 1 situation. PID2 controller is unsuccessful to balance the Pole in New 1 situation.

New 2 control situation (Figures 18-19).

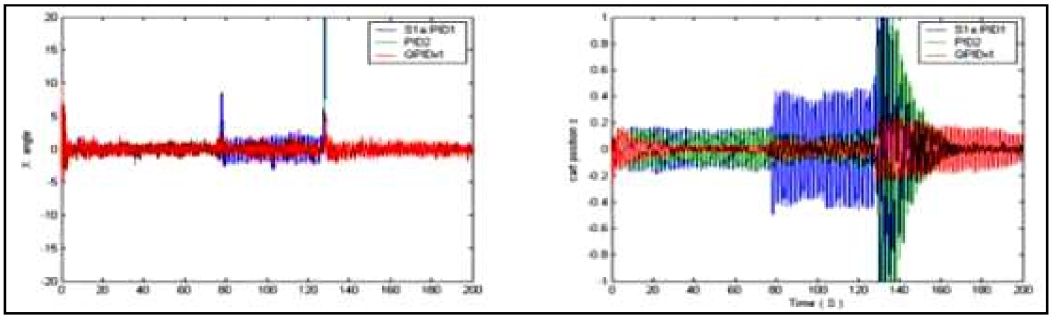


Figure 18. Pole motion (left) and cart motion (right) comparison in New 2 situation

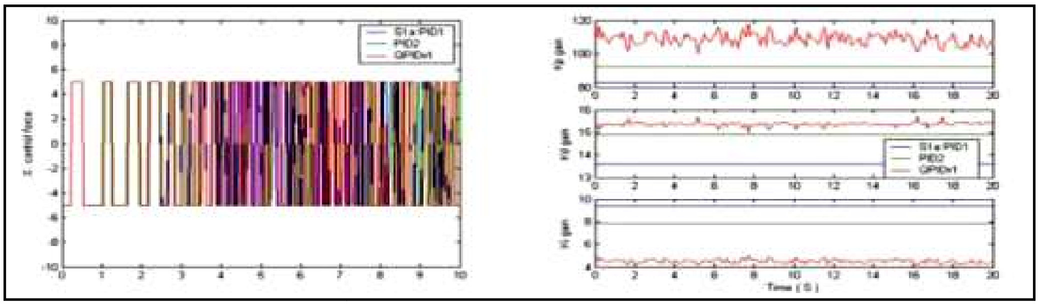


Figure 19. Control force and control laws in New 2 situation

Conclusion: QPID controller is successful to balance the Pole in *New* **2** situation. PID1 and PID2 controllers are unsuccessful to balance the Pole in *New 2* situation.

New 3 control situation (Figures 20-21).

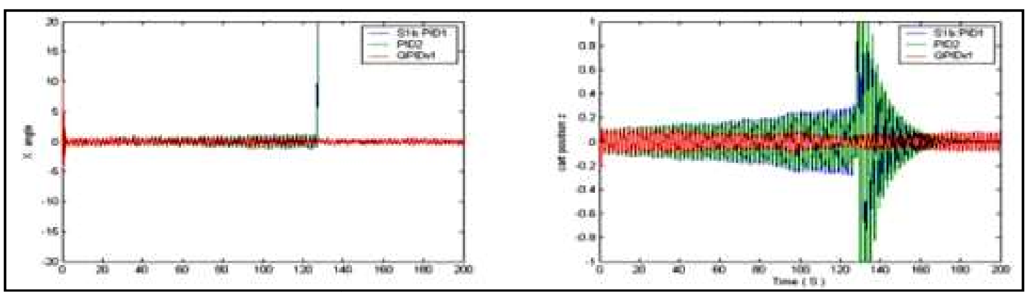


Figure 20. Pole motion (left) and cart motion (right) comparison in New 3 situation

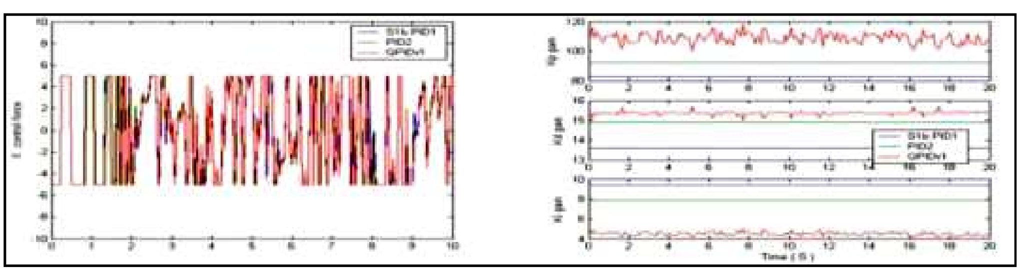


Figure 21. Control force and control laws in New 3 situation

Conclusion: QPID controller is successful to balance the Pole in *New 3* situation. PID1 and PID2 controllers are unsuccessful to balance the Pole in *New 3* situation.

Investigation of different types of quantum correlations:Temporal correlations. Investigate now robustness of temporal QI correlations and compare with spatial type of QI for the given control object. For QI we consider the following temporal quantum correlations:

$$e_1 e_2 k_P^{1,2} k_P^{1,2}(t-\Delta t) \rightarrow k_P^{new} \cdot gain_P;$$
$$\dot{e}_1 \ \dot{e}_2 \ k_D^{1,2} k_D^{1,2}(t-\Delta t) \rightarrow k_D^{new} \cdot gain_D;$$
$$Ie_1 \ Ie_2 \ k_I^{1,2} k_I^{1,2}(t-\Delta t) \rightarrow k_I^{new} \cdot gain_I.$$

Comparison QPID control performance under spatial and temporal correlations. Consider dynamic motion and control laws comparison of two types of QPID: with spatial and temporal quantum correlations(Figures 22-23).

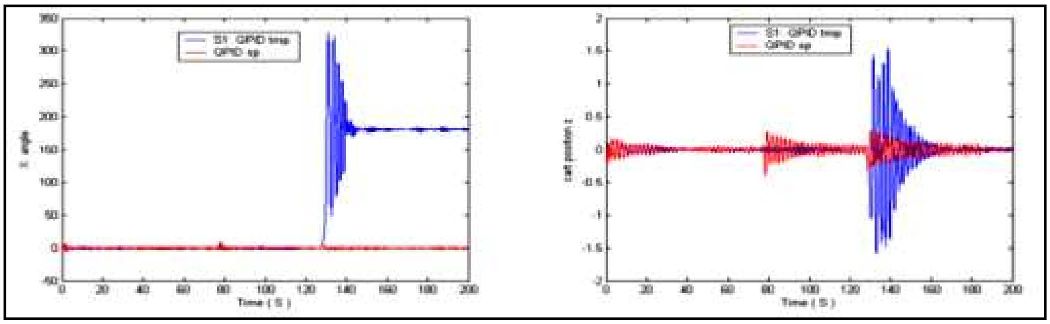


Figure 22. Pole motion (left) and cart motion (right) comparison in New 1 situation

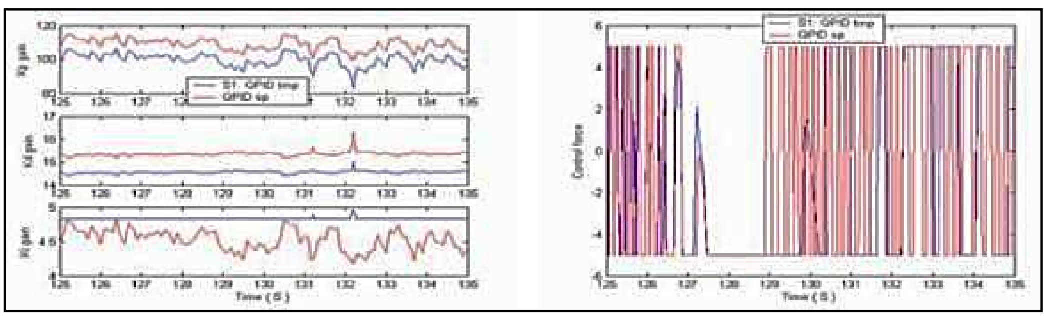


Figure23. Control force and control laws – QPID with spatial and temporal correlations comparison

Conclusion: QPID with temporal correlations is not robust in New 1 situation. So, choose spatial QI as the best for robust QPID control realization.

*Comparison of cart-pole motion under three types of cont*rol. On the Figure24is shown the comparison of a cart-pole motion under three types of control:

- QPID with variable (time dependent) K-gains obtained by on-line QI process;

- PID-average (with average values from obtained QPID *K*-gains) with constant gains K= [108.8507 15.3634 4.5209];

- PID-max (with $K = \max_t K_{QPID}$) with constant gains K= [119.2325 16.3510 5.1046].

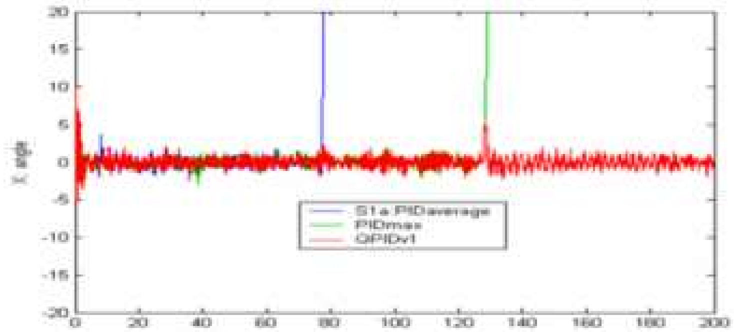


Figure 24. Pole motion under three types of control

Simulation results show that PID-average and PID-max controllers with *constant gains* are incapable to balance a Pole in the chosen control situation.But *variable* K-gains can do it!

Thus we have principally a new calculation process.

2.5. Conclusions

Simulation results represented on Figures 16-24 allows us to make the following conclusions:

- QPID controller is robust in all situations of *class1*;

- PID1 controller is robust in *New 1* situation only;

- PID2 controller is not robust in *class 1* situations;

- QPID based on new type of calculations increases robustness of designed PID controllers.

So, for practical applications, when we have deal only with PID controllers, we may increase robustness of control system by using quantum inference block.In this case only two sets of PIDconstant*K*-gains are needed.Simulation results show good robustness properties of QPID based on quantum inference block.Further investigations of different QPID models are considered as useful and important.

3. Control systems for a manipulator with 3DOF based on quantum computing

In this section, 3DOF manipulator control systems is considered both at the simulation level and at the physical test benchmark.

3.1. Control task

Three Fuzzy Controllers (FC) are implemented in the selected configuration of the Intelligent Control System (ICS) structure; each FC independently controls one ofthree links.

Figures 25 shows the structural diagram of ICS by 3DOF manipulator based on KBO on soft computing with separated control.

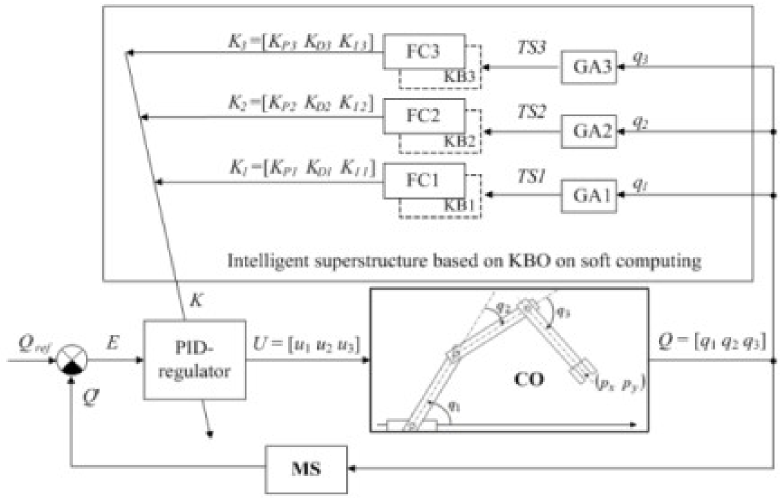


Figure 25. ICS with separated control based on KBO for 3DOF manipulator

On Figure 25 the symbols mean the following:K is the matrix of proportional, differential and integral coefficients of the PID controller K_{Pi}, K_{Di}, K_{Ii}, $i=\overline{1,3}$, i is the number of the corresponding link of the robot of the manipulator, TS_i is the training signal , GA_i is a GA that generates a teaching signal for the formation of the i-th KB.

As a standard control situation for the FC_i, a typical control situation appears in the conditions of which a teaching signal TS_i received. Unexpected control situations divided into external and internal. Designed ICS based on KBO on soft computing with separated divided control (Figure 25) contain information about three situations of control (standard or unexpected) for each of three links.

In the designed ICS based on KBO on soft computing with separated control FC1 contains information about the standard situation 1 (KB1) for link 1, FC2 contains information about the standard situation 1 for link 2 (KB2), and FC3 contains information about the standard situation 1 for link 3 (KB3).

The scheme for extracting hidden information about the relationships between existing FCs designed using soft computing technologies for three manipulator links with KBs obtained for standard control situations using QFI unit shown on Figure 26.

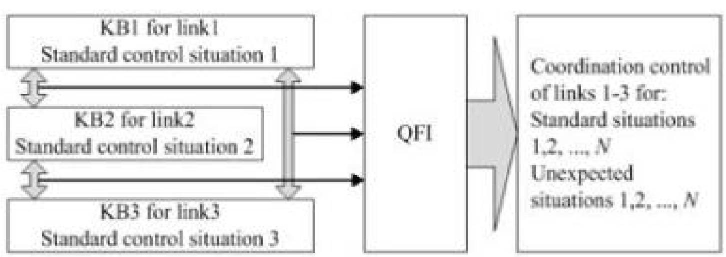


Figure 26. Methodology for extracting hidden information of the relationships of the KB

We will add the QFI block to ICS based on KBO on soft computing, which can realize the self-organization of the KBs.

3.2. Modelling and experiment: control quality

The performance of the considered ICSs evaluated based on the results of MatLab / Simulink modeling and the results of a series of experiments on CO Testbench.

Let us compare the work of ICS based on KBO on quantum computing using spatial, spatio-temporal and temporal correlations and ICS based on soft computing with separated control.

On Figures 27-28, a comparison of ICS is given for MatLab/Simulink models and manipulator Testbench according to the introduced system of quality criteria.

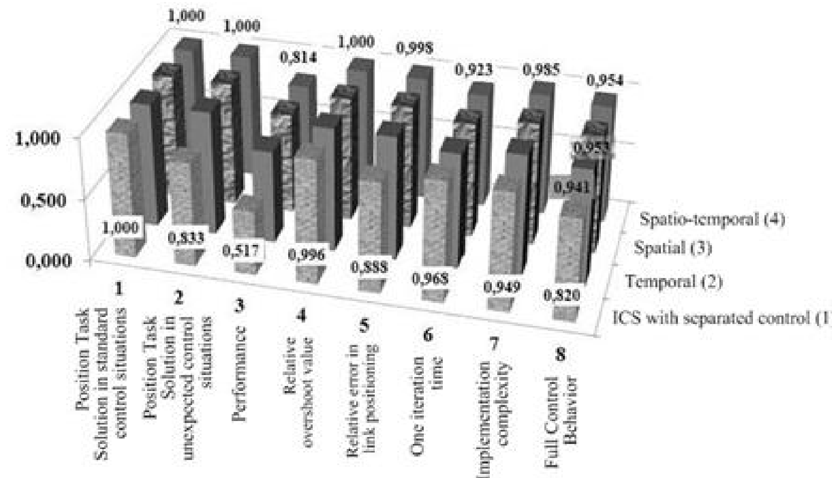


Figure 27. Comparison of the results of ICS based on KBO on soft computing with separate control (1) and ICS based on quantum computing using temporal (2), spatial (3) and spatio-temporal (4) correlations when testing Matlab/Simulink models

From the comparison results, we conclude that the addition of the QFI unit to ICS with separated control the control task is solved for both standard and unexpected control situations; the performance increases; the accuracy of link positioning improves; and the implementation complexity of control decreases. The complexity of the implementation control depends on the dynamics of the control signal; we consider the robustness of the generated control laws below.

Because of QFI block apply in ICS, all quality criteria are improved as a result of eliminating the mismatch of the work of separated independent KBs by organizing coordination control. Moreover, if for MatLab/Simulink models the best indicator of full control behavior provided when using spatio-temporal correlation, and then manipulator Testbench determines the optimal choice of spatial correlation.

Next, we will consider the ICS based on KBO on quantum computing only with the use of spatial correlation.

Figure 28 compares the operation of ICS based on KBO on soft computing with separated control in the conditions of an external unexpected control situation in comparison with the ICS based on quantum computing.

The forced displacement of the second link is an unexpected situation in this case.

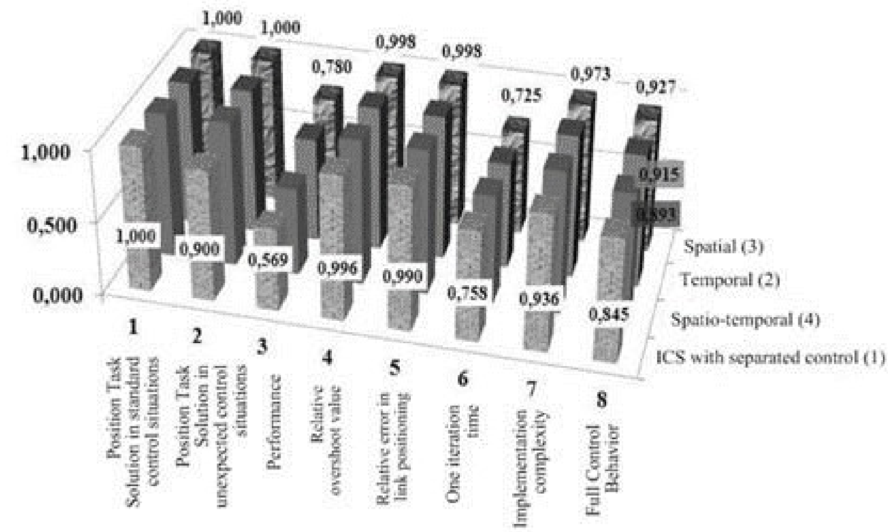
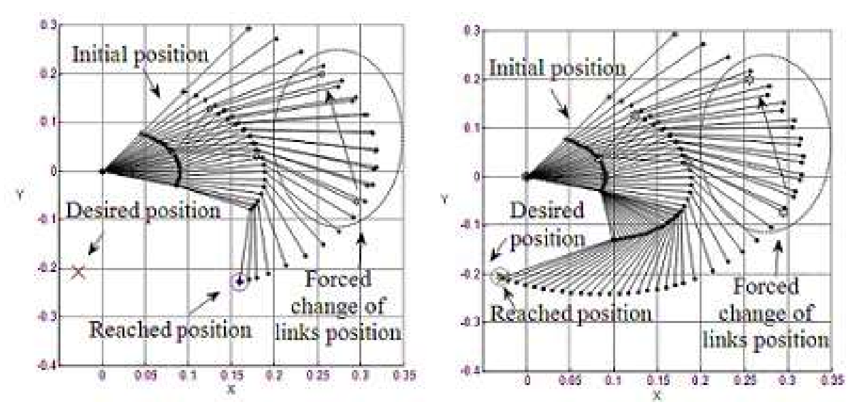


Figure28. Comparison of the results of ICS based on KBO on soft computing with separate control (1) and ICS based on quantum computing using temporal (2), spatial (3) and spatio-temporal (4) correlations when testing manipulator Testbench

From Figure29 it can be seen that in the considered unexpected control situation, ICS based on KBO on quantum computing decides with the positioning problem with a given accuracy, in contrast to ICS based on KBO on soft computing with separated control.

The inability of ICS based on soft computing to solve the problem of exact position control in Figure30 also illustrated. FC responsible for managing the second link for the allotted time was not able to rehabilitate after a powerful external impact. Because of which the positioning error of the second link was more than 50 degrees, the control goal has not achieved and the control system as a whole was not robust.



(a) (b)

Figure 29. ICS based on KBO on soft computing with separated control in unexpected control situation (a); ICS based on KBO on quantum computing (b)

Consider internal unexpected control situations. Let us compare ICS based on KBO on soft computing with one FC and ICS based on KBO on quantum computing in the conditions of changing restrictions of the control channel.

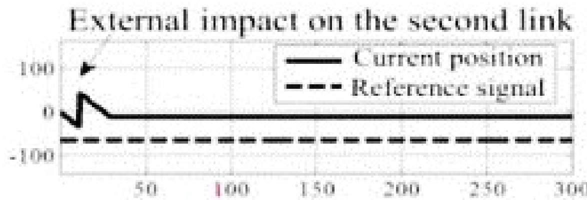


Figure 30. The change in the position of the second link under the control of ICS based on KBO on soft computing with separated control

In Figures 31-32 ICS is compared respectively for MatLab / Simulink models and for manipulator Testbench, taking into account internal and external unexpected control situations.

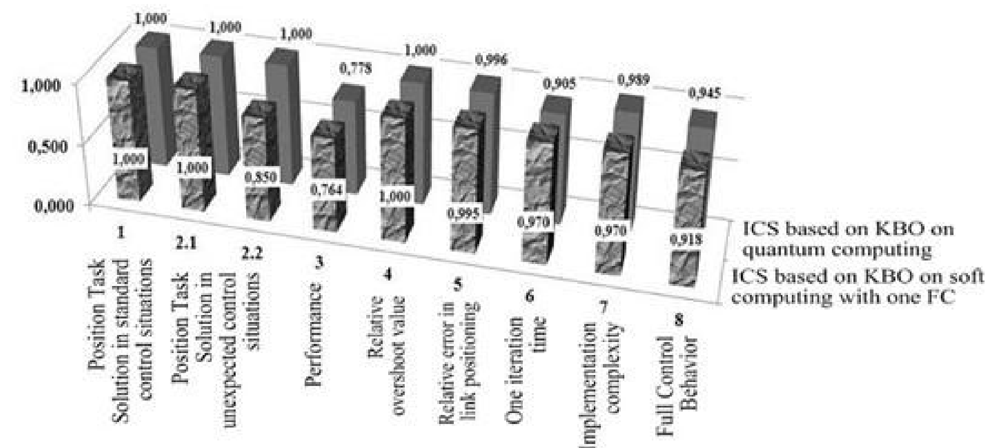


Figure 31. Comparison of the results of ICS based on KBO on soft computing with one FC and ICS based on quantum computing when testing Matlab / Simulink models

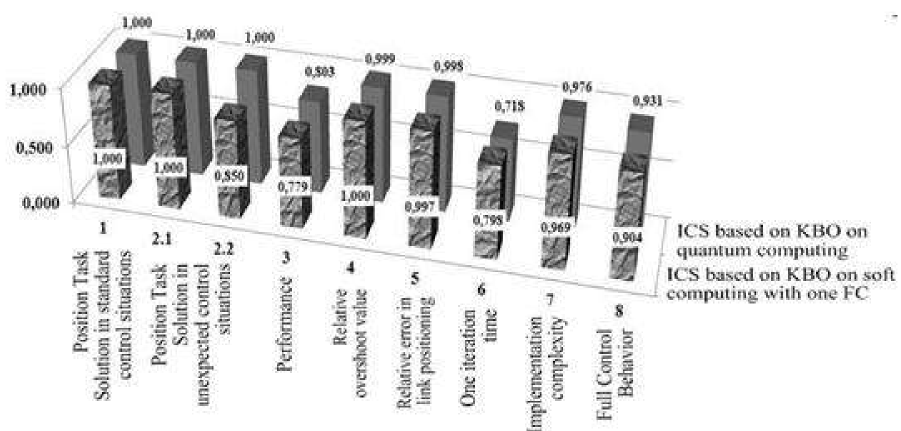
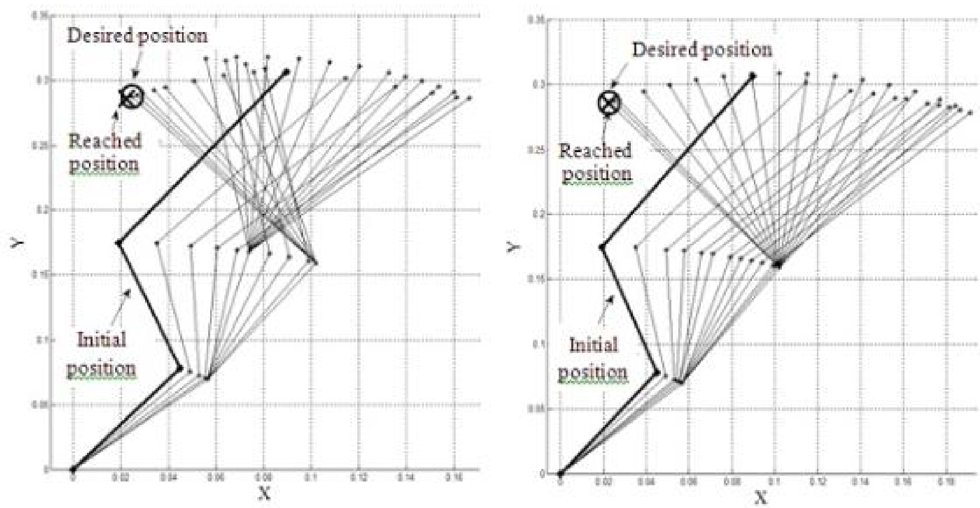


Figure 32. Comparison of the results of ICS based on KBO on soft computing with one FC and ICS based on quantum computing when testing manipulator Testbench

From the comparison results we can see that ICS based on KBO on soft computing and ICS based on quantum computing solves the positioning problems for standard and external unexpected situations. ICS based on soft computing with one FC not always coping with internal unexpected control situations. Full Control Behavior for ICS on quantum computing is higher, both for MatLab/Simulink models and for the manipulator Testbench.

Let us demonstrate the operation of ICS based on KBO on soft computing with one FC in the conditions of an internal unexpected control situation (Figure 33) in comparison with ICS based on KBO on quantum computing.

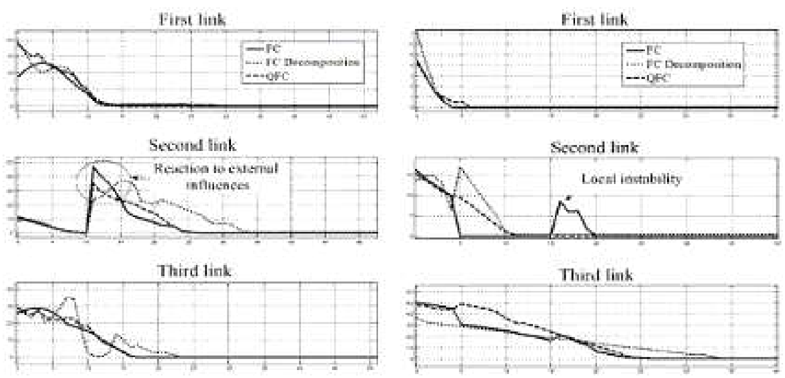


(a) (b)

Figure33. ICS based on KBO on soft computing with one FC in the conditions of an internal unexpected control situation (a); ICS based on quantum computing (b)

From Figure 33 it can be seen that ICS based on KBO on quantum computing provides a better solution quality than ICS based on soft computing with one FC.

Consider the control signals generated by the considered types of ICS based on soft and quantum computing.



(a) (b)

Figure 34. Control signals generated by different types of ICS in unexpected control situations

On Figure34: *QFC* are the control signals of ICS based on KBO on quantum computing, *FC* are the control signals generated by ICS on soft computing with one FC, *FC Decomposition* are the control signals generated by ICS on soft computing with separated control.

From Figure 34 (a) it can be seen that the control signals generated by ICS based on KBO on quantum computing under external disturbing influences are similar to those generated by ICS on soft computing with one FC. However, the amplitude of the control signal at the time of external influence is significantly lower for ICS based on quantum computing. The control signal formed by ICS based on soft computing with separated control have become overshoot.

From Figure 34 (b) it can seen that the control signal generated by ICS based on KBO on soft computing with one FC for the second link has a local instability section, while ICS based on quantum computing generates robust control signals under conditions of external disturbing influences.

Thus, the minimum consumption of useful resource in the formation of control signals ensured when using ICS based on KBO on quantum computing.

Based on the new types of computation (soft and quantum computing) our approach to intelligent control systems design has the following advantages:

- maintains basic advantages of conventional, classical, control systems such as controllability and stability;
- based on the given criteria of control quality supplies an optimal FC KB design;
- guarantees the achievement of the given control quality on the base of designed KB;
- has the property of robustness and self-organization. It means that ISC allows to maintain the given control quality even in the case of *unpredicted control situations*.

Using two benchmarks of varying complexity (cart-pole system and 3DOF manipulators) as an example, these advantages were demonstrated. On the example of 3DOF manipulator, the minimal difference between the results of the physical Manipulator Testbench and the MatLab/Simulink model demonstrated.

Further research focused on the development and analysis of the physical Testbench of Manipulator with 7 DOF, as well as its integration with the mobile platform.

Figure 35 shows a generalized comparison of ICS based on KBO on soft and quantum computing for 3DOF and 7DOF manipulators for standard and unexpected control situations of the examples considered in this article.

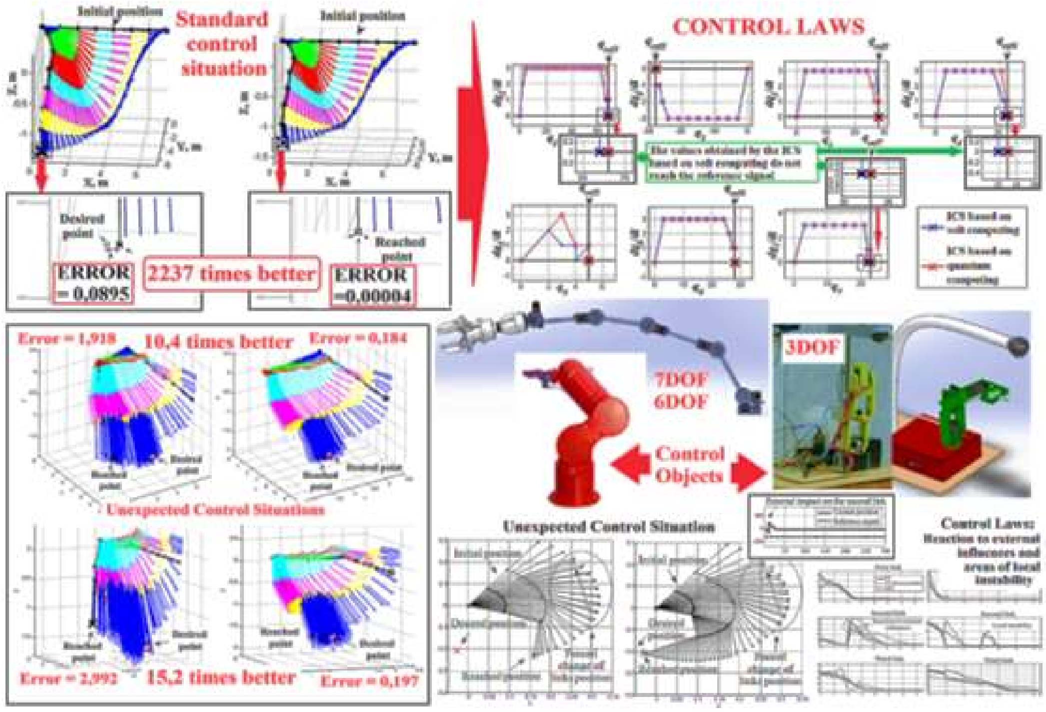


Figure35. Comparison of ICS based on soft and quantum computing for 3DOF and 7DOFrobotic manipulator

Further research focused on the development and analysis of the physical Testbench of Manipulator with 7 DOF, as well as its integration with the mobile platform.

4. CONCLUSION

- The developed computational intelligence toolkit implements mechanisms for creating, configuring, and transmitting control parameters in the form of control signals received from KB of FC without destroying the low executive level [10-12]. The use of soft computing and developed intelligent control system design technologies reduces the impact of expert judgment in the training and its configuration [13,14].
- From computer science viewpoint, QA of QFI model plays the role of the information algorithmic and SW-platform support for design of knowledge self-organization process. Quantum computing, which ensures robustness of intelligent control system, introduces the property of self-organization, allows control object to function effectively in conditions of a lack of a priori information. The use of this kind of computing can reduce the influence of the hardware (for example, reducing the number of sensors) on the effectiveness of the control system.

- Technologies for remote configuration and transmission of KB allow the control object to receive KB from the optimizer unit or from other control object, which makes it possible to manage structurally new objects, such as teams of robots, multi-agent systems, complex automated production, etc. In addition, this technology gives control object ability to update and adapt KB for a specific control situation, including contingency.

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