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Original article

IT Modeling of Self-Organizing Intelligent Controllers Based on Quantum Deep Machine Learning

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Abstract

The physical interpretation of the process of controlling self-organization at the quantum level is discussed on the basis of quantum information-thermodynamic models of exchange and extraction of quantum (hidden) valuable information from/between classical particle trajectories in the "swarm of interacting particles" model. The main physical and information-thermodynamic aspects of the model of quantum intelligent control of classical control objects are discussed and described. An approach is considered for constructing reference control models based on new laws of quantum deep machine learning applying Lagrange/Hamilton neural networks.

This work develops the approach of self-organized intelligent control, describing the strategy of designing intelligent cognitive control systems based on quantum and soft computing. The synergetic effect of the quantum self-organization of the knowledge base, extracted from the non-robust knowledge bases of the intelligent fuzzy controller, is demonstrated. The information-thermodynamic law of quantum self-organization of the optimal distribution of the basic qualities of control (stability, controllability and robustness) and the law of quantum information thermodynamics on the possibility of extracting additional useful work based on the extracted quantum information hidden in classical states are applied. Formed (without violating the second law of quantum thermodynamics) on the basis of the extracted amount of hidden quantum information, the "thermodynamic" control force allows the robot (as an object of control) to perform quantitatively more useful work compared to the amount of work spent (on extracting quantum hidden information). The guaranteed achievement of the goal of controlling the robot is carried out on the basis of a designed intelligent cognitive control system using the quantum knowledge base optimizer – QCOptKBTM, the structure of which includes a quantum fuzzy inference – QFI. The quantum algorithm of self-organization of non-robust QFI knowledge bases is structurally based on the synergetic effects of hidden quantum information to implement the optimal distribution of management qualities. This technology makes it possible to increase the reliability of intelligent cognitive control systems in control situations under uncertainty. The examples demonstrated the effectiveness of introducing the QFI scheme as a ready-made programmable algorithmic solution for embedded intelligent control systems.

Keywords : quantum intelligent controller, quantum algorithm gate, quantum deep machine learning, classical efficient simulation, intelligent robotics

Conflict of intersts: The authors declare no conflict of interets.

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ИТ моделирования самоорганизующихся интеллектуальных контроллеров на основе квантового глубокого машинного обучения

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Аннотация
Обсуждается физическая интерпретация процесса управления самоорганизацией на квантовом уровне на основе квантовых информационно-термодинамических моделей обмена и извлечения квантовой (скрытой) ценностной информации из/между классическими траекториями частиц в модели «рой взаимодействующих частиц». Представлены и описываются основные физические и информационно-термодинамические аспекты модели квантового интеллектуального управления классическими объектами управления. Рассматривается подход построения эталонных моделей управления на основе новых законов квантового глубокого машинного обучения с применением квантовых нейронных сетей Лагранжа/Гамильтона. Данная работа развивает подход самоорганизующегося интеллектуального управления, описывая стратегию проектирования интеллектуальных систем когнитивного управления на основе квантовых и мягких вычислений. Продемонстрирован синергетический эффект квантовой самоорганизации базы знаний, извлеченный из не робастных баз знаний интеллектуального нечеткого регулятора. Применяется информационно-термодинамический закон квантовой самоорганизации оптимального распределения базисных качеств управления (устойчивость, управляемость и робастность) и закон квантовой информационной термодинамики о возможности извлечения дополнительной полезной работы на основе извлеченной квантовой информации, скрытой в классических состояниях. Сформированная (без нарушения второго закона квантовой термодинамики) на основе извлеченного количества скрытой квантовой информации «термодинамическая» сила управления позволяет роботу (как объекту управления) совершить количественно большую полезную работу по сравнению с количеством затраченной (на извлечение квантовой скрытой информации) работу. Гарантированное достижение цели управления роботом осуществляется на основе спроектированной интеллектуальной когнитивной системы управления с применением инструментария квантового оптимизатора баз знаний QCOptKBTM, в структуру которого включен квантовый нечеткий вывод – КНВ. Квантовый алгоритм самоорганизации не робастных баз знаний КНВ структурно опирается на синергетические эффекты от скрытой квантовой информации для осуществления реализации оптимального распределения качеств управления. Данная технология позволяет повысить надежность интеллектуальных когнитивных систем управления в ситуациях управления в условиях неопределенности. Примеры продемонстрировали эффективность введения схемы КНВ в качестве готового программируемого алгоритмического решения для встраиваемых интеллектуальных систем управления.

Ключевые слова: квантовый интеллектуальный контроллер, квантовая алгоритмическая ячейка, квантовое глубокое машинное обучение, эффективный классический симулятор, интеллектуальная робототехника

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1. Introduction

New information-thermodynamics law of intelligent self-organized control and intelligent cognitive robotics was introduced as the background for the guaranteed achievement of control goal in unpredicted control situations[1] [1, 2]. Quantum self-organization algorithm of imperfect knowledge bases (KB) of hybrid fuzzy controllers developed for the design in on-line of robust KB from non-robust individual KB. This new synergetic effect is impossible in classical information domain and can be created by a new type of quantum search algorithm as quantum fuzzy inference (that is the particular case of quantum self-organization algorithm.) This report is concerned with the problem of discovering a new family of quantum search and decision-making algorithms (QA's) based on quantum genetic algorithm анв quantum neural networks. Quantum software engineering created with the platform of quantum deep machine learning applied toolkit of quantum genetic algorithm анв quantum neural networks. The presented method and relative hardware implement matrix operations performed in second and third step of a QA the so-called interference and entanglement operators). These operators allow to achieve a substantially increasing in computational speed-up with respect to the corresponding software realization of a traditional and a new quantum search algorithm (QSA). A high-level structure of a generic entanglement block that uses logic gates as analogy elements is described [3, 4]. This model has the advantage that proving lower bounds is tractable which allows one to demonstrate provable speed-up over classical algorithms or to show that a given QA is the best possible[2] [2], [5]. Next, we will describe the method of designing main quantum operators and hardware implementation for fast search in large unstructured database and related topics concerning the intelligent control in robotic of an ill-defined process including search-of-minima entropy uncertainty intelligent operations is described. Quantum supremacy of intelligent robotic control with quantum fuzzy inference demonstrated on Benchmarks.

2. General Structure of QA

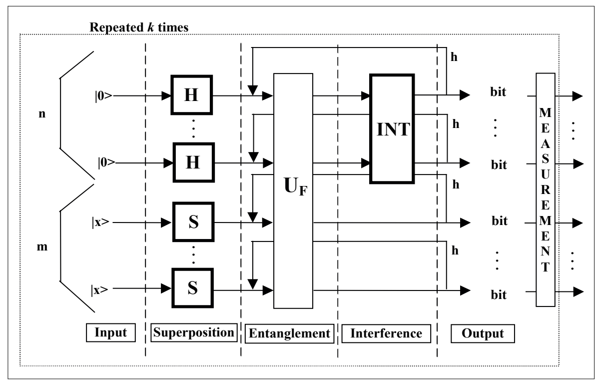
A QA estimates (without numerical computing) the qualitative properties of the function *f*. From a mathematical standpoint, a function *f* is the map of one logical state into another. The problem solved by a QA can be stated in the symbolic form as follows:

Input	A function f: $\{0,1\}^n \longrightarrow \{0,1\}^m$
Problem	Find a certain property of function f

The general structure of QA on Fig. 1 is demonstrated.
In general, the superposition operator consists of the combination of the tensor products Hadamard H operators with identity operator I: $H = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}, I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. The superposition operator of most QAs can be expressed (see Fig. 1) as following: $Sp = \left(\overset{n}{\underset{i=1}{\otimes}} H\right) \otimes \left(\overset{m}{\underset{i=1}{\otimes}} S\right)$, where n and m are the numbers of inputs and of outputs respectively. Operator S may be or Hadamard operator H or identity operator I depending on the algorithm. Numbers of outputs m as well as structures of corresponding superposition and interference operators are presented in [5] for different QAs.
The quantum circuit is a high-level description of how these smaller matrices are composed using tensor and dot products in order to generate the final quantum gate as shown in Fig. 1.
The structure of QA on fig. 1 can be presented as quantum algorithmic gate as following:

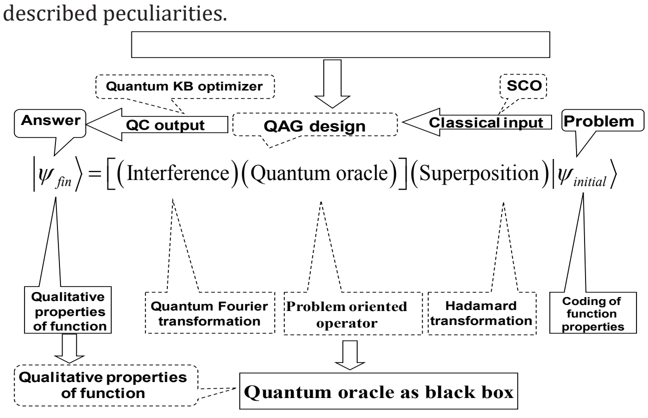
$$QAG = \left[\left(Int \otimes^n I\right) \cdot U_F\right]^{h+1} \cdot \left[{}^n H \otimes {}^m S\right]. \tag{1}$$

Therefore, QA structure has three main quantum operators: superposition; entanglement (quantum oracle) and interference in quantum massive parallel computing.



F i g. 1. General structure of quantum algorithm gate
Source: Hereinafter in the article, all tables and figures are compiled by the authors.

Figure 2 shows the general structure of QA that includes almost of described peculiarities.



F i g. 2. General structure of QA

Let us consider interrelations between control quality and information thermodynamic measures.

[1] Ulyanov S.V. Self-organized control system. United States Patent US-6411944B1. USA, 1997. Available at: https://patents.google.com/patent/US6415272B1/en (accessed 01.04.2023); Ulyanov S.V. Self-organizing quantum robust control methods and systems for situations with uncertainty and risk. United States Patent US-8788450B2. USA, 2011. Available at: https://patents.google.com/patent/US8788450B2/en?oq=8788450 (accessed 01.04.2023).

[2] Ulyanov S.V. System and method for control using quantum soft computing. United States Patent US-6578018B1. USA, 2000. Available at: https://patents.google.com/patent/US6578018 (accessed 01.04.2023).

3. Information and thermodynamic trade-off between control quality measures

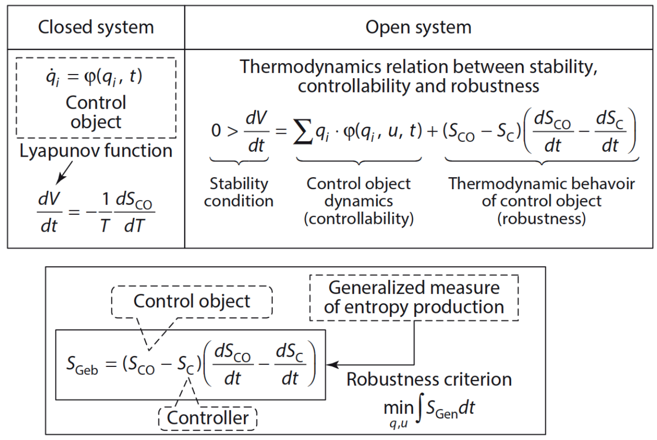
Assume that the control object is described in general form by the equation $\dot{q}_i = \varphi(q,t,S(t),u)$ where the generalized coordinate q_i describes the movement of the control object, u is the control and $S(t) = S_{CO}(t) - S_C(t)$ is the generalized entropy of the system, as the difference between the production of control object entropy $S_{CO}(t)$ and the entropy production $S_C(t)$ of the controller.
Consider the following equation:

$$\underbrace{\frac{dV}{dt}}_{\text{stability}} = \underbrace{\sum_{i=1}^{n} q_i \varphi(q,t,S(t),u)}_{\text{controllability}} + \underbrace{(S_{CO}-S_C)(\dot{S}_{CO}-\dot{S}_C)}_{\text{robustness}} \qquad (2)$$

Equation (2) relates in analytical form such qualitative concepts of control theory as stability V (Lyapunov function), controllability and robustness based on the concept of entropy of phenomenological thermodynamics [1].
This approach allows to find the necessary distribution between the levels of stability, controllability and robustness, which allows to achieve the goal of control in unforeseen situations with a minimum consumption of useful resource by using as a fitness function in the genetic algorithm the minimum production of generalized entropy, which is included in the right part (2).
For fig. 3 the equation of distribution of qualities of control of dynamic system connects in the analytical form on the basis of concept of entropy of phenomenological thermodynamics such qualitative concepts of the theory of control as stability, controllability and robustness.
As a result, the necessary distribution between the levels of stability, controllability and robustness, as a fitness function in the genetic algorithm, the criteria for the minimum production of generalized entropy applied, which allows to achieve the goal of control in unforeseen situations with a minimum consumption of useful resources.
The thermodynamic definition of S and information entropy H are related by the von Neumann relation as: $S = kH = -k\sum_i p_i \ln p_i$, where $k = 1.38\times10^{-23}$ is the Boltzmann constant. For fig. 3 the following notations are introduced: V-Lyapunov function; S_{CO}, S_C entropy production in the of control object (CO) and the controller, respectively;

$$V = \frac{1}{2}\sum_{i=1}^{n} q_i^2 + \frac{1}{2}S^2; \quad S = S_{CO} - S_C .$$

In quantum thermodynamics the entropy production of a system can be expressed as the product of a thermodynamic force and a thermodynamic flow. The generalized minimal work formulation of thermodynamics for non-equilibrium distributions gives an important relation between two major concepts in physics, energy and information: in non-equilibrium quantum thermodynamics the internal energy can also be decoded (negative irreversible work) to be used by the system to perform more work than what is expected.



F i g. 3. Thermodynamic criterion of distribution of quality of robust control

Consider now (2) with regard to the relation of thermodynamic entropy to Shannon information entropy. Substitute the Shannon information entropy - H in equation (1) instead of $S(t)$. As a result, we obtain:

$$\underbrace{\frac{dV}{dt}}_{\text{stability}} = \underbrace{\sum_{i=1}^{n} q_i \varphi(q,t,k(H_{CO}-H_C),u)}_{\text{controllability}} + k\underbrace{(H_{CO}-H_C)(\dot{H}_{CO}-\dot{H}_C)}_{\text{robustness}} \qquad (3)$$

Thus, Eq. (3) also relates stability, controllability and robustness, but already on the basis of Shannon information entropy, which also allows to determine the control for the guaranteed achievement of the control goal in unforeseen situations with the requirement of a minimum amount of information about the external environment and the state of the control object. Consequently, (2) and (3) constitute a system of equations, the solution of which determines the control, guaranteeing the achievement of the control goal in unforeseen situations with a minimum consumption of useful resources and the minimum required initial information [1], [4].

4. Quantum fuzzy inference based on quantum genetic algorithm in intelligent robotics

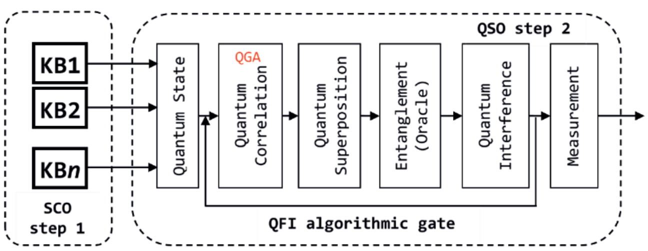
PID controller is a widespread type of controller in control loops. The controller is used in 70% of the industrial automation, most of them require constant adjustment, as a result of which they do not work very effectively, especially if the situation differs from the calculated one. Increasing robustness and efficiency is possible through the use of quantum computing and quantum search algorithms, and as a special case - quantum fuzzy inference (QFI). Without increasing the cost of a temporary resource – in online. An example of such a control structure is shown in fig. 4, which shows the integration of several fuzzy controllers into a single control system in the QFI block which allows creating a new quality in control – online self-organization of KB [2], [5].
In general, the structure of a QAG based on a quantum genetic algorithm (QGA) described in the form:

$$.QAG = \left[\left(Int \otimes^{n} I\right) \cdot U_{F}\right]^{h+1} \cdot \left[QGA\right]\left[{}^{n}H \otimes^{m} S\right] \tag{4}$$

QGA have already been actively used in human action recognition [6, 7] and fault diagnosis of gearbox [8]. Structure of corresponding QAG on fig. 4 is shown.

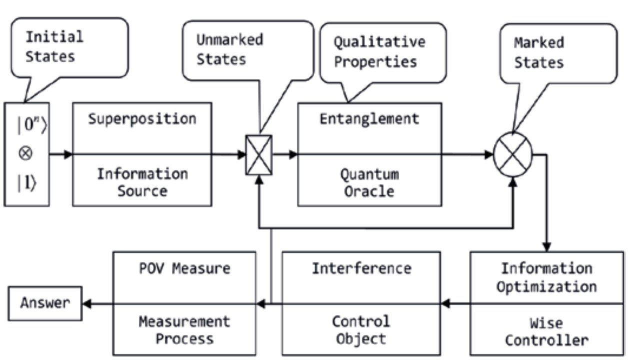
The first part in designing Eq. (4) is the choice of the type of the entangled state of operator U_F. Developed by quantum genetic search algorithm (QGSA) (see, fig. 5), is the basic unit of such an intelligent control system (ICS).

The simulation results showed (see, below) that from two non-robust knowledge bases, it is possible to create a reliable intelligent controller. Thus, show computing effectiveness of robust stability and controllability of (QFI + QGA) – controller and new information synergetic effect introduced. Algorithms of this type in intelligent control systems can be realized either on classical or on quantum processors (as an example, on D-Wave processor type).

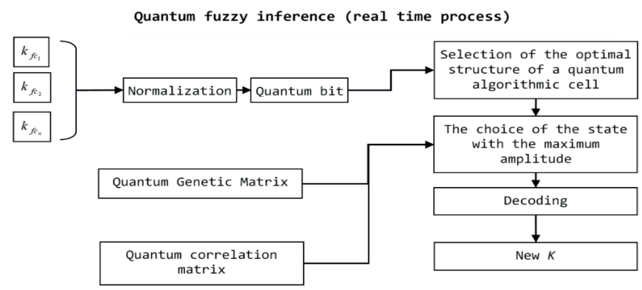


F i g. 4. QAG structure of QFI with QGA

Two classes of quantum evolution (4) are described: QGA and hybrid genetic algorithm (HGA). The QFI algorithm for determining new PID coefficient gain schedule factors *K* (see, below fig. 6) consists of such steps as: normalization; the formation of a quantum bit, after which the optimal structure of a QAG is selected; the state with the maximum amplitude is selected; decoding is performed and the output is a new parameter *K*.



F i g. 5. Intelligent self-organizing quantum search algorithm for intelligent control systems



F i g. 6. Quantum fuzzy inference algorithm

The input to the QFI are the values of the coefficient gains obtained from the fuzzy controllers.

In the next step, the received signals are normalized by dividing the current values of the control signals by their maximum values (max *k*), which are known in advance. Next, the formation of quantum bits is performed based on the probability density function. This allows you to determine the real and virtual state of the control signals for shaping at the next stage of superposition by means of the Hadamard transformation of the current state of the input control signals. The law of probability is used: $p(|0\rangle)+(|1\rangle)=1$, where $p(|0\rangle)$ is the probability of the current real state and $p(|1\rangle)$ is the probability of the current virtual state. The superposition of the quantum system «real state – virtual state» has the following form:

$$|\psi\rangle = \frac{1}{2}\left(\sqrt{p\left(|0\rangle\right)}\,|0\rangle + \sqrt{1-p\left(|0\rangle\right)}\,|1\rangle\right) \tag{5}$$

The next step is constructing operation of entanglement with selection of the type of quantum correlation. Three types of quantum correlation are considered: spatial, temporal and spatial temporal. Each of them contains valuable quantum information hidden in a KB.

Solving classical algorithmically intractable problems and increasing the success of finding solutions is carried out on the basis of quantum correlation, which is considered as an additional information resource. In our case, the solution of the problem of ensuring global robustness of functioning of the CO under conditions of unexpected control situations by designing the optimal structure and laws of changing the PID controller gain factors by classical control methods is an algorithmically intractable problem. One of the ways to solve this problem is based on quantum computing using the QFI algorithm [2], [4], [9].

In a multi-agent system, there is a new synergistic effect arising from the exchange of information and knowledge between active agents (swarm synergetic information effect) [2]. The output parameters of the PID-regulators are considered as active information-interacting agents, from which the resulting controlling force of the control object is formed [3].

Remark. One of the interesting ideas was proposed in 2004, taking the first steps in implementing the genetic algorithm on a quantum computer [5]. The author proposed this quantum evolutionary algorithm, which can be called the reduced quantum genetic algorithm (RQGA). The algorithm consists of the following steps: 1) Initialization of the superposition of all possible chromosomes; 2) Evaluation of the fitness function by the operator F; 3) Using Grover's algorithm; 4) Quantum oracle; 5) Using of the diffusion operator Grover G; 6) Make an evaluation of the decision. The search for solutions in RQGA is performed in one operation. In this case the matrix form is the result of RQGA action[3] [10].

5. Benchmark «cart – pole» system

This example was not chosen by chance, in the theory of control, an inverted scaffold is a typical task for checking the quality of control systems and technologies for their design. The aim of the control is to keep the pendulum in the vertical position. Dynamic of the system «cart – pole» is described by the following differential equations:

$$\ddot{\theta}=\frac{g\sin\theta+\cos\theta\left(\dfrac{u+\xi(t)+a_1\dot{z}+a_3z-ml\dot{\theta}^2\sin\theta}{m_c+m}\right)-k\dot{\theta}}{l\left(\dfrac{4}{3}-\dfrac{m\cos^2\theta}{m_c+m}\right)}$$
$$\ddot{z}=\frac{u+\xi(t)-a_1\dot{z}-a_2z+ml\left(\dot{\theta}^2\sin\theta-\theta\cos\theta\right)}{m_c+m} \qquad (6)$$

A mathematical model (6) of the control object presented above contains the following variables: θ is the pendulum deviation angle (degrees); z is the movement of the cart (*m*); *g* is the acceleration of gravity (9.8 m/s^2); m_c is the pendulum mass (kg); *l* is the pendulum half-length (m); $\xi(t)$ is the stochastic excitation; and u is the control force acting on the cart (N).

The studies considered control options both on the example of a mathematical model and a real object. The model was verified beforehand.

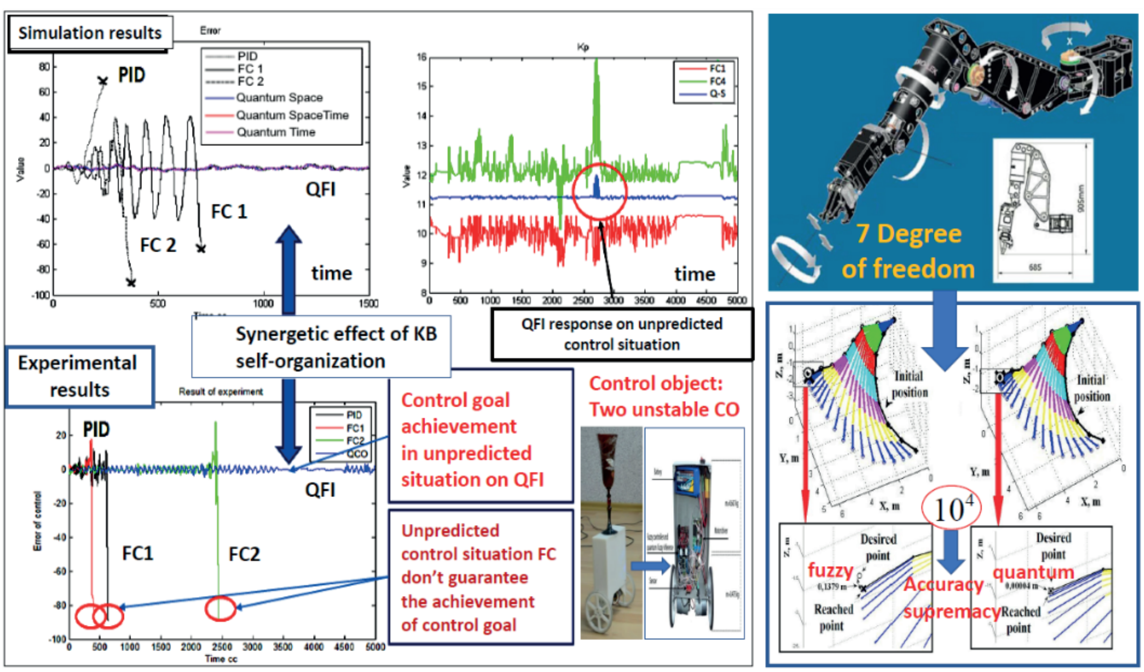
Compare the different regulators: classic PID controller, with constant coefficients, fuzzy controllers FC1 and FC2, based on soft computing optimizer (SCO), and QFI controllers based on different types of correlations: Quantum-Spatio-Temporal (Q-ST), Quantum-Temporal (Q-T), Quantum-Spatial (Q-S). These QFI controllers are based on FC1 and FC2, and optimized using remote connection.

To compare the robustness of the developed regulators and technologies, the mathematical modeling and physical experiments in two situations control:

- typical situation (S1), the delay of control – 0.015 sec;
- unforeseen situation (S2), the delay of the control – 0.035 sec.

The simulation results are shown in fig. 7.

The experiment compares the different controllers: PID controller, two fuzzy controllers (FC1, FC2) and three QFI controllers based on different types of correlations: Quantum-Time (Q-T), Quantum-Space (Q-S), Quantum-Space Time (Q-ST). In the simulation and experiment, the structure of a robust ICS based on QFI (see Fig. 5) and QAG (see Fig. 1) was used. Based on the training signal taken directly from the control object, using the QCOptKB™ software toolkit, a KB of FC was designed. An abnormal situation was simulated by a threefold delay in the feedback sensor signal. The experimental results show that the accuracy of a quantum controller is more than 10,000 (see Fig. 3, right side) times higher than that of a controller based on soft computing.



F i g. 7. Simulation & experimental results comparison for unpredicted control situation in cases of PID-controller, fuzzy controller and QFI-controller (b)

[3] Ivancova O.V., Korenkov V.V., Ulyanov S.V. Quantum Software Engineering. Quantum supremacy modelling. Part I: Design IT and information analysis of quantum algorithms: Educational and methodical textbook. Textbook. Moscow: KURS; 2020. 328 p.

Under conditions of uncertainty, the controller based on soft computing dramatically increases the control error, thereby failing to achieve the control goal (see Table 1).

Comparison of controllers shows the presence of a synergistic effect of self-organization in the design of robust KBs based on imperfect KBs of FCs. The control coefficients of the PID controller are based on the feedback of imperfect KB (see the «QFI block» in Fig. 1), forming a control action in online. This is achieved by extracting an additional information resource using QFI in the form of quantum information hidden in the classical states of the control action as a new control error of the output signal of an imperfect KB [1, 2].

T a b l e 1. **Comparison of the different regulators**

Time, sec	Cart motion, cm					
	PID	FC1	FC2	QFI (Q-S)	QFI (Q-ST)	QFI (Q-T)
1	-1	-1	-1	1	-1	-1
2	5	3	5	5	3	4
3	-35	-4	-26	-4	-2	-3
4	60	5	36	6	4	5
5	-	-5	-60	-5	-4	-7
6	-	10	-	5	8	6
7	-	-14	-	-4	-6	-9
8	-	23	-	4	5	7
9	-	-32	-	-6	-8	-3
10	-	50	-	9	6	4
11	-	-	-	-9	-4	-7

Remark. In[4], a reduced quantum genetic algorithm (RQGA) was proposed, which is an implementation of a genetic algorithm on a quantum computer. The search procedure for the desired solution is performed in one operation. Structurally, the algorithm consists of the following steps:

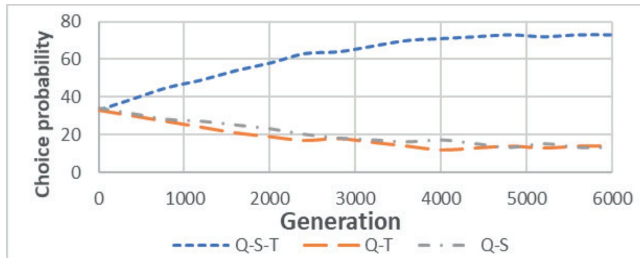
[1] initialization of the superposition of all possible chromosomes;
[2] assessment of the fitness function by operator *F*;
[3] applying Grover's algorithm;
[4] using a quantum oracle;
[5] using Grover's diffusion operator;
[6] evaluation of the solution.

As can be seen from Fig. 8, after 1000 generations about 70% of spatio-temporal correlations have the best probability. After 5000 generations, the probability remains unchanged.

As model of unpredicted control was the situation of feedback sensor signal delay on three times. Results of controller's behavior comparison confirm the existence of synergetic self-organization effect in the design process of robust KB on the base of imperfect (non-robust) KB of fuzzy controllers.

In unpredicted control situation control error is dramatically changing and KB responses of fuzzy controllers (FC 1 and FC 2) that designed in learning situations with soft computing are imperfect and do not can achieve the control goal. Using responses of imperfect KB (as control signals for design the schedule of time dependent coefficient gain in PID-controller) in Box QFI the robust control is formed in online.

This effect is based on the existence of additional information resource that extracted by QFI as quantum information hidden in classical states of control signal (as response output of imperfect KB's on new control error)[5] [11-13].

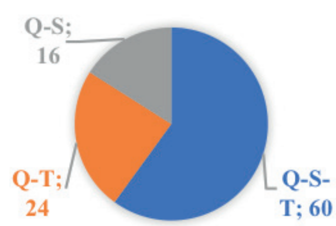


F i g. 8. The result of the QGA

However, after 200 generations the probability of spatio-temporal correlations decreases to 60% (see Fig. 9). The described method is differed from others results described in[6] [13-16].

In Fig. 7 shows the results of an experiment of control in unexpected situations for an object «cart-*double* pole» and a 7 degrees of freedom (DoF) *redundant* manipulator.

Remark. The choice of correlation type is determined by the properties of the considered CO [13]. Thus, in [12] multiple results of simulation of complex nonlinear control objects have shown that the spatial correlation is efficient for design of robust intelligent control systems for globally dynamically unstable control objects; temporal correlation is reasonable for locally unstable nonlinear control objects as (6); for nonlinear control objects with dynamic instabilities of different structure (as regards generalized coordinates) mixed spatio — temporal quantum correlation can be applied. The application of the chosen form of correlation in combination with different types (external or internal) of correlation between components of control signals extend the resource and increase the potential of quantum correlations. This approach is considered below for a particular example.



F i g. 9. The probability of spatio-temporal correlations after 200 generations

[4] Ibid.

[5] Litvintseva L.V., Tyatyushkina O.Yu., Ulyanov S.V. *Texnologii intellektualnyx vychislenij: Myagkie i drobnye vychisleniya* [Computational Intelligence Technologies: Soft and fractional computing]. Part 1. M.: INFRA-M; 2020. 288 p. (In Russ.) EDN: MRDAZL; Ivantsova O., Korenkov V., Ulyanov S. *Texnologii intellektualnyx vychislenij: Kvantovye vychislenija i algoritmy. Kvantovyj algoritm samoorganizacii. Kvantovyj nechetkij vyvod* [Computational Intelligence Technologies: Quantum computing and quantum algorithms quantum algorithm of self-organization quantum fuzzy inference]. Part 2. M.: INFRA-M; 2020. 296 p. (In Russ.) EDN: XHBLVV

[6] Ivancova O.V., Korenkov V.V., Ulyanov S.V. Quantum Software Engineering. Quantum supremacy modelling. Part II: Quantum search algorithms simulator – computational intelligence toolkit: Educational and methodical textbook. Moscow: KURS; 2020. 344 p.

The relation between the complete, classical, and quantum correlation types (as the measure of quantum state uncertainty) is determined as follows [13]:

Complete uncertainty = Classical part + Quantum part. (7)

Relation (7) is satisfied for closed quantum states in the case of measurement without message exchange between these parts. In the open-loop system, additional message exchange between active agents (situated on classical and quantum levels) and self-organization levels is possible [2]. This means that *mutual* (mixed) correlation between *real* and *virtual* states of normalized control signals is present. Classical correlation in this case is a particular case of complete quantum correlation. In this case, according to [4], [12], messages are sent via quantum channels providing organization of transmission of signal superposition with different forms of correlation between agents.

According to [2], [9], [13], such quantum channels of information transmission are a *special class of quantum correlated (between input and output) communication channels, in which it is sufficient to have finite memory and it is possible to realize new quantum strategies of message transmission with simple communication protocol. Coding of messages in such communication channels with finite memory and specific features of mixed communication channels provide efficient transmission of information flows via quantum mechanisms of data extraction* (decoding).

Therefore, complete correlation consists of the following parts: classical (between real values of the normalized control signal); quantum (between virtual values of normalized control signal); and mixed (between real and virtual values of normalized control signal). The first two types of correlations are studied in the correlation theory of random (classical and quantum) processes. In this case, the intensity of quantum correlation is higher than that of classical correlation (Bell's inequality).

The third type is new in the theory of quantum random processes and reflects the effect of *interference* of classical and quantum correlations. This type of complete correlation contains hidden classical correlation in quantum sates of formed superposition of quantum bits and serves as the information resource for extraction of additional (unobserved) valuable quantum information [13].

Thus, physically classical correlation is responsible for self-organization of the structure on the macrolevel; quantum and mixed correlations are responsible for the microlevel and information transmission from micro- to macro-levels, respectively. Information exchange and coordinated control between gains of designed robust fuzzy PID controller is performed using internal and external correlation types.

Let us consider the effect of extraction of hidden and increment of additional quantum information from the point of view of quantum information theory and its software formation in the structure of quantum algorithm of knowledge base self-organization.

The application of the chosen form of correlation in combination with different types (external or internal) of correlation between components of control signals extend the resource and increase the potential of quantum correlations.

The textbook[7] considered the quantum self-organization algorithm model of wise knowledge base design for intelligent fuzzy controllers with required robust level. Background of the model is a new model of quantum inference based on quantum genetic algorithm and design optimal structure of quantum neural network. Quantum deep machine learning toolkit applied developed platform titled as «Quantum Computing Optimizer of Knowledge Base» (QCOptKB™). Recently, parameterized quantum circuits (PQCs) were widely considered, because PQCs can be efficiently implemented on NISQ devices. Several NISQ quantum machine learning models based on PQCs, such as quantum generative adversarial networks, quantum circuit Born machine, and quantum kernel methods, were proposed[8]. Several approaches are shown that PQCs have the potential abilities in machine learning tasks including approximating functions, classification, and data generating. PQCs are also called quantum neural networks (QNNs) because of its layer wise circuit structure, and QNNs are used for machine learning tasks. the quantum deep neural network (QDNN) which is a composition of multiple quantum neural network layers (QNNLs). The QDNN can uniformly approximate any continuous function and has more representation power than the classical DNN. Unlike other approaches of quantum analogs of DNNs, the QDNN still keeps the advantages of the classical DNN such as the non-linear activation, the multi-layer structure, and the efficient backpropagation training algorithm. The inputs and the outputs of the QDNN are both classical which makes the QDNN more practical. Because the QNNL is based on PQCs, the QDNN has the potential to be used on NISQ processors. As shown in experiments, a QDNN with a small number (eight) of qubits can be used in image classification and control. In summary, QDNN provides a new class of neural networks which can be used in near-term quantum computers and is more powerful than classical DNNs.

A PQC is a quantum circuit with parametric gates, which is of the form $U\left(\vec{\theta}\right)=\prod_{j=1}^{l}U_j\left(\theta_j\right)$ where $\vec{\theta}=\left(\theta_1,\ldots,\theta_l\right)$ are the parameters, each $U_j\left(\theta_j\right)$ is a rotation gate $U_j\left(\theta_j\right)=\exp\left(-i\frac{\theta_j}{2}H_j\right)$, and H_j is a 1-qubit or a 2-qubits gate such that $H_j^2=I$. For example, when H_j is one of Pauli matrices $\{X, Y, Z\}$, $U_j(\theta_j)$ is the single qubit rotation gates R_X, R_Y, R_Z.

As shown in Fig. 10, once fixed an ansatz circuit $U\left(\vec{\theta}\right)$ and a Hamiltonian H, we can define the loss function of the form $\left\langle 0\middle|U^{\dagger}\left(\vec{\theta}\right)HU\left(\vec{\theta}\right)\middle|0\right\rangle$. Then, we can optimize L by updating parameters $\vec{\theta}$ using optimization algorithms[9]. With gradient based algorithms, one can efficiently compute the gradient information $\frac{\partial L}{\partial\vec{\theta}}$ which is essentially important in the model [15].

[7] Ibid.

[8] Ibid.

[9] Ibid.

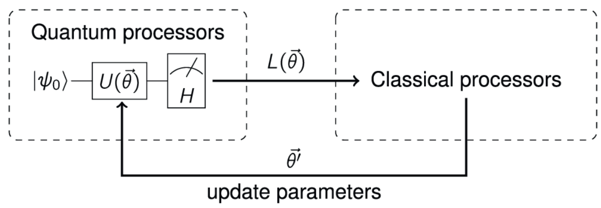


Fig. 10. Hybrid quantum-classical scheme

Quantum algorithm applied on line for the quantum correlation's type searching between unknown solutions in quantum superposition of imperfect knowledge bases of intelligent controllers designed on soft computing (SCOptKB™ toolkit). Disturbance conditions of analytical information-thermodynamic trade-off interrelations between main control quality measures (stability, controllability and robustness) as new control design laws discussed. The smart control design with guaranteed achievement of these trade-off interrelations is the main goal for quantum self-organization algorithm of imperfect KB. Sophisticated synergetic quantum information effect introduced: a new robust smart knowledge base can be created on line from responses on unpredicted control situations of any imperfect KB applying quantum hidden information extracted from quantum correlation. Within the toolkit of classical intelligent control based on soft computing the achievement of the similar synergetic information effect is impossible. Structure of quantum computing optimizer of knowledge base (QCOptKB™) equivale to the structure on fig. 8 and realize in on-line quantum deep machine learning with quantum genetic algorithm in the structure (4) of QFI[10].

Benchmarks of intelligent cognitive robotic control applications considered.

This approach is considered below for a particular important example for mega-science project NICA (JINR).

6. Intelligent robust liquid nitrogen flow control system in the collector of a cryogenic plant for control of superconducting magnets

By controlling the nitrogen supply valve, it is necessary to regulate the pressure and flow rate of nitrogen in the collector. The control loop status is monitored by a pressure sensor and a nitrogen level sensor. In this state of superconductivity (SC), the magnet winding must be maintained at the equilibrium point of the permissible range of changes in current, temperature and magnetic field.

The SC magnetic element of the accelerator complex itself during the tests has the following features: heat gain due to eddy currents leading to heating of the core, heat gain from the walls and uneven cooling in the connecting nodes. These features of an individual magnetic element also impose the complexity of managing a group of similar elements.

The principle of intelligent control implies compensation for the uncertain and imperfect parameters of a magnetic element existing in a real object through the use of soft and quantum computing technologies and taking into account the peculiarities of individual KBs.

In [17] shows the input data - indicators of the state of the system and output - parameters of the actuators controlled by an intelligent control system for the conditions of the state of nitrogen in the stand collection. The efficiency of pumping, cooling the magnetic element and maintaining the SC regime depends, among other things, on the pressure in the cooling system, and therefore on the nitrogen pressure in the collector and its level. In this case, it is necessary to take into account the increase and decrease in the nitrogen consumption in the process of heating and cooling the magnetic element, taking into account the inaccuracy of the actuator (valve).

Figure 11 shows the control loop of the first level, implemented in the form of a proportional-integral-differential (PID) controller with adjustable control parameters (K_P, K_I, K_D).

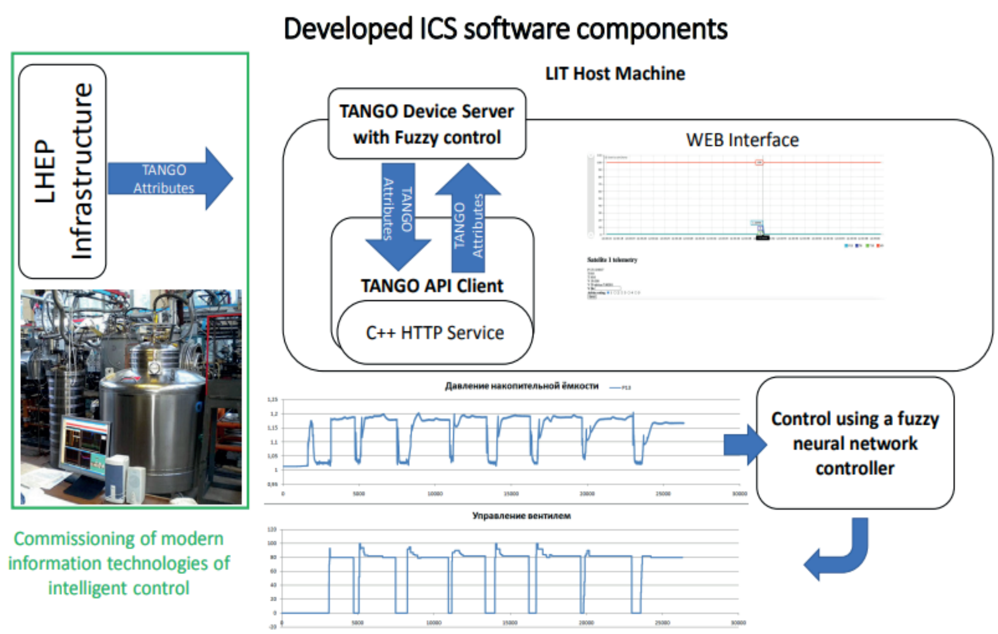
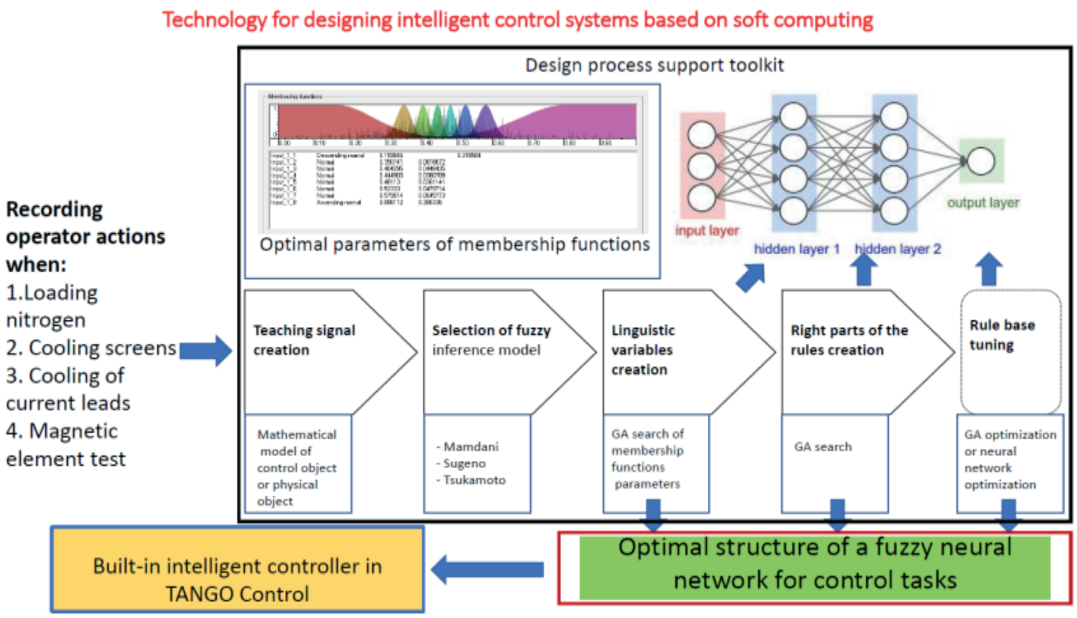


Fig. 11. Developed and implemented software and hardware components of the control system

[10] Ibid.

The choice of optimal control parameters depends both on the listed features in the implementation of a separate magnetic element, and when controlling a group of magnetic elements.

Let us consider an example of designing an ICS for pressure control in a storage tank with nitrogen of a test bench of a magnet factory. At the first design stage, the indicators and parameters set by the operator in the control system were recorded (Fig. 11). Further, the most effective trajectories of valve control (operator actions) were selected from the point of view of maintaining the required pressure level and nitrogen flow rate. Based on these data, using soft computing software tools, a FC was designed (Fig. 12).



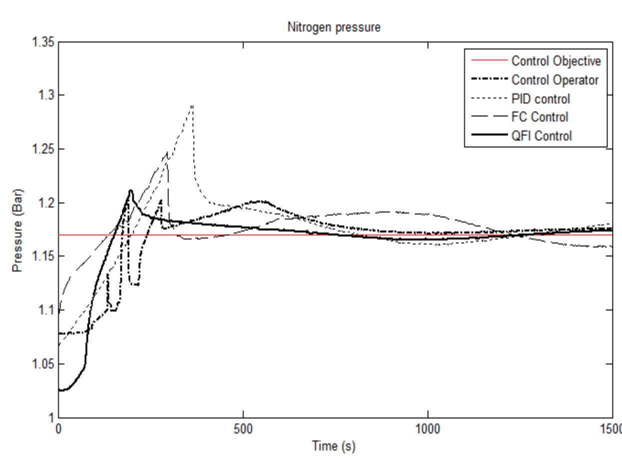
F i g. 12. ICS design technology and interaction with Tango-Control

Example. A very important control task in this mode is to maintain the required pressure when filling nitrogen. The fact is that during the test, the cooling must be continuous, and the refueling process itself implies a decrease in pressure for the supply of nitrogen, while the pressure in the nitrogen source through the communicating vessels affects the pressure in the collector. The complexity of this mode lies in the need to maintain a given pressure (for continuous cooling) and at the same time refuel the storage tank. Sharing plays an important role V19 (pressure control) and V20 (volume control) valves. Typically, the operator opens V19 to release pressure, primes the system with nitrogen, and then proceeds to equalize the pressure. For this technological stage, it is possible to use the automatic mode, and to control both V19 and V20 (nitrogen supply) at the same time. For the automatic control mode V19, the PID, FC, QFI controllers were considered.

Let's consider the results of the conducted studies in the nitrogen cooling mode. Figure 13 shows the time dependence for the pressure level (in bars) during nitrogen cooling for a period of about 40 minutes.

Designations: Control Objective – the target pressure value (1.17 bar), Control Operator – the pressure value when controlled by the operator, PID Control – automated control of the standard means of the regulator, FC Control – automated control using a fuzzy controller, QFI Control – automated control mode using a quantum FC.

It is clearly seen that all regulators cope with the task of stabilizing the pressure in the collection in 40 minutes. However, the analysis of the results shows that the classic PID controller has a low speed and a high level of overshoot (1.29 bar), which is critical and can be considered as close to an emergency (1.30 bar). At the same time, the FC and the quantum controller (QFI control on Fig. 13) on the QFI - model demonstrate high performance (relaxation time 210 and 215 seconds, respectively) with a low level of overshoot (1.24 and 1.21 bar, respectively). The operator coped well enough with the task of setting the required pressure (overshoot 1.21 bar and speed 280 sec), but could not set the required pressure value (steady-state mode 1.18 bar) (Table 2).



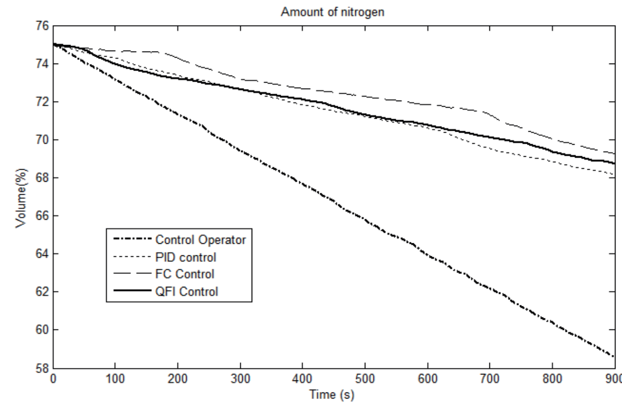
F i g. 13. Pressure in the nitrogen collector during nitrogen cooling

T a b l e 2. **Comparison of the quality criteria of the transition process in nitrogen cooling mode**

Type of control	Overshoot	Performance	Control complexity
Operator	0.013	0.5	0.2
PID	0.021	0.78	0.5
FC	0.017	0.65	0.91
QFI	0.012	0.3	0.52

Figure 14 shows the consumption of the useful resource (nitrogen) of the installation. It is clearly seen that automatic control due to continuous monitoring demonstrates a more efficient use of a useful resource and allows you to reduce consumption by 50%, in particular, the PID controller - by 50%, the fuzzy controller FC– by 54%, the quantum fuzzy controller QFI – by 53%. Moreover, from the point of view of the consumption of a useful resource, QFI and FC reduce nitrogen consumption by more than 50% (Fig. 14), i.e. they reduce the number of nitrogen refills by 2 times.

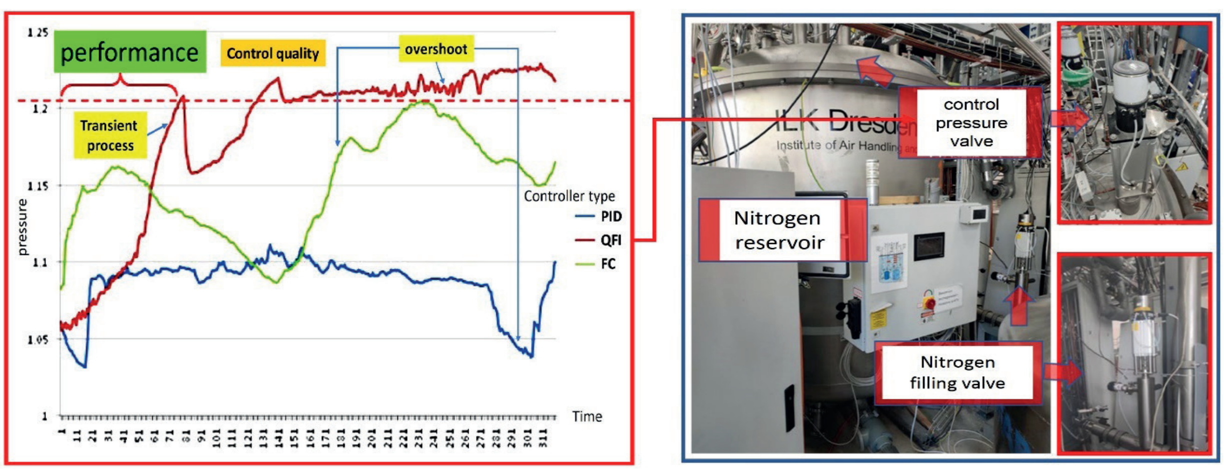
A very important control task in this mode is to maintain the required pressure level when refueling nitrogen. The fact is that the cooling must be continuous, and the refueling process itself implies a decrease in pressure for nitrogen intake, while the pressure in the nitrogen source through the communicating vessels affects the pressure in the collector. The complexity of this mode lies in the need to maintain a set pressure (for continuous cooling) and simultaneously refuel the storage tank.



F i g. 14. Nitrogen consumption in the storage tank

In this case, the joint use of valves V19 and V20 plays an important role. Usually, the operator opens the V19 valve to relieve pressure, refills the system with nitrogen, and then proceeds to equalize the pressure. An automatic mode can be applied to this technological stage, and for simultaneous synchronous control of both the V19 valve and the V20 nitrogen supply valve. For the automatic control mode V19, the regulators PID, FC, QFI were considered.

Figure 15 shows results of quantum supremacy in intelligent pressure control for nitrogen charging.



F i g. 15. Pressure P13 when filling with nitrogen in the mode of cooling current leads and screens

The preliminary results show that the heating of the magnet joint during refueling suits the test regulations. Automatic control allows you to maintain the required pressure level during refueling, which allows you to reduce the warming of the magnet and maintain the temperature in the specified ranges.

This circumstance shows the possibility of using intelligent control when cooling superconducted magnets in conditions of optimization according to the criterion of contradictory indicators of control qualities.

In other words, intelligent control based on QFI has a low level of overshoot, allows you to reduce the consumption of useful life (nitrogen), increase the service life of the valve and increase the performance of the entire system with guaranteed achievement of the temperatures required by the testing regulations.

In general, at this stage, the work of the regulator was assessed as correct. The conducted studies show that the use of quantum and soft computing in the problem of controlling the pressure and flow of nitrogen increases the reliability of the system, reducing the amount of nitrogen flow.

The studies carried out have shown that when regulating in the control mode of a FC, the nitrogen flow rate decreases. Thus, with the considered example of the process of designing an ICS of inverted pendulum (see, Fig. 7), the possibility of creating an intelligent robust control system with an increased level of robustness due to the application of quantum computing technologies and various information resources in the process of extraction and formation of KB demonstrated.

7. Main contributions of quantum end-to-end IT: Quantum supremacy of quantum intelligent control of classical control objects

In[11] applied Benchmarks of the developed information technology design discussed in detail. In particular cases, in the design stage framework of robust KBs applying the model of quantum fuzzy inference: two different models of robots - mobile manipulator and inverted swing pendulum («cart – pole» system) are shown in Fig. 7. It is remarkable that two globally unstable control object («cart – pole» system and glass) globally stable only under quantum self-organized controller with KB designed in on-line from two imperfect KBs of fuzzy controllers.

A comparison of the quality control in the fuzzy controllers and quantum fuzzy controller in various control modes in [9] presented. The ability to connect and work with a real CO, without using his mathematical model described. The implemented technology of knowledge sharing in a swarm of intelligent robots, with quantum controllers, allows to achieve the goal of control and to gain additional knowledge by creating a new information source based on the synergetic effect of combining knowledge. The results of the experiments demonstrate the possibility of the ensured achievement of the control goal of a group of robots using soft / quantum computing technologies in the design of KBs of fuzzy controllers in control systems. The developed software toolkit allows to design and setup complex ill-defined and weakly formalized technical systems on line.

The physical interpretation of self-organization control process on quantum level is discussed based on the quantum information-thermodynamic models of the exchange and extraction of quantum (hidden) value information from/between classical particle's trajectories in particle swarm [1, 2]. Main physics and information thermodynamics aspects of quantum intelligent control of classical control objects discussed and described from control Benchmark models viewpoint design on the basis of new laws of quantum Lagrange / Hamilton deep machine learning.

1. *Physics of quantum hidden information phenomena*. 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.

2. *Quantum logic of intelligent classical system control*. The structure of developed quantum fuzzy inference (QFI) model includes necessary self-organization properties and realizes a self-organization process as a new quantum search algorithm (QSA). In particular case, in intelligent control system (ICS) structure, QFI system is a QSA block, which performs post-processing of the results of fuzzy inference of each independent fuzzy controller (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 each independent FC outputs (self-organization principle). For design of FC - KB original structures of quantum neural networks and quantum genetic algorithm developed and applied.

3. *Quantum software engineering of quantum intelligent control physics law*. Quantum soft computing optimizer toolkit of KB – design processes is described. Benchmarks of robust KB design from imperfect FC - KB as the new quantum synergetic information effects of extracted quantum information demonstrated. Moreover, the new force control law from quantum thermodynamic described: with extracted hidden quantum information from classical control signal states (on micro-level) possible to design in on-line new control force that can produce on macro-level more value work amount than the work losses on the extraction of this amount of hidden quantum information.

It is a new control law of physics-cybernetics open hybrid systems including port-Hamiltonian controlled dynamic objects[12].

4. *Applications*. Effective application of new quantum intelligent controller in mega-science project NICA, intelligent cognitive robotics and quantum drones for applications in project «Industry 5.0» demonstrated. Perspective applications of quantum software engineering discussed. Therefore, the operation area of such ICS 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 intelligent control system of unstable essentially nonlinear control object in unpredicted control situations (autonomous mobile robots, robotic manipulators, swarm robotics with information exchange etc.).

Remark (the second law of thermodynamics). A consequence of theorem, reflected in the maximization of the entropy of a density over beliefs about external states, is that adaptive systems do not avoid the second law of thermodynamics; rather, they leverage it, offloading the increase in entropy to their environments, and changing their beliefs accordingly. Much like self-evidencing is native to the constrained entropic view but is still apparent in the free energy view, this disordering is a signature of free energy present on the constraint-based side of the adjunction, in that this is what creates the aforementioned ontological potential which organizes the system into itself. It is thus the case that adaptive systems are engines which 'eat' order and produce entropy, disordering their environments to keep themselves organized. It has indeed been argued that complex systems are in fact statistically favored due to their role as vehicles of dissipation. organized systems do indeed maximize self-entropy over system-like states, accepting the second law up to what is allowable within the confines of system-ness. This lack of determination of what constitutes a system-like state is important for the flexibility and itinerancy characterizing adaptive systems, and more generally, models an inexorable tendency for agents to fluctuate and explore.

The accuracy constraint is a signature of the maximum self-entropy view on the side of beliefs—recall, adjointly, we have established that we can model an object by maximizing the entropy of our own beliefs about the system, assuming the system can be understood as

[11] Ibid.

[12] Ibid.

maximizing its entropy against some constraints on what it means to be such a system. In both views we suggest a belief corresponds to a physical maximization of entropy, in that the believed and actual probabilities of states disperses. For instance, we suggest this belief includes or reflects the process of environmental disorder.

Since the entropy of the agent-environment loop is controlled by the individual components of the loop, and introducing constraints that imply a coupling decreases that joint entropy, the integrity of the loop is precisely dependent on the integrity of its components. This statement is in some sense a statement that, by maximizing constrained entropy both ways—or identically, by leveraging the coupling between agent and environment—self-organization is possible. In so doing, it reveals the importance of the Markov blanket formulation, as a symmetric statistical relationship between the system and its environment. Likewise, this joint entropy decrease out of constrained entropy maximization can be taken as a feature of self-organization, in that no loop exists if the system joins its environment.

5. *Thermodynamic Machine Learning through Maximum Work Production*

Finding the maximum-work agent is «thermodynamic learning» in the sense that it selects a device based on measuring its thermodynamic performance—the amount of work the device extracts. Ultimately, the goal is that the agent selected by thermodynamic learning continues to extract work as the environment produces new symbols. However, we leave analyzing the long-term effectiveness of thermodynamic learning to the future. Here, we concentrate on the condition of maximum-work itself, deriving and interpreting it. While demons continue to haunt discussions of physical intelligence, the notion of a physical process trafficking in information and energy exchanges need not be limited to mysterious intelligent beings. Most prosaically, we are concerned with any physical system that, while interacting with an environment, simultaneously processes information at some energetic cost or benefit. Avoiding theological distractions, we refer to these processes as thermodynamic agents. In truth, any physical system can be thought of as an agent, but only a limited number of them are especially useful for or adept at commandeering information to convert between various kinds of thermodynamic resources, such as between heat and work. Here, we introduce a construction that shows how to find physical systems that are the most capable of processing information to affect thermodynamic transformations.

Adaptive systems—such as a biological organism gaining survival advantage, an autonomous robot executing a functional task, or a motor protein transporting intracellular nutrients—must model the regularities and stochasticity in their environments to take full advantage of thermodynamic resources. Analogously, but in a purely computational realm, machine learning algorithms estimate models to capture predictable structure and identify irrelevant noise in training data. This happens through optimization of performance metrics, such as model likelihood. If physically implemented, is there a sense in which computational models estimated through machine learning are physically preferred? It was introduced the thermodynamic principle that work production is the most relevant performance metric for an adaptive physical agent and compare the results to the maximum-likelihood principle that guides machine learning. Within the class of physical agents that most efficiently harvest energy from their environment, we demonstrate that an efficient agent's model explicitly determines its architecture and how much useful work it harvests from the environment. We then show that selecting the maximum-work agent for given environmental data corresponds to finding the maximum-likelihood model. This establishes an equivalence between nonequilibrium thermodynamics and dynamic learning. In this way, work maximization emerges as an organizing principle that underlies learning in adaptive thermodynamic systems. Machine learning invokes the principle of maximum-likelihood to guide intelligent learning. This says, of the possible models consistent with the training data, an algorithm should select that with maximum probability of having generated the data. The exploration of the physics of learning asks whether a similar thermodynamic principle guides physical systems to adapt to their environments.

Remark. According to the conventional definitions of heat and work given by $\delta Q = \mathrm{Tr}\left(d\rho H\right)$ and $\delta W = \mathrm{Tr}\left(\rho dH\right)$, respectively, when the Hamiltonian is time independent the whole energy exchange is only of the heat type. In the entropy-based definitions, however, heat is assigned to the energy change due to the change in the eigenvalues of the state and work is assigned to the energy change due to the change in the eigenvectors of the state as well as the change in the system Hamiltonian. The prospect of injecting energy from a quantum system into a heat bath, or vice versa, without increasing the temperature of local subsystems has profound implications. For example, it is possible to store/extract heat in/from a bipartite system without changing the local temperatures of its constituents [18-25].

Remark. An operational approach to characterizing the energy change of an open quantum process described by a completely-positive trace-preserving (CPTP) map. Such maps are ubiquitous in modern quantum physics and arguably the most encompassing generic description available for quantum processes (i.e. all processes that can be described by coupling to an initially uncorrelated ancilla, joint unitary evolution, and tracing out over the ancilla). Interestingly, a second law for CPTP maps consider in the context of equilibrium thermodynamics. The Clausius inequality states that the thermodynamic entropy of any system and its environment is non-decreasing. For systems in equilibrium, owing to the notions of temperature β^{-1}, thermodynamic entropy ΔS and heat $\langle Q \rangle$ being well defined, the second law can be stated as $\Delta S \geq \beta \langle Q \rangle$. To generalize this to the quantum regime, von Neumann entropy, $S(\rho) := \mathrm{Tr}[\rho \log(\rho)]$, is considered in the place of thermodynamic entropy (being equivalent for thermal states). The second law for arbitrary states undergoing CPTP evolution is a direct consequence of the fact that relative entropy, defined as $S\left(\rho \| \sigma\right) := \mathrm{Tr}\left(\rho \log \rho - \rho \log \sigma\right)$ obeys contractivity under CPTP maps $S\left(\rho \| \sigma\right) \geq S\left(M\left(\rho\right) \| M\left(\sigma\right)\right)$. Since we are interested in the change in entropy $\Delta S := S(M(\rho)) - S(\rho)$, we have the choice of a reference state σ. The obvious choice of σ is the fixed-point e of the map M, i.e. $M(e) = e$. Rearranging the contractivity inequality, we arrive at the quantum version of the Hatano-Sasa inequality $\Delta S \geq -Tr\left[\left\{M\left(\rho\right) - \rho\right\} \log\left(e\right)\right]$. While the first law relates to the partitioning of energy into heat and work, the (Clausius form of the) second law relates only to the increase in entropy. Specifically, the quantum Hatano-Sasa inequality is valid for CPTP evolution where neither heat nor temperature are well defined quantities. Hence, in general it is difficult to verify the internal consistency between a quantum generalization of the first law and a similar generalization of the second law that is applicable to arbitrary CPTP dynamics. However, it is possible establish a relation between the two laws by considering thermal maps. All thermal states are passive. In order to make the connection to the second law a cyclic process is considered, i.e., $H = H'$. The input and output states ρ and ρ' are not restricted and can both be out-of-equilibrium.

The quantum Hatano-Sasa inequality now reduces to the familiar version of the second law:

$$\Delta S = S(\rho') - S(\rho) \geq -\beta \mathrm{Tr}\left[(\rho' - \rho)(H - F)\right] = \beta\left(\Delta W + \langle Q \rangle_{\mathrm{op}}\right),$$

with the change in ergotropy playing the role of heat along with $\langle Q \rangle_{\mathrm{op}}$. This restatement of the quantum Hatano-Sasa inequality is interesting in that it lower bounds the entropic change by the sum of two terms, the change in ergotropy and the operational heat which are both measurable and operationally well defined. Complete-positivity and trace-preservation guarantee that output states are in fact 'physical'. For such processes we have then operationally defined heat and connected it to an operational second law. Both heat and change in entropy are shown to be positive when the input majorizes the output, making a strong connection between the operational laws [13].

The modern understanding of Maxwell's demon no longer entertains violating the Second Law of Thermodynamics. In point of fact, the Second Law's primacy has been repeatedly affirmed in modern nonequilibrium theory and experiment. That said, what has emerged is that we now understand how intelligent (demon-like) physical processes can harvest thermal energy as useful work. They do this by exploiting an information reservoir —a storehouse of information as randomness and correlation. That reservoir is the demon's informational environment, and the mechanism by which the demon measures and controls its environment embodies the demon's intelligence, according to modern physics. We will show that this mechanism is directly linked to the demon's model of its environment, which allows us to formalize the connection to machine learning. Machine learning estimates different likelihoods of different models given the same data. Analogously, in the physical setting of information thermodynamics, different demons' harness different amounts of work from the same information reservoir. Leveraging this commonality, it introduces thermodynamic learning as a physical process that infers optimal demons from environmental information. Thermodynamic learning selects demons that produce maximum work, paralleling parametric density estimation's selection of models with maximum likelihood.

We establish background in density estimation, computational mechanics, and thermodynamic computing necessary to formalize the comparison of maximum-work and maximum-likelihood learning. The surprising result is that these two principles of maximization are the same, when compared in a common setting. This adds credence to the longstanding perspective that thermodynamics and statistical mechanics underlie many of the tools of machine learning. Avoiding theological distractions, we refer to these processes as thermodynamic agents. In truth, any physical system can be thought of as an agent, but only a limited number of them are especially useful for or adept at commandeering information to convert between various kinds of thermodynamic resources, such as between heat and work. Here, we introduce a construction that shows how to find physical systems that are the most capable of processing information to affect thermodynamic transformations. This completes the thermodynamic learning framework laid out and the model an agent holds affects its interaction with the symbol sequence and, ultimately, its work production. And so, from this point forward, when discussing an estimated process or a machine that generates that guess, we are also describing the unique thermodynamic agent designed to produce maximal work from the estimated process.

8. Conclusions

In this work presented new circuit implementation design method of quantum gates. The presented approach allows for fast classical efficient simulation of search QAs is developed.

On specific examples, the effectiveness of the application of the QAG approach in intelligent control systems with quantum self-organization of imperfect knowledge bases is shown, thereby demonstrating quantum superiority over classical computations.

Results of controller's behavior comparison confirm the existence of synergetic self-organization effect in the design process of robust KB on the base of imperfect (non-robust) KB of fuzzy controllers: from two imperfect KB with quantum approach robust KB can be created using only quantum correlation. In classical intelligent control based on soft computing toolkit this effect is impossible to achieve.

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