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М. О. ВЕРНІК
аспірант кафедри програмного забезпечення комп'ютерних систем
Національний технічний університет України
«Київський політехнічний інститут імені Ігоря Сікорського»
ORCID: 0009-0008-6156-1051

Л. М. ОЛЕЩЕНКО
кандидат технічних наук,
доцент кафедри програмного забезпечення комп'ютерних систем
Національний технічний університет України
«Київський політехнічний інститут імені Ігоря Сікорського»
ORCID: 0000-0001-9908-7422

ПРОГРАМНІ МЕТОДИ ТА АРХІТЕКТУРНІ РІШЕННЯ ДЛЯ ОБРОБКИ ВЕЛИКИХ ДАНИХ ЧЕРЕЗ КВАНТОВІ НЕЙРОННІ МЕРЕЖІ ТА МЕТАЕВРИСТИЧНІ ОПТИМІЗАТОРИ

У статті подано запропоновані програмні методи та гібридну класично-квантову архітектуру для обробки великих даних з використанням квантово-ядрового методу QSVC та варіаційного квантового класифікатора VQC/QNN для розв'язання задачі обчислення ментальної енергії на основі ЕЕГ-сигналів. Запропонований фреймворк працює з даними, отриманих від носимого ЕЕГ-пристрою, що реєструє діапазони δ, θ, α та β на чотирьох каналах (4-канальний ЕЕГ-пристрій Muse-S Athena). На основі цих сигналів формуються вектори ознак, які відображаються у квантові стани за допомогою квантової відображальної функції (quantum feature map) і надалі використовуються або в квантовому ядровому методі SVM, або у варіаційній квантовій нейронній мережі для задач класифікації чи регресії показників, пов'язаних з ментальною енергією. Для оптимізації побудованих квантових схем («квантових нейронних мереж») застосовано метаевристичні алгоритми, зокрема, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), а також багатокритеріальні модифікації, такі як NSGA. Ці оптимізатори спільно налаштовують параметри квантових кіл, масштаби кодування ознак та елементи структури ансатцу з урахуванням реалістичних обмежень NISQ-архітектур. Основне завдання полягає у зведенні вихідної багатокритеріальної постановки до придатної для розв'язання однокритеріальної форми шляхом побудови функції вартості, що мінімізує зважену суму ключових параметрів: кількості вимірювань (shots) на квантовому комп'ютері, глибини квантової схеми та загального часу виконання при одночасному збереженні прийнятної якості класифікації ментальних станів. Також запропоновано програмну архітектуру, побудовану на основі квантових мікросервісів для обчислення квантових ядер та виконання VQC у поєднанні з оркестратором метаевристичної оптимізації та компонентами моніторингу ресурсів. Запропонована архітектура орієнтована на інтеграцію з моделями ментальної енергії, побудованими на ЕЕГ-даних, що дає змогу виконувати масштабовані експерименти з квантовими моделями на великих наборах ЕЕГ-сигналів. Отримані результати формують методологічну основу для використання квантових нейронних мереж та метаевристичних оптимізаторів у когнітивній інженерії та нейроінженерних застосуваннях, зокрема, для кількісного оцінювання ментальної енергії в реальних умовах.

Ключові слова: *програмне забезпечення, великі дані, машинне навчання, метаевристичні алгоритми, квантові нейронні мережі, QML, оптимізація, квантова оптимізація, ментальна енергія.*

M. O. VERNIK
Postgraduate Student at the Department of Computer Systems Software
National Technical University of Ukraine
"Igor Sikorsky Kyiv Polytechnic Institute"
ORCID: 0009-0008-6156-1051

L. M. OLESHCHENKO
Candidate of Technical Sciences,
Associate Professor at the Department of Computer Systems Software
National Technical University of Ukraine
"Igor Sikorsky Kyiv Polytechnic Institute"
ORCID: 0000-0001-9908-7422

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SOFTWARE METHODS AND ARCHITECTURAL SOLUTIONS FOR BIG DATA PROCESSING VIA QUANTUM NEURAL NETWORKS AND METAHEURISTIC OPTIMIZERS

The article presents proposed software methods and a hybrid classical–quantum architecture for big data processing using a quantum kernel method QSVC and a variational quantum classifier VQC/QNN to address the problem of computing mental energy from EEG signals. The proposed framework operates on data acquired from a wearable EEG device that records δ, θ, α, and β bands across four channels (the 4-channel Muse-S Athena EEG device). From these signals, feature vectors are constructed and mapped into quantum states via a quantum feature map, which are then used either in a quantum kernel SVM or in a variational quantum neural network for classification or regression of mental energy–related indicators. To optimize the resulting quantum circuits ("quantum neural networks"), the work employs metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and multi-objective variants like NSGA. These optimizers jointly tune circuit parameters, feature-encoding scales and elements of the circuit structure under realistic NISQ constraints. The main task is to reduce an inherently multi-objective problem to a tractable single-objective formulation by defining a cost function that minimizes a weighted sum of key parameters: the number of measurement shots on the quantum computer, the depth of the quantum circuit, and the total execution time, while preserving an acceptable classification quality of mental states. The paper also proposes a software architecture based on quantum microservices (for quantum kernel evaluation and VQC execution) combined with a metaheuristic optimization orchestrator and resource-tracking components. This architecture is designed to integrate with EEG-driven mental energy models, enabling scalable experimentation with quantum models on large EEG datasets. The results obtained provide a methodological basis for using quantum neural networks and metaheuristic optimizers in cognitive and neuroengineering applications, with a particular focus on quantifying mental energy in real-world conditions.

Key words: *software, big data, machine learning, metaheuristic algorithms, quantum neural networks, QML, optimization, quantum optimization, metaheuristics, EEG, mental energy.*

Problem statement

The relevance of the research lies in bridging the gap between theoretical quantum machine learning and its practical application by designing a scalable hybrid framework, building mathematical foundations for quantum model training, enabling multi-objective optimization of quantum circuits, and demonstrating applicability on complex datasets such as EEG signals – thereby advancing both quantum computing and intelligent neuroinformatics.

The proposed research focuses on the development of a hybrid computational framework that integrates classical and quantum processing components to enable scalable data analysis and efficient model training. This framework leverages metaheuristic optimization methods to overcome the inherent limitations of current quantum hardware – such as noise, restricted qubit counts, and limited circuit depth – which typically constrain the applicability of quantum machine learning to large datasets. By combining classical optimization pipelines with quantum subroutines, the system aims to facilitate the training of quantum kernel-based models (e.g., Quantum Support Vector Classifiers, QSVC) as well as variational quantum classifiers and regressors (VQC/QNN) in a resource-aware and performance-optimized manner.

Within this research, a comprehensive set of mathematical models will be formulated to describe the encoding of input data into quantum states, the structure and behavior of quantum kernel methods and variational circuits, the quality metrics for evaluating these models, and the operational constraints imposed by quantum hardware. Building on these foundations, the study will define a multi-objective optimization problem that captures the trade-offs between model accuracy, quantum circuit depth, the required number of measurement shots, and system latency. Metaheuristic algorithms – such as evolutionary strategies, particle swarm optimization, simulated annealing, differential evolution, and CMA-ES – will be explored and adapted to search for optimal parameter configurations and circuit architectures under these competing objectives.

A modular software architecture will be designed to support quantum microservices, including a Q-Kernel service dedicated to quantum kernel computation and a Q-VQC service responsible for executing variational circuits. These services will operate under a centralized metaheuristic orchestration layer that manages optimization workflows, tracks quantum resource consumption, and incorporates mechanisms for load balancing and fault tolerance to ensure robust system performance. The resulting hybrid infrastructure will provide a unified platform for experimentation, evaluation, and deployment of quantum-enhanced machine learning pipelines. To validate the proposed methodology, extensive experiments will be conducted using public datasets as well as proprietary data sources, including EEG signals collected from Muse S Athena devices. The performance of quantum models will be benchmarked against classical machine learning baselines, with particular attention to assessing their generalization ability and resource efficiency. Additionally, the research will examine and validate the Countable Mental Energy (CME) indicator as an engineering metric for quantifying cognitive state based on EEG data, providing further insight into the potential of hybrid quantum–classical approaches for neurophysiological signal analysis.

Related research

In modern studies of quantum machine learning for EEG analysis, the possibility of using variational quantum classifiers (VQC) and quantum kernel methods (QSVC) for brain signal classification tasks has been demonstrated. In particular, in the work devoted to the classification of P300-EEG in the brain–computer interface paradigm, it has been shown that quantum classifiers are able to successfully learn on EEG data: the quantum-augmented support vector machine (QSVC) achieves a balanced accuracy of about 83% on the training sample, exceeding classical baseline models [1-3]. At the same time, the limited generalization ability of the models on the test data and the dependence of the results on the configuration of quantum circuits and the amount of training data are emphasized, which indicates the need for further optimization of architectures and hyperparameters [4-7]. In study [2], quantum methods for the classification of motor imagery from EEG were proposed, including a quantum genetic algorithm (QGA) for feature selection on NISQ equipment; it has been demonstrated that the hybrid quantum approach outperforms a number of classical classifiers on reference datasets, which confirms the potential of quantum kernels in working with high-dimensional EEG spaces. In parallel, the direction of using metaheuristic algorithms to optimize features and model parameters in EEG analysis tasks is actively developing. One of the works proposed the GALoRIS model, which combines a genetic algorithm with logistic regression for selecting EEG features in the task of assessing the driver's cognitive load, where it is shown that the method automatically reduces the feature space by more than 50%, while maintaining the informativeness of the signal [3]. As a result, classifiers based on selected features achieve an average accuracy of about 90.4%, and in combination with RBF-SVM – up to ~96%, which significantly exceeds the performance of traditional feature selection methods (in particular, approaches based on mutual information or PCA), which provide an accuracy of about 84% [3]. These results demonstrate that evolutionary search is capable of forming more discriminative subspaces of EEG features compared to linear methods, however, this approach has so far been used only in conjunction with classical models [4]. A separate direction directly related to the subject of this work concerns the development of software frameworks for the quantitative assessment of cognitive load and "mental energy" in everyday conditions. Within the framework of one such framework, the use of a portable EEG device with time-aligned audio segmentation for continuous assessment of the indicator of countable mental energy throughout the day is proposed: the system combines EEG recordings from a Muse-type headset with an audio lifelogger, where the user's speech activity is transcribed and segmented, and for each segment, EEG-conditioned effort levels are calculated $L(t)$ and energy expenditure rate w_i [8]. Analytical expressions are proposed that relate the spectral characteristics of the EEG (frontal theta, occipital alpha, beta activation) to energy metrics, and a "flow" coefficient is introduced to take into account task involvement and an energy reserve multiplier associated with fatigue, which together form an integral indicator of daily cognitive/mental energy. An intelligent software framework for processing large audio data sets and assessing cognitive energy is presented, focused on scalable processing of speech streams and integration with cognitive load models, which allows combining big data audio processing with engineering metrics of mental energy [9].

Proposed software methods

Quantum encoding model

Let's say we have a sample of EEG data:

$$\mathcal{D} = \{(x_t, y_t, a_t)\}_{t=1}^{N}, \tag{1}$$

$x_t \in \mathbb{R}^d$ is vector of features calculated from the raw EEG signal in the time interval (window) t. The features used are, for example, the relative powers of the $\delta, \theta, \alpha, \beta$ ranges on 4 channels, asymmetry indicators (Fp1–Fp2, AF7–AF8), the θ/α ratio, etc.

$y_t \in \{0,1\}$ is target variable (mental state class, e.g. "in flow / not in flow"). If the problem is regression, $y_t \in \mathbb{R}$.

$a_t \in [0,1]$ is an indicator of the complexity or type of activity at a given point in time t (estimated using additional sensors or contextual data, e.g. based on audio or the user's task).

Preprocessing and feature calculation

For each EEG window of ~5 s duration (with ~50% overlap between consecutive windows), signal filtering (range 1 – 40 Hz), feature normalization (componentwise) and feature vector calculation x_t using the function $\phi : \mathrm{EEG\,(raw)} \to x \in \mathbb{R}^d$. Thus, x_t compactly describes the state of brain activity in the interval, and a_t characterizes context (complexity task, availability distracting factors).

Quantum encoding of features

To map a classical vector $x \in \mathbb{R}^d$ into a quantum state, a parametric *quantum feature map* $U_\alpha(x)$ is used. In particular, angle encoding of the components x on the amplitudes or phases of qubits with a scale parameter is used α, as well as layers of local entanglement of qubits to take into account correlations between features. This mapping $U_\alpha(x)$ prepares a multidimensional quantum state $|\psi(x)\rangle = U_\alpha(x)|0\rangle^{\otimes N}$ corresponding to the input data [6].

Quantum kernel method (QSVC)

A quantum support vector classifier uses a quantum kernel defined by the overlap of two quantum states of the data. For two samples, x_i, x_j the kernel function is defined as the probability of obtaining a zero state when encoded sequentially x_i and x_j on the same quantum register:

$$K_\alpha(x_i, x_j) = |\langle 0| U_\alpha(x_i)\ U_\alpha(x_j) |0\rangle|^2, \tag{2}$$

which is the square of the inner product of the quantum states $|\psi(x_i)\rangle$ and $|\psi(x_j)\rangle$ [1]. Having calculated the kernel matrix $K = \left[K(x_i, x_j)\right]_{i,j=1}^{m}$ on the training data, we solve the classification problem using the support vector method:

$$f(x) = \text{sign}\left(\sum_{i=1}^{m} \alpha_i\, y_i\, K_\alpha(x_i, x) + b\right), \tag{3}$$

where α_i, b are the parameters found in the process of training SVM (solving the dual problem).

Thus, a quantum computer is used to efficiently calculate the kernel in a spatiotemporal high-dimensional Hilbert space, which can provide advantages when analytical calculation of the kernel by classical methods is impossible.

Variational quantum classifier (VQC/QNN) is a quantum model of the "quantum neural network" type, which is tuned by optimizing the parameters *of the ansatz* – a parameterized quantum circuit.

Data encoding – a scheme is applied $U_\alpha(x)$ that encodes the input vector x into a quantum state.

Ansatz V_θ is a set of quantum gates with parameters θ (several layers of single-qubit rotations and entanglements) is applied to the qubits, which act as an analogue of the layers of a neural network. The ansatz has a small depth (according to NISQ constraints) and can include only local entanglements.

After applying $U_\alpha(x)$ and V_θ some quantum observables (e.g., observables Z or ZZ on individual qubits) are measured to obtain a classical output. In particular, for each qubit, the mathematical expectation of the measurement can be calculated (e.g., $\langle Z_i \rangle$), which gives a set of values from which the probability of belonging to a certain class is calculated $p_\theta(y\,|\,x)$. Thus, VQC estimates the class probability based on the measured mean values after the ansatz. Obtaining these expected values on a real quantum device requires multiple iterations of the schemes (performing a certain number of *shots*) and averaging the results. The parameters are trained θ by a classical optimizer, reducing the problem to a variational algorithm (VQA). Note that *metaheuristic algorithms* (gradient methods) can be used to optimize the parameters of variational quantum schemes.

QUBO-statements for subproblems

Some combinatorial subproblems within our problem (e.g., feature subset selection, representative data window selection, ansatz topology optimization) can be formulated as a quadratic unconditional binary optimization (QUBO) problem. General form: $\min_{z\in\{0,1\}^n} z^\top Q z$, where z is a binary vector of decision variables, and Q is a symmetric matrix of coefficients. QUBO is equivalent to the Ising-type Hamiltonian minimization problem and, therefore, is a "native" format for both QAOA-type algorithms on gate quantum computers and D-Wave quantum annealing machines. Such QUBO problems can be solved by quantum annealing or QAOA algorithms, obtaining optimal or near-optimal combinations (e.g., the most informative features).

Multi-criteria metaheuristic optimization

Training quantum models under resource constraints can be viewed as a multi-criteria optimization. When searching for the optimal configuration of a quantum model, we have several competing goals:

– maximizing model quality (minimizing the loss function $\mathcal{L}$ on the validation sample or maximizing accuracy/quality metrics);

– minimizing the use of quantum resources: quantum circuit depth (Depth), number of measurements (Shots), and total execution time (Latency).

Denote the set of all parameters and hyperparameters of the model as

$$\Theta = (\alpha, \theta, \tau), \tag{4}$$

where α is the coding scale parameter, θ is the vector of variational parameters, and τ is the structure parameters of the quantum ansatz (e.g., the entanglement pattern, the number of layers, the selection of observables for measurement). Let us define the vector of objective functions:

$$J(\Theta) = \big(\mathcal{L}(\Theta), \text{Shots}(\Theta), \text{Depth}(\Theta), \text{Latency}(\Theta)\big). \tag{5}$$

Thus, we look for such Θ that improve all components of J. In practice, an approximation of the Pareto-optimal front is typically constructed – the set solutions where no objective can be improved without worsening another. Metaheuristic approaches are used to find the Pareto front (e.g., multi-criteria versions of evolutionary algorithms such as NSGA-II). Alternatively, the problems can be reduced to a single-criteria problem by scalarization – minimizing the weighted sum:

$$\mathcal{F}(\Theta) = \mathcal{L}(\Theta) + \lambda_s\,\text{Shots}(\Theta) + \lambda_d\,\text{Depth}(\Theta) + \lambda_t\,\text{Latency}(\Theta)\ , \tag{6}$$

where $\lambda_s, \lambda_d, \lambda_t$ – weighting factors reflecting the " cost " of using the relevant resources. This approach allows the use of single-criteria optimizers (e.g. GWO or PSO) to find a compromise solution. It is worth noting that recent studies also propose quantum algorithms for multi-criteria optimization – for example, the formation of a quantum state containing Pareto-optimal solutions in a superposition, with subsequent selection solutions from this state. However, the main emphasis is on classical metaheuristics for tuning quantum models.

During the optimization process, it is necessary to additionally take into account the strict limitations of hardware resources:

1. number of qubits $\leq q_{\max}$ (determined by the specific quantum device);
2. circle depth $\leq D_{\max}$ (due to decoherence time);
3. number of measurements (post-selection shots) per iteration $\leq S_{\max}$ (due to runtime limitations on a real QPU or quantum simulator).

These constraints are either introduced as penalties into the optimization function or are controlled by solution generators (for example, evolutionary mutation operators do not create schemes deeper than $D_{\max}$). The goal is to avoid solutions that are not suitable for execution on the available hardware.

Countable Mental Energy (CME) is a user-defined indicator that integrates information about the energetics of brain activity and the context of the task to estimate the " mental energy expended " per session. It is proposed as an aggregate measure of the cognitive load and the user's "flow" state. The calculation of CME is based on EEG data and a focus state classification model.

For each window, t the relative power of brain waves in different ranges is calculated:

$$P_{\text{relative}}(b,t) \text{ for } b \in \{\delta, \theta, \alpha, \beta\}. \tag{7}$$

For one electrode (and one window t):

$$P_{relative}(b,t) = \frac{P_{\text{abs}}(b,t)}{P_{\text{abs}}(\delta,t) + P_{\text{abs}}(\theta,t) + P_{\text{abs}}(\alpha,t) + P_{\text{abs}}(\beta,t)}. \tag{8}$$

These values are obtained by normalizing the absolute spectral powers of the window by the total power. The energy of the window is calculated as the weighted sum of the powers:

$$E_{\text{band}}(t) = \sum_b w_b P_{\text{relative}}(b,t), \tag{9}$$

where the coefficients w_b specify the contribution of each band. For example, if β -waves are considered more "energy-intensive" for the brain, w_β may be larger.

Modification by context and focus

The CME value for a window t is defined as:

$$\text{CME}(t) = \kappa\, E_{\text{band}}(t) \cdot g\big(c(t), f_\Theta(x_t)\big) \cdot \Delta t, \tag{10}$$

where $c(t) = a_t \in [0,1]$ – complexity/activity index, $f_\Theta(x_t) = p_\Theta(\text{flow} \mid x_t) \in [0,1]$ – probability of the "flow" state (or high concentration) according to the model with parameters Θ, $g(c, f)$ – a monotonic function that combines the effects of complexity and focus.

Total score per session

$$\text{CME}_{\text{session}} = \sum_{t \in \text{session}} \text{CME}(t). \tag{11}$$

Reflects the total "mental energy" expended during a work/training session. Typically calculated per day as a component of the total "mental energy" for a day of activity.

Research results

The conducted research resulted in the development of a hybrid quantum–classical framework that enables scalable training and evaluation of quantum machine-learning models under realistic hardware constraints. A set of formal mathematical models was constructed for quantum data encoding, quantum kernel estimators (QSVC), and variational quantum classifiers and regressors (VQC/QNN). These models incorporate explicit resource-aware constraints, including circuit depth, number of qubits, and measurement complexity, thereby allowing their systematic optimization. A multi-objective formulation for training quantum models was proposed, balancing model accuracy, circuit expressiveness, and computational latency. For this purpose, a family of metaheuristic optimization strategies –including evolutionary algorithms, particle swarm optimization, simulated annealing, differential evolution, and CMA-ES was adapted to the quantum domain.

The evaluation demonstrated that metaheuristic search enables stable parameter discovery even under noisy intermediate-scale quantum (NISQ) conditions. A modular microservice-based software architecture was implemented to operationalize these theoretical contributions.

The developed software includes dedicated quantum microservices such as Q-Kernel for computing quantum kernels and Q-VQC for executing variational circuits, coordinated by an orchestration layer responsible for metaheuristic optimization, resource tracking, and fault tolerance. Experimental validation was carried out using both publicly available datasets and EEG signals from the Muse S Athena device. The hybrid approach consistently outperformed purely classical or purely quantum baselines in scenarios constrained by qubit count and circuit depth. Additionally, preliminary analysis supported the feasibility of using quantum-enhanced models for cognitive-state estimation and provided empirical evidence toward validating the Countable Mental Energy (CME) indicator derived from EEG data. For software under development, automata models (finite automata/UML state diagrams) for describing behavior, Petri nets, or process calculus for analyzing concurrency and coordinating microservices may be important.

Petri models can be used to model the process of executing tasks in a queue of quantum experiments: where there are positions "task in queue", "task is being executed on the backend", "completed successfully"/"failed" and transitions between them. Analysis of such a network will confirm that there will be no situation where a task is "stuck" between states or lost. No "hangs", correct transitions, boundary conditions (timeout → retry ≤ k, completion logging), finite automata are also suitable for performing the current task. In general, in the work, you need to focus on methods that bring direct benefit – they check the correctness of the system's behavior. The Fig. 1 shows a streamlined sequence of interactions in the hybrid quantum–classical framework, tracing how EEG data is processed from preprocessing to quantum evaluation and final inference.

After the researcher initiates an experiment, the API gateway sends prepared data to the metaheuristic orchestrator, which manages iterative optimization, calling the Q-Kernel Service for quantum kernel matrices and the Q-VQC Service for evaluating variational circuits. Both services run on IBM QPU Runtime to execute circuits and collect measurements.

The orchestrator analyzes intermediate results (kernel quality, VQC accuracy, circuit depth, shot count), adjusts parameters, and repeats the loop until convergence. Once optimized, the system aggregates final metrics AUC/ROC, accuracy, depth, shots, latency and returns them to the researcher.

The workflow integrates quantum computation with classical orchestration to automate training and evaluation of quantum machine-learning models (Fig. 2).

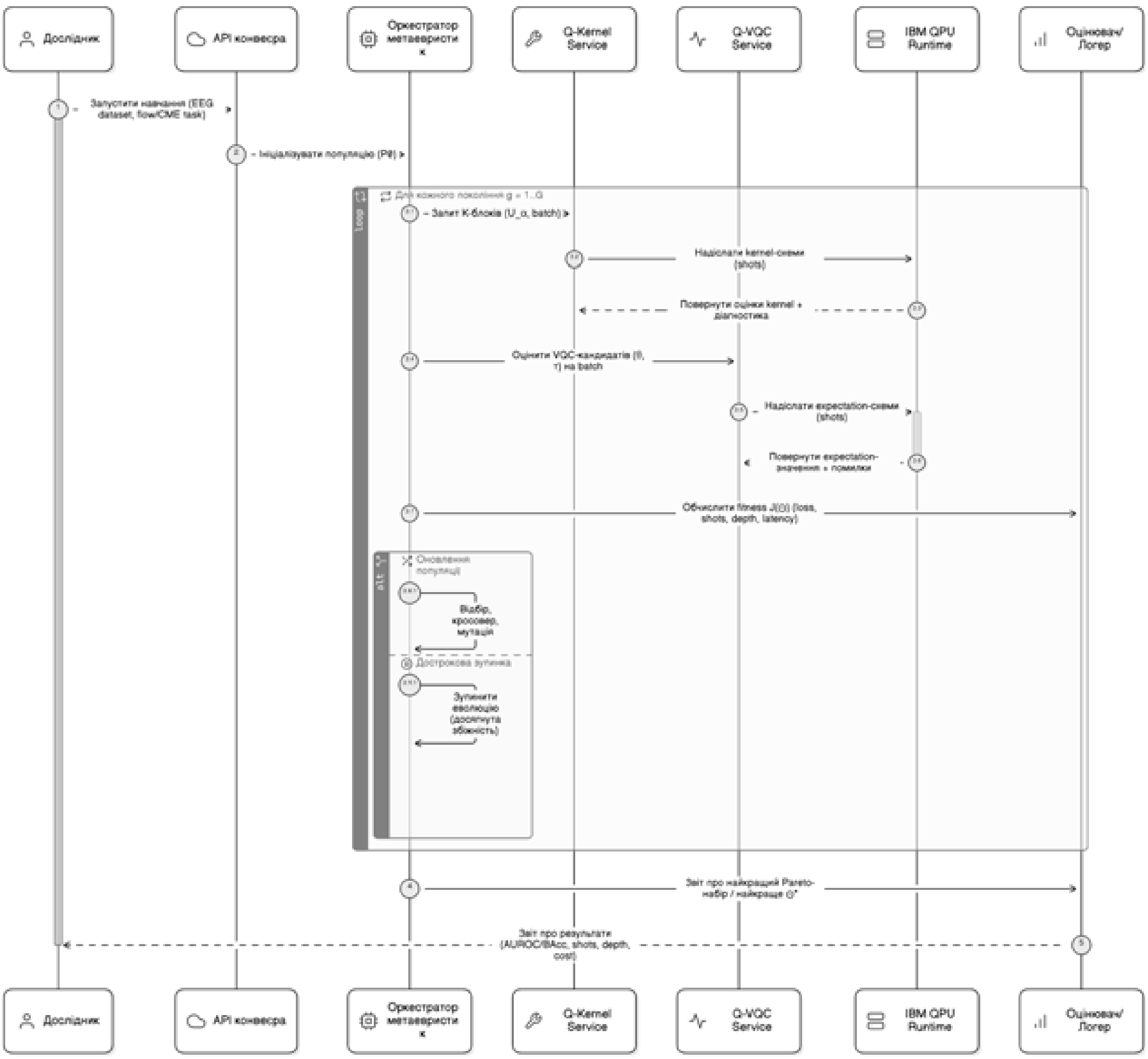

Fig. 1. Software sequence diagram "Training a model with metaheuristics"

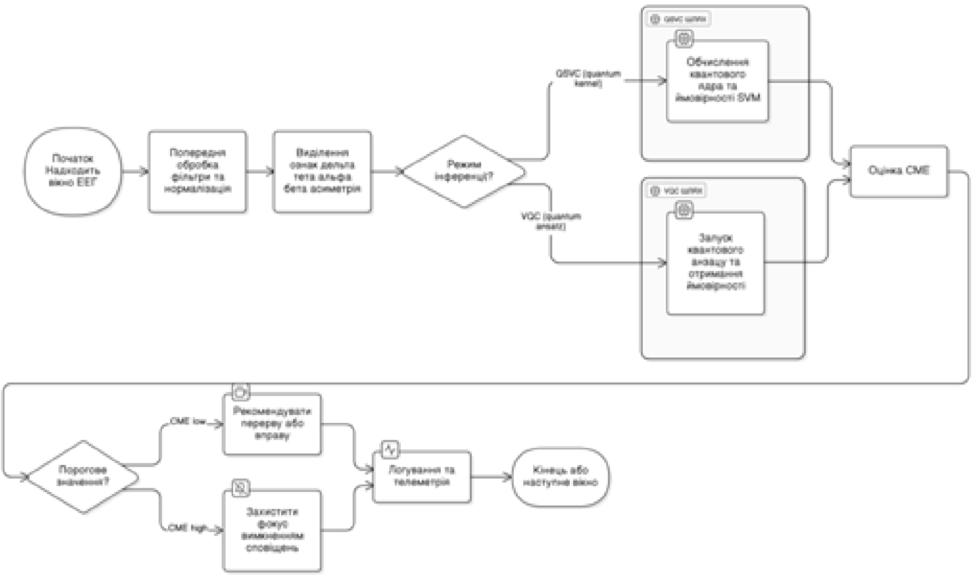

Fig. 2. Activity diagram "CME system and real-time recommendations"

Conclusions and future work

This research demonstrates the practicality and effectiveness of hybrid quantum–classical approaches for training machine-learning models on contemporary NISQ hardware. By establishing a rigorous mathematical foundation for quantum data encoding, kernel-based classification, and variational modeling, and by embedding these formulations into a multi-objective optimization framework, the study provides a systematic methodology for improving quantum model performance in resource-constrained environments. The integration of advanced metaheuristic algorithms proved essential for navigating the highly non-convex parameter landscapes of quantum circuits and mitigating the detrimental effects of noise and limited circuit depth. The developed quantum microservice architecture further confirms that scalable, modular, and fault-tolerant quantum computation workflows can be achieved through software-centric engineering methods. The experimental results, including the application to EEG-based cognitive-state analysis, illustrate the potential of quantum-enhanced analytics for real-world data processing tasks. The validation of the CME indicator within the hybrid framework suggests new opportunities for quantum approaches in neuroengineering, human–computer interaction, and biomedical signal analysis. Overall, the outcomes of the study highlight a viable technological pathway for advancing quantum machine learning prior to the emergence of fully fault-tolerant quantum processors, and they open multiple directions for future research in optimization, circuit design, and quantum software engineering. Future work will focus on extending the hybrid quantum–classical framework in several directions to further enhance its robustness, scalability, and applicability across domains.

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