Quantum Software Engineering (QSE) in intelligent robotic cognitive control Quantum Computational Intelligence Supremacy and Quantum Control

Perspective of collaboration development between JINR and IN2P3 in the next decades

- **1. Definition and structure of QSE**
- 2. Quantum computational intelligence toolkit
- **3. Quantum Software Engineering in JINR projects**

Measurement result of quantum computing





Sergey V. Ulyanov Laboratory of Information Technologies Joint Institute for Nuclear Research

18 May 2021



Superposition

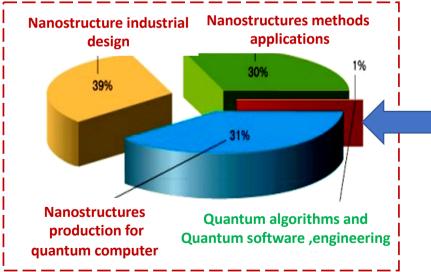
Prof. Sergey V. Ulyanov: 略歴

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至平方口 国籍 経歴	1940年12月13日 ロシア [1974] Ph.D "Statistical analysis of seismic excitation on dynamical systems with random time-dependent parameters" [1992] State Dr. of Physics and Mathematical Sciences (IFTP) "Physical models of control objects and robust intelligent control - relativistic, quantum and thermodynamics-information aspects"				
1965	Moscow State Technical University (Bauman Technical College)				
1971	(自動制御システム) 入学 同上 卒業 (кафедра П -1: Системы управления)				
1965 [~] 75	Research Engineer and Senior Manager				
	Central Institute of Building Construction, Ministry of Building Construction				
1975 [~] 83	Chief of Laboratory				
	Central Institute of Biomedical Engineering, Ministry of Biomedical Engineering				
1983 [~] 92	Professor, Chief of Department of Quantum and Relativistic Control Systems				
	Institute of Physical -Technical Problems, Soviet Academy of Sciences				
1992 [~] 94	Professor, Chief of Artificial Intelligence Robotic Laboratory				
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1994 ~ 97	教授				
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1. Definition and structure of QSE



Software Engineering (SE) (Friedrich L. Bauer): The establishment and use of sound engineering principles in order to obtain economically software that is reliable and works efficiently on real machines



Jianjun Zhao (2020), Quantum Software Engineering Landscapes and Horizons <u>https://arxiv.org/pdf/2007.07047.pdf</u>)

Quantum software engineering (QSE) is the use of sound engineering principles for the development, operation, and maintenance of quantum software and the associated document to obtain economically quantum software that is reliable and works efficiently on quantum computers.

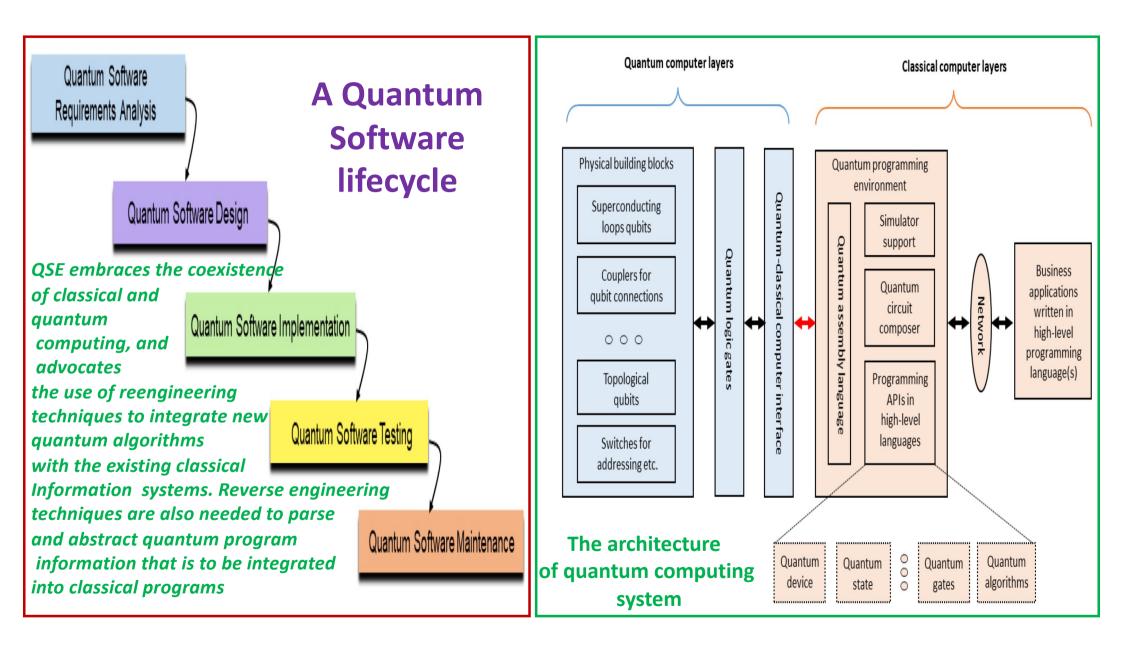
In this definition, we would like to highlight *three important issues in QSE*.

First, it is important to apply the "sound engineering principles" to quantum software development.

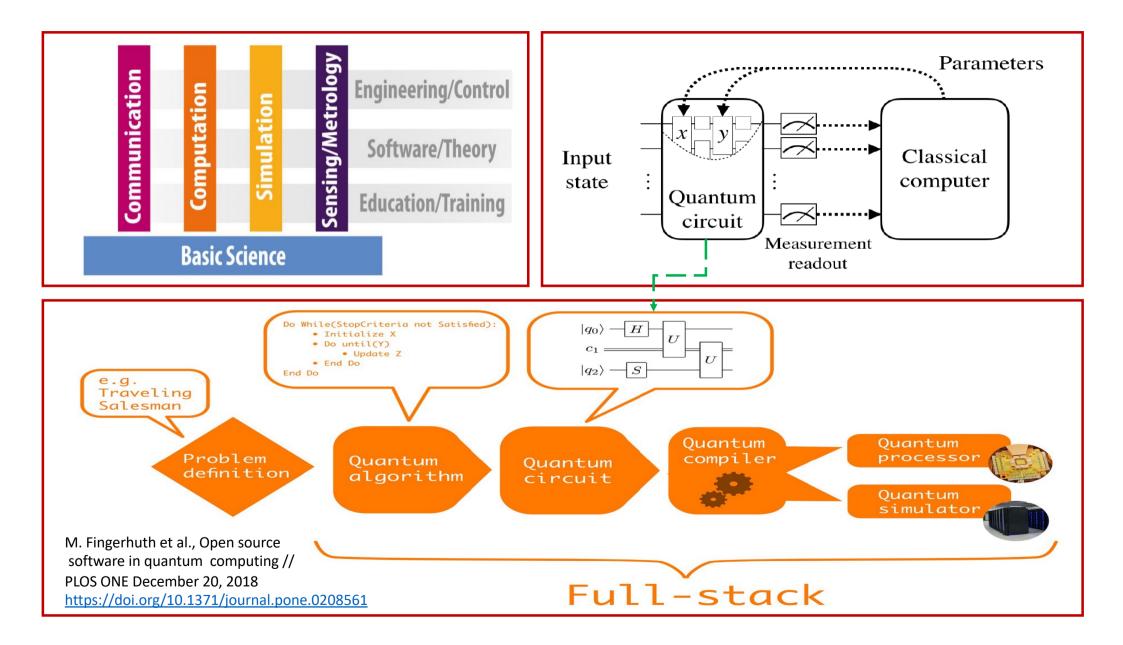
Second, the quantum software should be built "economically." *Finally*, the quantum software should be "reliable" and needs to work "efficiently" on quantum computers.

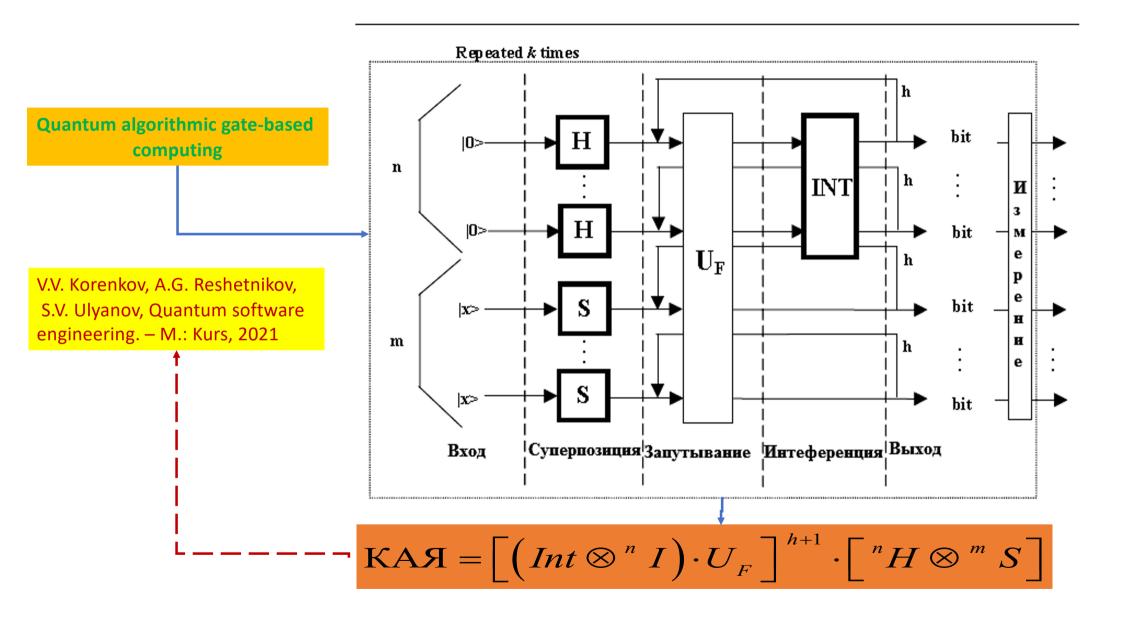
Quantum software engineering can be regarded as a branch of systems engineering, which involves the development of large and complex quantum software systems.

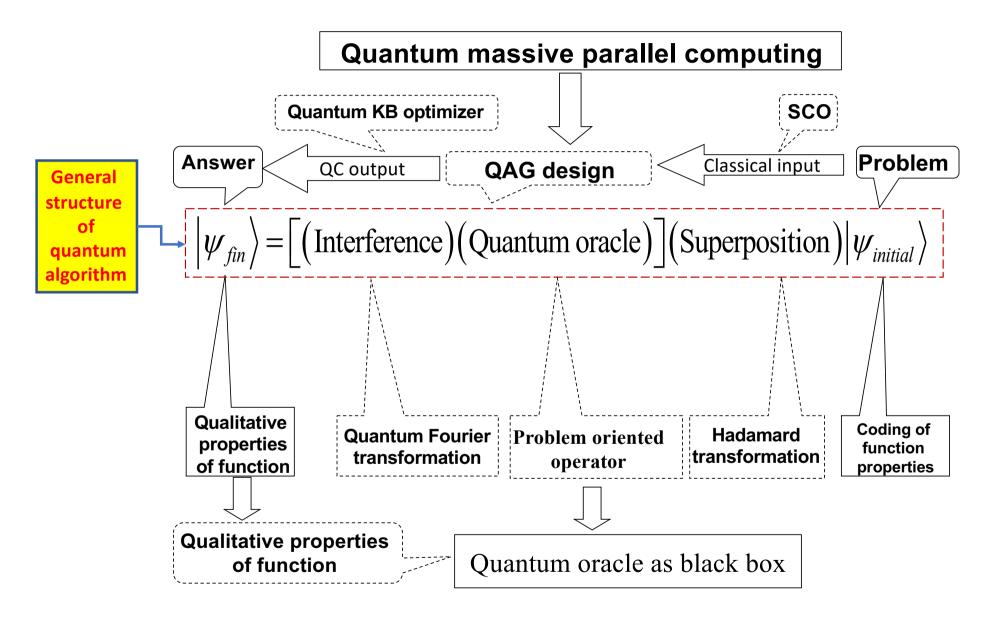
V.V. Korenkov, A.G. Reshetnikov, S.V. Ulyanov, Quantum software engineering Pt 3: Quantum supremacy modelling. – M.: Kurs, 2021.

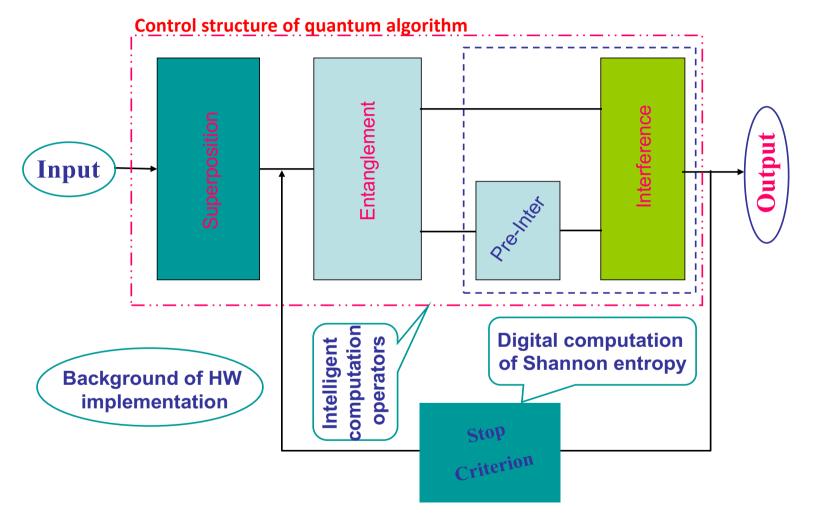


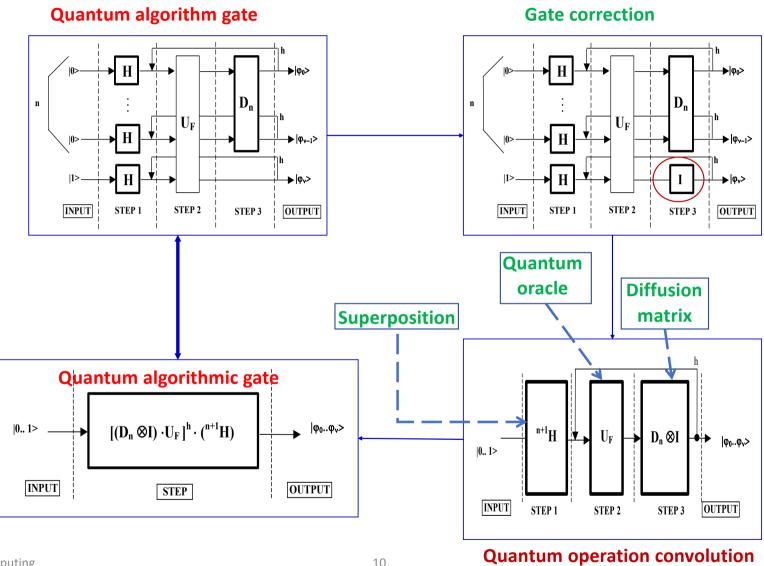
2. Quantum computational intelligence toolkit





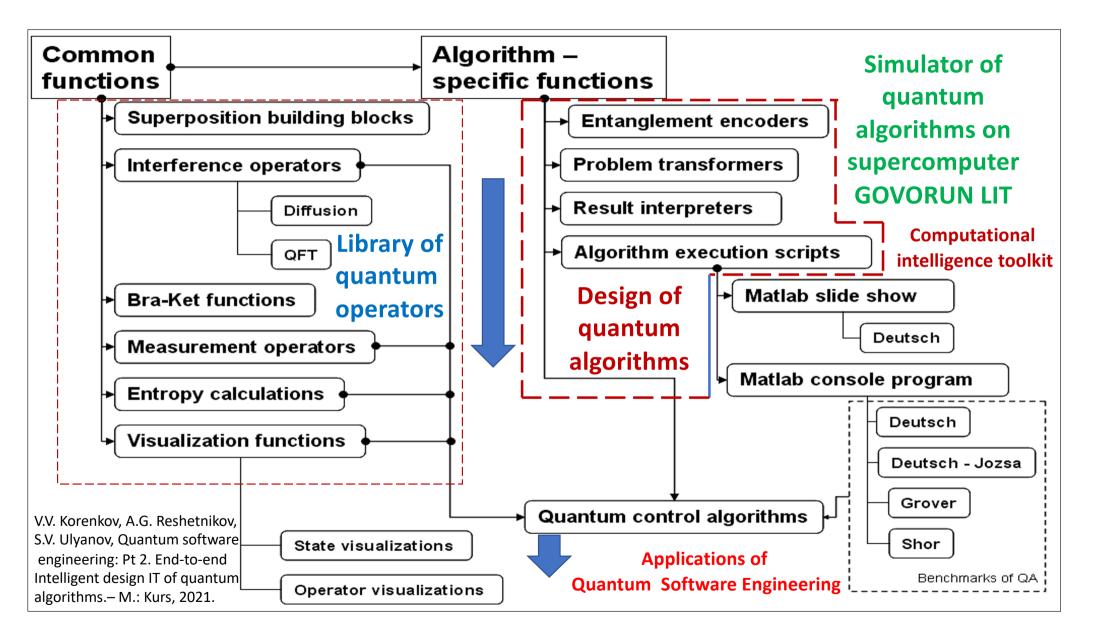






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Quantum Computing

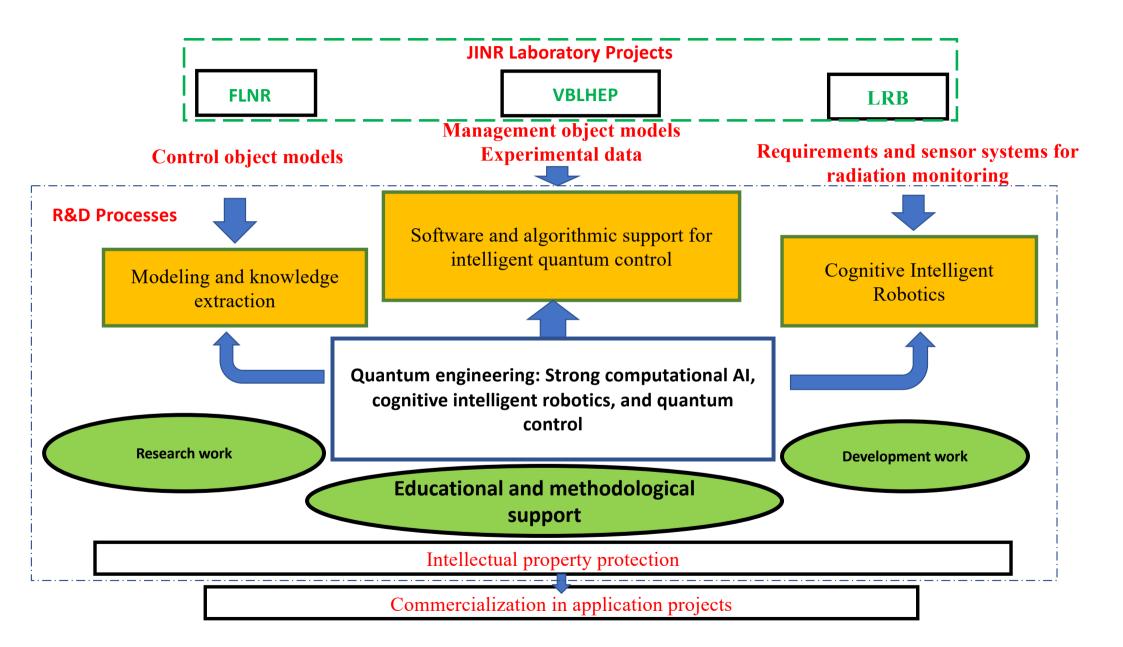


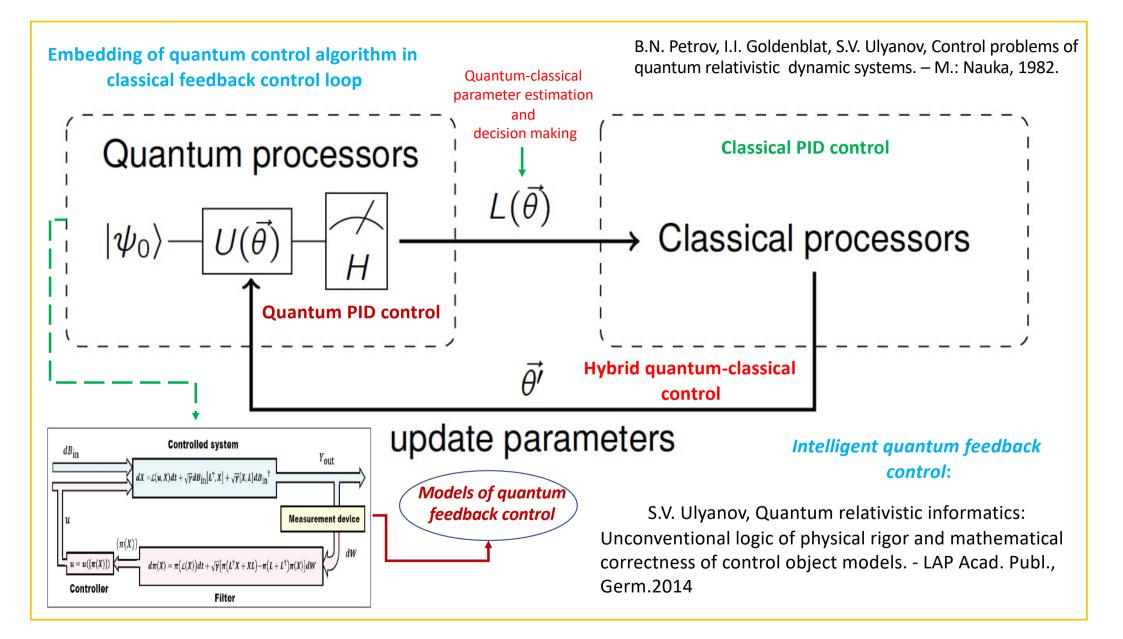
3. Quantum Engineering LIT: JINR projects examples

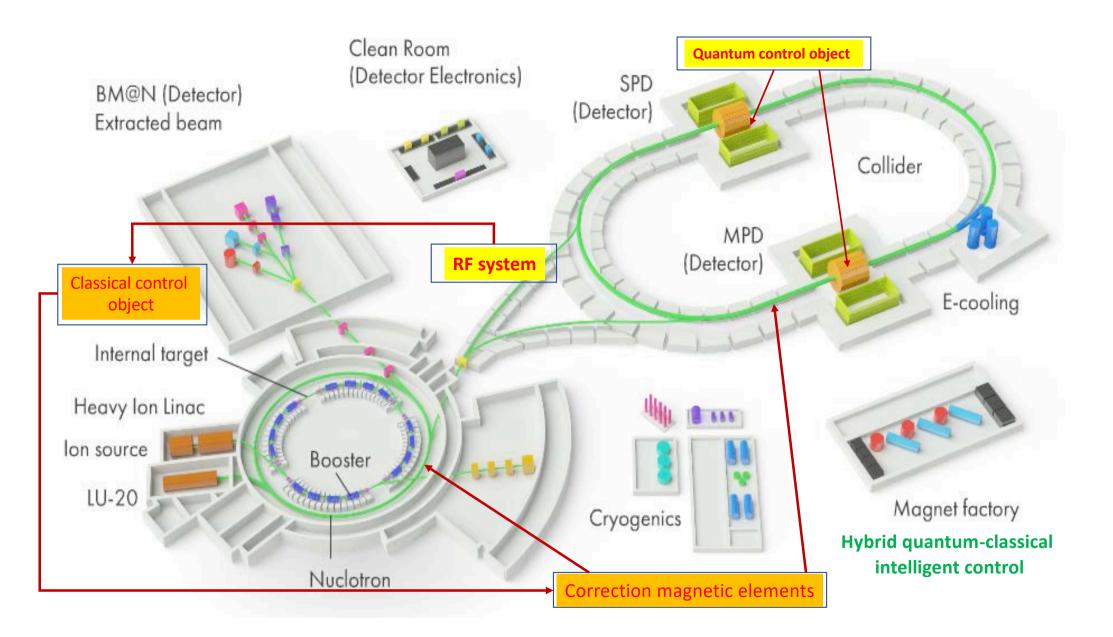
Quantum computing in quantum robust control design

- Control of nitrogen consumption in superconducting-coil electromagnet
- Control of high frequency station
- Intelligent robotics control

Quantum algorithms approach in the search structure of super-heavy elements



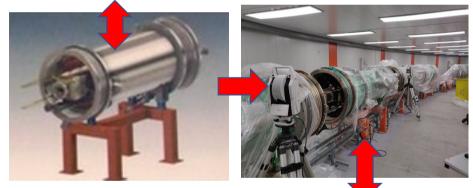




Physical features of the control object and the physical process

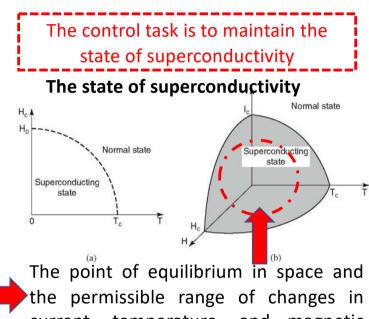
Features of an autonomous object

- •Non-standard heat intakes
- •Eddy currents in the core (heat the core)
- •The dependence of the quality of the magnetic field on the quality of cooling
- •Flashing of the wall and uneven cooling in the connecting nodes



Features of the group of magnetic elements •Different eddy currents in the core •Minor differences in magnets elements





current, temperature, and magnetic field

The principle of intelligent control: Compensation of the indeterminate and inaccurate parameters of the magnetic element existing in a real object through the use of soft and quantum computing technologies

Intelligent robotic quantum control

Intelligent robotics based on quantum fuzzy inference

- Structure of self-organized intelligent control system
- Robotic redundant 7 DoF manipulator
- Autonomous and swarm robots with information exchange (video)

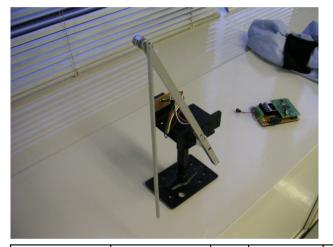
Robust Intelligent Control in Unpredicted Control Situations Relative to Quantum Knowledge: KB Self-organization Phenomena based on Quantum Fuzzy Inference

• Examples of simulation and benchmarks <u>demo</u> (cart – pole dynamic system)

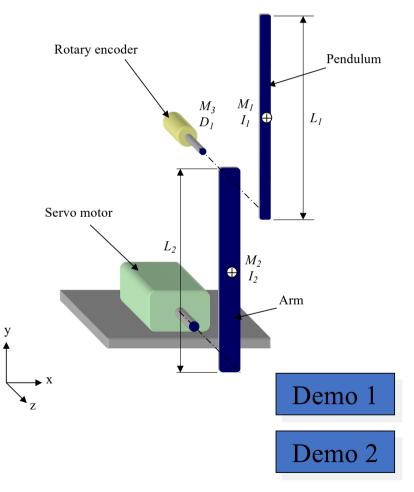
Inverted Pendulum

Intelligent control of the pendulum based on the physical measurements Without The knowledge of his mathematical model

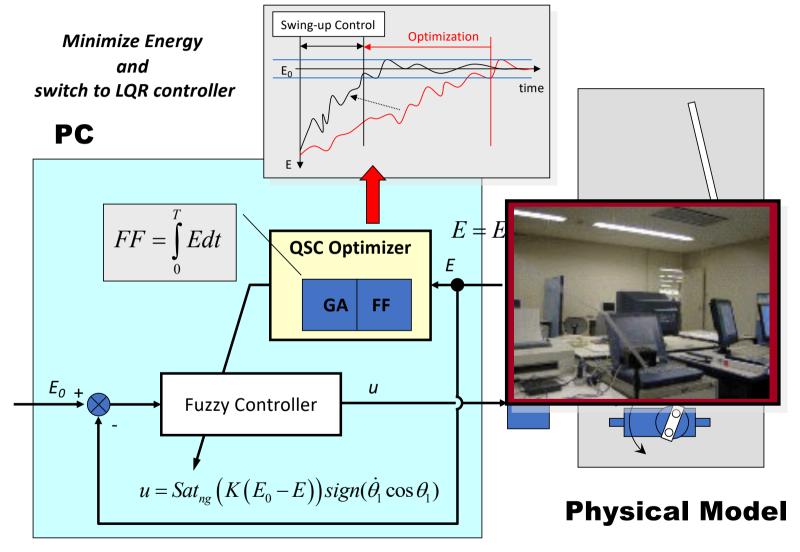
Inverted pendulum hardware model

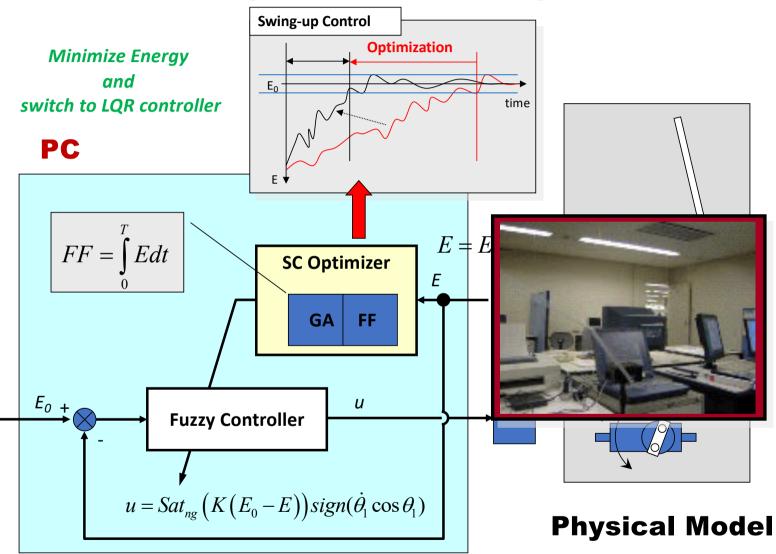


	length	L1	0.29	m
Pendulum	mass	M ₁	1.23E-2	kg
	momentum inertia	11	8.62E-5	kgm ²
	length	L ₂	0.23	m
Arm	mass	M ₂	1.12E-2	kg
	momentum inertia	12	4.93E-5	kgm ²
Boton: oncodor	mass	M ₃	1.00E-2	kg
Rotary encoder	damping	Dı	5.00E-5	Ns/m

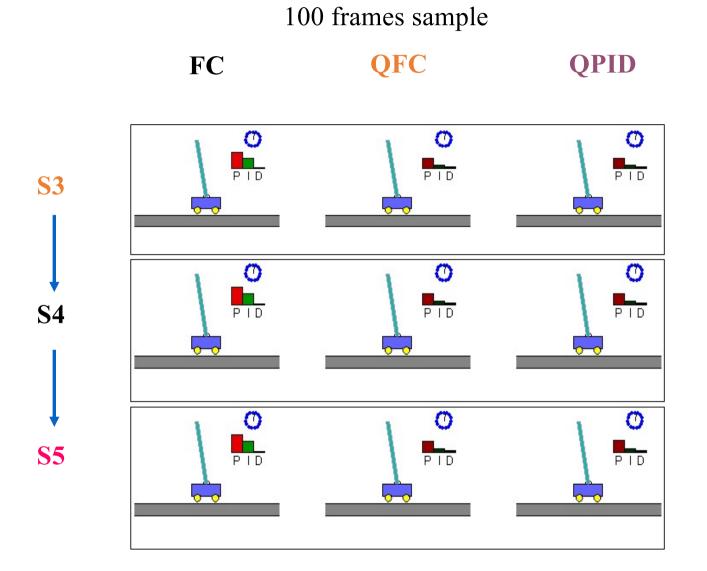


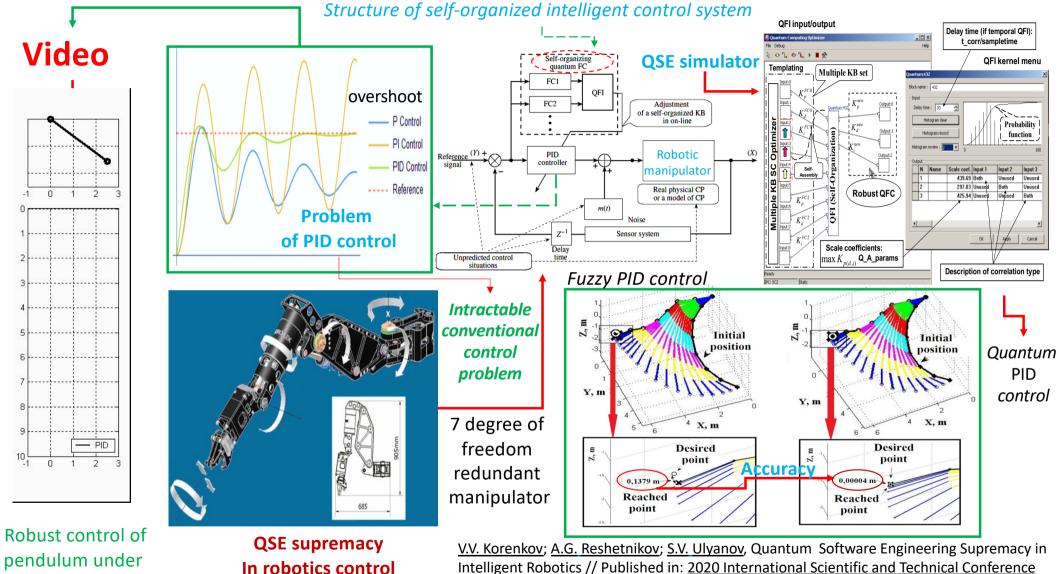
Direct Swing-Up Optimization by QSCOptimizer





Direct Swing-Up Optimization by SCOptimizer





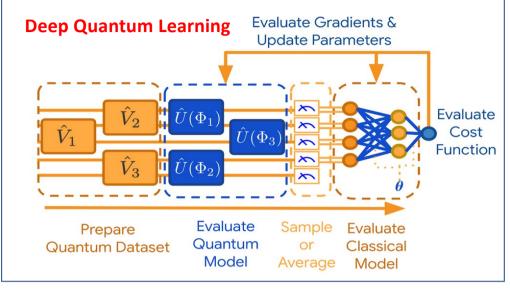
pendulum under random excitation

Intelligent Robotics // Published in: 2020 International Scientific and Technical Conference Modern Computer Network Technologies (MoNeTeC)



Quantum intelligent control

- Quantum deep learning
- Quantum control of relativistic physical objects

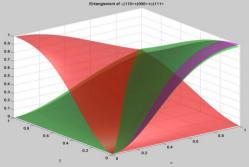


The 2 qubit operations are CNOT gates, R is a rotation about a designated axis on the Bloch sphere, and the w values are functions of the system parameters K.

Figure shows entanglement of $|110\rangle + \beta |111\rangle + |000\rangle$ as a function of both α and β , and compared with the three-way "tangle" agreement is quite good. The red surface shows the pairwise entanglement between qubits A and B, the green; 3-way entanglement among A, B, and C; the magenta is the (analytically calculated) 3-tangle.

J.E. Steck. E. C. Behrman. and N. Thompson.

- Machine Learning applied to Programming
- ¹ Overstyre Computers // Conference server 2010
- Quantum Computers // Conference paper, 2019.
- https://www.researchgate.net/publication/330199278



Lagrangian quantum deep learning

The density matrix, p, of a quantum system as a function of time obeys the Schrödinger equation

$$\frac{d\rho}{dt} = \frac{1}{i\hbar} [H, \rho]$$

and has the formal solution as $\rho = \exp(iLt)\rho(t_0)$. The time evolution equation for the density matrix maps the

initial state $\rho(t0)$ (input data for the quantum computer) to the final state $\rho(t_f)$ (output calculated result). Parameters in the system Hamiltonian *H* are physical interactions and fields in quantum hardware and can be adjusted experimentally as functions of time. "Programming" this quantum computer involves finding the parameters using machine learning that yield the desired computation. Thus, we can train the system to evolve in time initial (input) to target final (output) states; yielding a quantum system that accurately approximates a chosen function, such as: logic gates, benchmark classification problems, or, since the time evolution is quantum mechanical, a quantum function like entanglement.

The learning rule for the quantum system based on dynamic backpropagation is derived as follows. Given an input (initial density matrix), ρ_0 , and a target output, *d* (a "training pair"), we develop a weight update rule based on gradient descent to adjust the system parameters, i.e., train the system "weights", to reduce the squared error between the target, *d*, and the output, Output. While minimizing the squared error, the system's density matrix, $\rho(t)$, is constrained to satisfy the Schrödinger equation for all time in the interval (t₀, t_f). We define a Lagrangian, *L*, to be minimized, as

$$L = \frac{1}{2} \left[d - \langle O(t_f) \rangle \right]^2 + \int_{t_0}^{t_f} \lambda^+(t) \left(\frac{\partial \rho}{\partial t} + \frac{i}{\hbar} [H, \rho] \right) \gamma(t) dt$$

where the Lagrange multiplier vectors are $\lambda'(t)$ and $\gamma(t)$ (row and column, respectively), and *O* is an output measure (or some function of a measure), which is chosen for the particular problem under consideration. As an example, for our entanglement witness application, we defined the output as:

$$\langle O(t_f) \rangle = tr[\rho(t_f)O] = \sum_i p_i \langle \psi_i(t_f) | O | \psi_i(t_f) \rangle$$

where tr stands for the trace of the matrix, and where the density matrix is represented in terms of the chosen basis as

 $\rho = \sum_{i} p_i |\psi_i\rangle \langle \psi_i |$. We take the first variation of *L* with respect to ρ , set it equal to zero, then integrate by parts to give the following equation which can be used to calculate the vector elements of the Lagrange multipliers ("error

deltas" in neural network terminology) that will be used in the learning rule:

$$\gamma_i \frac{\partial \gamma_j}{\partial t} + \frac{\partial \lambda_i}{\partial t} \gamma_j - \frac{i}{\hbar} \sum_k \lambda_k H_{ki} \gamma_j + \frac{i}{\hbar} \sum_k \lambda_i H_{jk} \gamma_k = 0$$

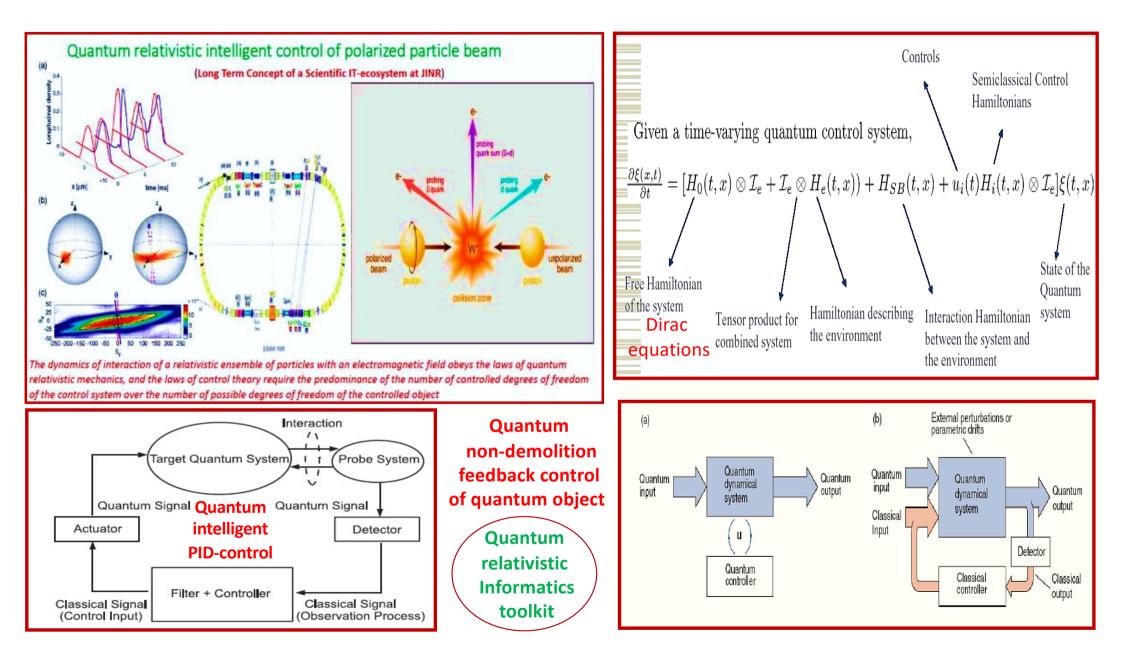
which is solved backward in time, with the boundary conditions at the final time $t_{\rm f}$ given by

$$-\left\lfloor d-\left\langle O\left(t_{f}\right)\right\rangle \right\rfloor O_{ji}+\lambda_{i}\left(t_{f}\right)\gamma_{j}\left(t_{f}\right)=0.$$

The gradient descent rule to minimize L with respect to w is $w_{new} = w_{old} - \eta \frac{\partial L}{\partial w}$ or each "weight" parameter w, where η is the learning rate, and where the derivative is given by

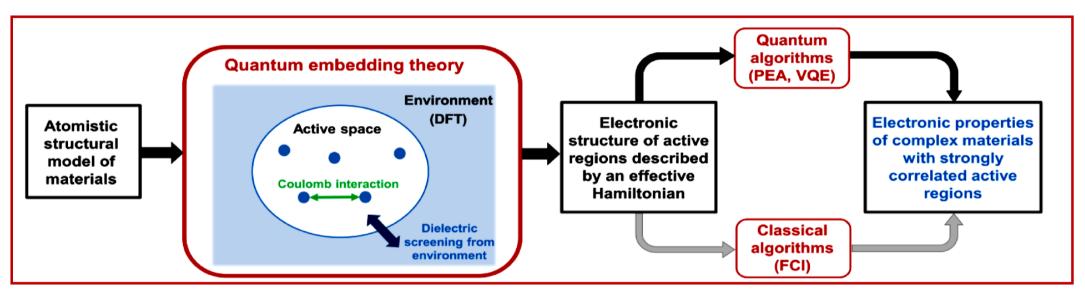
$$\frac{\partial L}{\partial w} = \frac{i}{\hbar} \int_0^{t_f} \lambda^+(t) \left[\frac{\partial H}{\partial w}, \rho \right] \gamma(t) dt = \frac{i}{\hbar} \int_0^{t_f} \sum_{ijk} \left(\lambda_i(t) \frac{\partial H}{\partial w} \rho_{kj} \gamma_j - \lambda_i(t) \rho_{ik} \frac{\partial H_{kj}}{\partial w} \gamma_j \right) dt$$

The above technique, since it uses the density matrix, is applicable to any state of the quantum system, pure or mixed.



Quantum simulation of super-heavy elements of Mendeleev's table: Quantum gate based approach

General strategy for quantum simulations of materials using quantum embedding



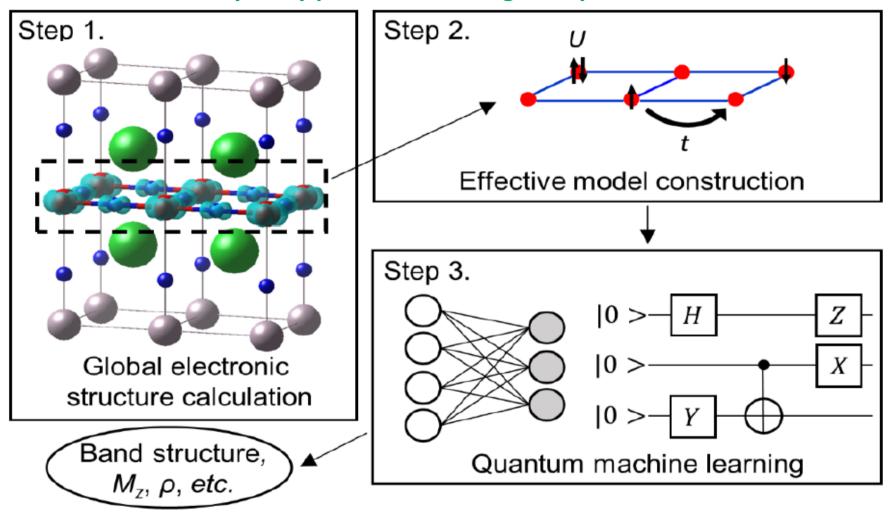
Quantum simulator

Example of effective application in quantum chemistry

Quantum simulator

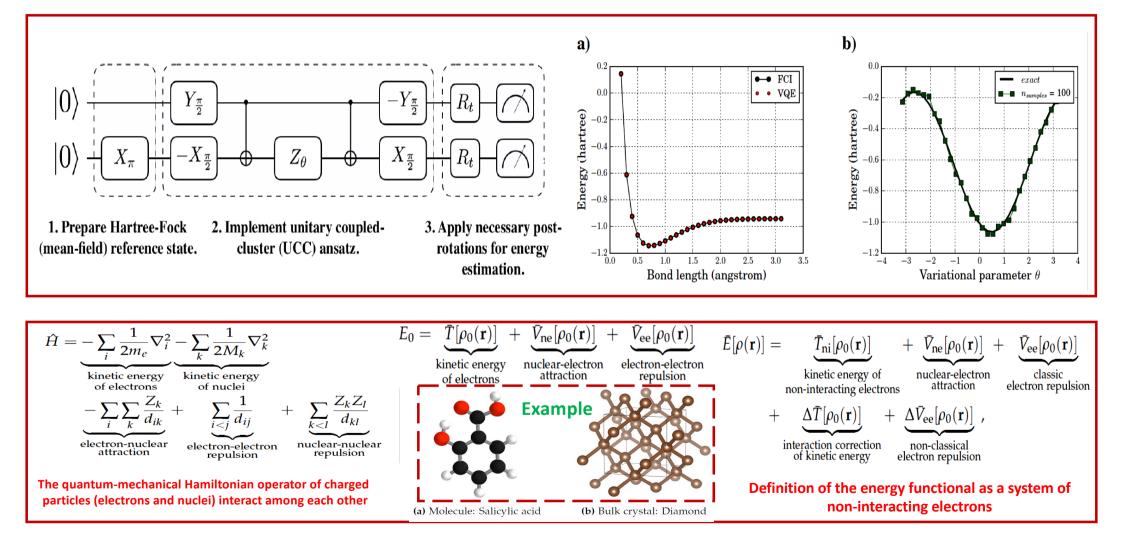
Example of effective application in quantum chemistry

Workflow for calculation of materials properties using quantum algorithm for many-body problems of inorganic systems



The quantum circuit used in VQE to estimate the ground state energy for molecular hydrogen in the minimal basis

VQE simulation results for molecular hydrogen in the minimal basis (STO-6G)



Thank You for your attention