EERA
European Energy Research Alliance

White paper

Quantum computing in the net-zero transition: energy production, management, and efficiency

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Preface

The global energy landscape is undergoing a profound transformation, driven by the urgent need for sustainable, efficient, and resilient and secure energy solutions. We believe that quantum computing, though still in its early infancy, holds immense promise to accelerate this transition by tackling challenges currently beyond the reach of classical computing methods.

This white paper explores the distinctive potential of quantum computing in revolutionising the energy sector. Unlike traditional computers that operate on bits, quantum computers harness the unique properties of quantum mechanics, such as superposition and entanglement, to perform complex calculations in fundamentally new ways. This unlocks the ability to address previously intractable problems, enabling breakthroughs across the energy value chain.

The paper illustrates how quantum computing offers a disruptive approach to a range of key energy challenges such as:

- *Materials Discovery*: Accelerating the design of novel materials for more efficient solar cells, batteries, and catalysts, crucial for renewable energy technologies and energy storage.
- *Grid Operation*: Enhancing the management and control of complex energy grids, enabling the seamless integration of renewable energy sources and optimising energy distribution, thereby improving both sustainability and reliability.
- *Energy Trading and Management*: Developing more sophisticated models for energy forecasting, risk management, and trading strategies, leading to more efficient energy markets and resource allocation.

As we suggest wider use of quantum computing in accelerating the energy transition, it is essential to consider its intrinsic environmental impact. As this white paper highlights, the energy needed for cooling and operating current quantum systems must be given adequate consideration. Our long-term vision is to develop more energy-efficient quantum computers and algorithms, ultimately achieving a "quantum energy advantage" i.e., the ability to solve complex problems with significantly lower energy consumption than with classical computing. Our research is dedicated to not only advancing the computational capabilities of quantum computing but also to minimising its environmental footprint. We are committed to exploring energy-aware algorithms, optimising quantum hardware designs, and promoting sustainable practices in the development and deployment of this transformative technology.

This white paper provides a comprehensive overview of the current state of quantum computing in the energy sector, highlighting its unique capabilities, potential applications, and the crucial considerations surrounding sustainability. At a juncture where society is confronted with multiple inter-related challenges, quantum computing offers a promising, disruptive approach to tackle complex systemic challenges increasingly intractable through traditional computing approaches. We hope it inspires further innovation, collaboration, and responsible development of quantum computing to create a cleaner, more sustainable energy future.

Adel El Gammal

Secretary General

EERA

Motivation

Global primary energy consumption has been growing steadily and rapidly since 1950, reaching almost 180,000 TWh in 2022, and kept growing thereafter at a rate of 1%-2% a year. Of these, 20236 TWh were obtained from renewable sources, and 137,237 TWh were obtained by burning fossil fuels (coal, oil, and natural gas). In the European Union, the final consumption of energy in 2022 was 10,493 TWh, of which 6,198 TWh were produced using fossil fuels.

The negative effects of the continuous and extensive utilisation of fossil fuels are widely acknowledged: climate change, air pollution, increased risk for respiratory diseases[1], increased energy dependency and decreased energy security. To address these issues, the European Green Deal set a goal of 0 net emissions by 2050 and a shorter-term goal of reducing greenhouse gas emissions by 55% by 2030 ('Fit for 55' legislation). Also, the revised Renewable Energy Directive EU/2023/2413 has raised the EU's binding renewable target for 2030 to a minimum of 42.5%, up from the previous 32% target, with the aspiration to reach 45%.

It is also evident that the widespread use of renewable energy sources is only one aspect of the transition to net-zero energy production. Substantial advances in all key areas of renewable energy technology will be required, ranging from the improvement and discovery of materials for the sources, the location of the sources themselves, the management of energy networks and the support of large and numerous producer-consumer communities.

In most, if not all, of these key areas, research and development have become increasingly reliant on the availability of high-performance computing (HPC) environments for a variety of tasks, such as optimisation, simulation, analysis, and prediction. While existing energy sources and grids are characterised by computational problems which can be satisfactorily solved employing current computing technology, the generation, distribution and management of renewable energy pose new computational challenges and scale up existing ones. Many relevant problems are inherently computationally hard, and their complexity is compounded by the much larger instance sizes that are typical of renewable energy applications. Other problems are not solvable to the required degree of correctness because the underlying physical laws are too difficult to be accurately simulated.

These challenges are an ideal field of application for quantum computing (QC), and there is a growing consensus about its relevance to solving the problems associated with the development of net-zero energy networks. For example, quantum computing devices have the potential to solve computationally difficult problems, even when the size of the problem does not allow a suitable solution with conventional devices; they can be used to simulate material behaviour and to process and learn from data in fundamentally new ways. Therefore, we believe it is strategically important to give support and attention to research in the science of quantum computing and to the development of quantum technologies focused on solving the scientific, technological and management problems of net-zero energy networks.

Energy materials

In a wide perspective, improvements in performance, durability, and cost effectiveness of technologies for renewable energy generation, conversion, and storage rely on advanced materials solutions. Accelerating the development and technological integration of next-generation materials is therefore pivotal under the current urge for creating sustainable and reliable energy supply chains. Computer simulations play a central role in nowadays materials research, and latest advancements in high-performance computing are contributing to the acceleration of the research and development pipeline[2].

In this realm, quantum computers can provide unique advantages over classical computing systems. Since Richard P. Feynman, Nobel laureate in physics, formulated the pioneering vision to leverage the principles of quantum mechanics in computers[3], the simulation of the electronic structure of materials, which itself is governed by the principles of quantum mechanics, has been acknowledged as a key application of quantum computers, bearing the potential to significantly enhance the efficiency and accuracy of simulation-based predictions of materials properties. The stunning evolution of quantum computing hardware during the past years has enabled putting Feynman's vision into practice and numerous promising applications of quantum computers in materials simulations have been demonstrated[4].

Finding new cathode materials for batteries is particularly crucial for our society, where the need for energy storage systems is increasing due to the high demand for electric energy. In this scenario, the discovery of new alternatives to lithium is essential for sustainability and cyclability purposes. In this regard, advanced machine learning (ML) algorithms have been developed to accelerate the study of new cathode materials and potentially propose new alternatives to lithium-ion batteries. Among them, graph neural networks (GNN) are extremely promising, notably convolutional graph neural networks (CGNN)[5] and many other variants of them, like iCGCNN[6], GeoCGNN[7], GATCGNN[8], MBVGNN[9], and many more. They have been shown to predict formation energy with precision comparable to that of more traditional methods based on DFT[7]. Similar results were obtained for average voltage predictions[10,11,12]. These two quantities are essential for constructing battery-grade materials. However, ML models, including GNNs, can be quite demanding in terms of computational resources, specifically running time and memory usage, during the training phase. The study of quantum versions of graph neural networks is an extremely recent field which is promising for solving such problems of classical algorithms.

Quantum computing for energy materials

The exploration and optimisation of new material compositions and atomic configurations represent a class of problems which is particularly suited for quantum computing approaches. Quantum annealers are specialised hardware designed for such classically hard-to-solve combinatorial problems. Promising applications of quantum annealing (QA) have been demonstrated, e.g., in the design of catalyst materials[13], or the optimisation of the structure of battery materials[14,15].

So far, the development and demonstration of quantum computing methods in energy materials research have focused on specific problem cases feasible for current quantum computing hardware. In the current noisy intermediate-scale quantum (NISQ) era, the integration of quantum computing approaches with classical simulation methods in a divide-and-conquer strategy is a promising route to their wider adoption[4,16–18]. Intensified efforts for the co-development of quantum and classical simulation methods and their demonstration for relevant use cases are required for leveraging the potential of quantum computers in the research and development of energy materials.

Concrete applications of quantum computing in energy materials research:

- **Electronic structure simulations** using quantum algorithms, e.g., based on the variational quantum eigen solver (VQE) for current NISQ platforms, and quantum phase estimates (QPE) for future fault-tolerant quantum computers (FTQC) for accurate description of electronic properties of active materials with strong electronic correlation and localisation.

- **Combinatorial optimisation** using methods of quantum annealing and quantum approximate optimisation algorithms (QAOA) for the exploration of configurational and compositional materials spaces in computational materials design and discovery.
- **Development of integrated workflows** combining approaches of quantum simulation and quantum optimisation with classical methods for accelerated materials simulations.

Quantum graph neural networks in the search for new materials for energy

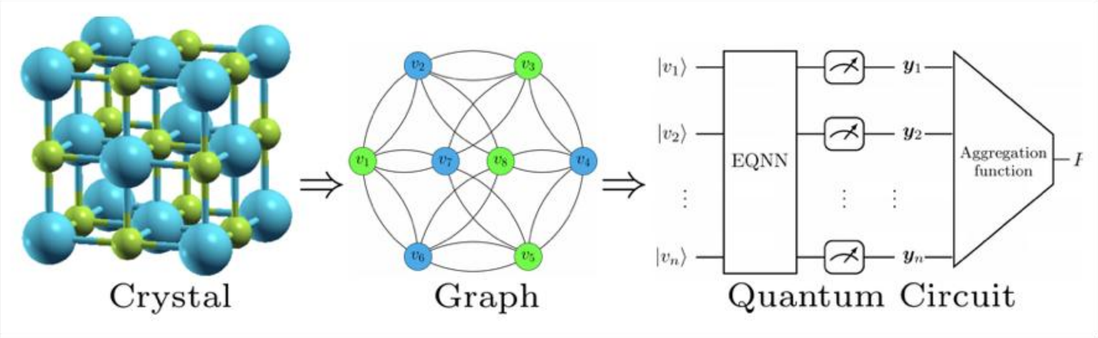
Some quantum machine learning (QML) algorithms have been found to be faster than their classical counterparts or to provide better quality inferences. Their speed-up can be quadratic or also exponential in the best scenario, depending on the algorithm considered and how training data is encoded in the quantum circuit[19,20]. This raises hopes that similar achievements can hold also for graph neural networks working on crystals. The study of quantum graph neural networks (QGNN) and their implementation on material discovery is therefore essential. However, applying plain QGNN algorithms is not feasible at present, since they can be quite demanding in terms of number of qubits and gates, and, unfortunately, NISQ devices are limited by the number of qubits and quantum gates can introduce errors which propagate through the quantum circuit of the QGNN. For this reason, hybrid classical-quantum approaches using shallow variational circuits are currently used with NISQ systems[21]. In this case, the optimisation process, instead of being performed by a quantum circuit[22], is carried out by classical algorithms. This allows to reduce the dimensionality of the data as well as the number of gates to use. However, as the number of qubits increases, hybrid approaches of quantum neural networks suffer from the vanishing gradient problem, known as barren plateaus[23]. For this reason, different strategies have been proposed to overcome barren plateaus. One is using Gaussian initialisation of the learnable parameters[24], others concern a change in the architecture of the quantum circuits. Indeed, it has been shown that for quantum convolutional neural networks barren plateaus are absent[25] and the same occurs for permutation-equivariant neural networks[26]. Other quantum circuits which do not seem to have barren plateaus are the equivariant quantum graph circuits (EQGC)[27]. EDU-QGC[21], a particular variant of EQGC, has been considered for material search, showing faster convergence in the training phase with respect to a classical graph neural network.

Up to now, studies applying quantum graph neural networks for material search are very few. However, quantum graph neural networks, despite limitations due to NISQ computers, look extremely promising. Therefore, their natural application in the study of materials properties for batteries is certainly an appealing field of research. We already know that classical machine learning enables us to make predictions comparable to those made by traditional algorithms, accelerating the discovery of materials for batteries. We can expect that this acceleration can be greatly improved by the application of quantum algorithms.

Concrete applications of quantum graph neural networks in energy materials research:

- Designing novel materials-specific quantum circuit architectures. Many machine learning methods, currently employed in materials science, use graph neural networks that are equivariant with respect to node permutations. The use of permutation-equivariant quantum neural networks therefore represents a valid option for material predictions, since the absence of barren plateaus for this type of networks is an important condition for trainability. A conceptual scheme on how it could be implemented for crystals using EQNNs[27] is reported in the figure below.
- Harnessing the power of graph neural networks on quantum devices to predict material properties and help to explore a vast compositional space of materials as an alternative or complement to first-

principles methods. In the NISQ era, this goal can be extremely challenging, and advances in quantum technologies are crucial for achieving it.



Energy grids

Enabling the shift from fossil fuels to renewable energy sources, power systems are effectively the backbone of our societal decarbonisation efforts. However, the growing reliance on renewables presents new challenges for ensuring the robust and reliable operation of electrical systems. Those challenges often translate into the need for more extensive analysis (both in the planning phase as well as during operation) that take into consideration multiple simultaneous contingencies and include dynamic analyses. Computational cost is typically kept under control by limiting the number of contingencies and scenarios considered, the size of the system analysed (trough spatial aggregation) and the time horizon of dynamic studies. The ongoing energy transition strongly challenges those simplifications. While some of those challenges—e.g., the need for longer simulation horizon while increasing temporal resolution with spatially disaggregated models—can be approached using traditional HPC methods, in some cases—e.g., for combinatorial problems—even HPC architectures are inadequate. In this framework, preliminary applications of quantum computing to power systems[28,29] appeared in the last few years.

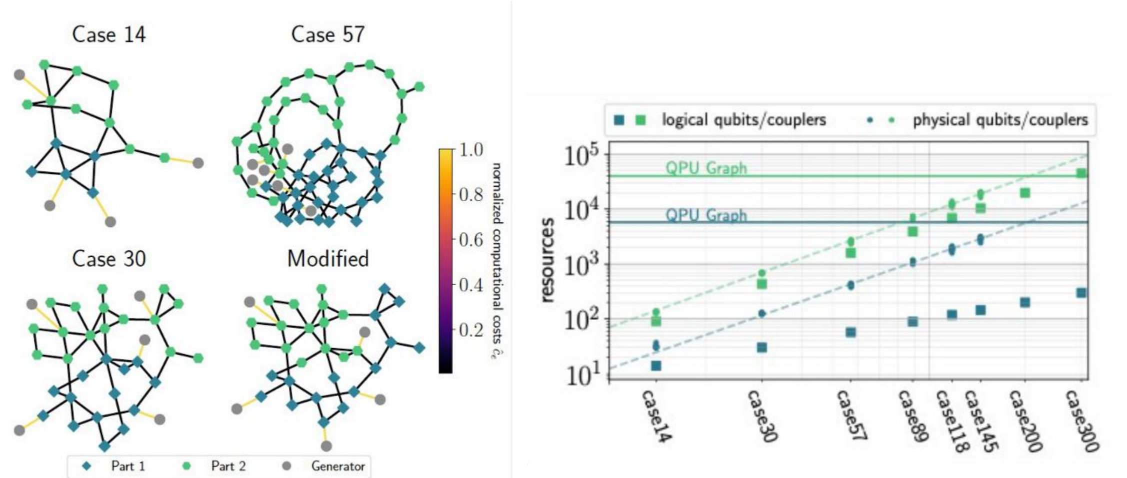
The Unit Commitment (UC) problem, a central one in power system operations, is a notable case. It determines which power generators to turn on or off over a given planning horizon to meet electricity demand at minimum cost, while simultaneously satisfying a variety of operational constraints such as generator ramping limits, minimum up/down times, fuel costs, reserve requirements, and transmission constraints. The problem is typically formulated as a Mixed-Integer Linear Program (MILP) or Mixed-Integer Nonlinear Program (MINLP)[30], and its complexity grows combinatorially with the number of generators, time steps, and coupled constraints—making large-scale UC instances computationally intensive even for state-of-the-art classical solvers[31]. When batteries and renewable uncertainties are incorporated into the problem, the UC problem generalises into a type of problem that can dramatically increase the dimensionality and constraint density of the problem thereby pushing traditional solvers toward scalability limits. Quantum computing has recently emerged as one potential game changer to tackle this problem, as it may be a promising candidate to leverage some of quantum computing's unique capabilities to solve complex optimisation problems.

Challenging computational problems arise in the management of distributed energy resources as well, particularly in the integration of renewable energy sources, which requires efficient coalition formation (CF) strategies[32]. These strategies enable decentralised coordination among various energy assets, such as electric vehicles with vehicle-to-grid (V2G) capabilities, photovoltaic (PV)-equipped households, and storage systems, to optimise energy distribution and consumption. Traditional computational approaches, including game-theoretic models and mixed-integer programming, face significant scalability challenges when addressing real-time coalition formation problems in complex energy networks. By harnessing quantum computing, coalition formation in energy systems can be accelerated, leading to more efficient grid management, lower operational costs, and enhanced sustainability. The integration of quantum methods into energy markets and grid management tools will help ensure stable and resilient renewable energy adoption.

Finally, renewable energy sources are key to Europe's net-zero transition, and the therefore necessary and on-going integration of decentralised energy sources such as solar panels, wind turbines, and biogas plants poses challenges for the power grid's stability. While quantum assisted learning has been applied to fault analysis in power systems[33], quantum computing might benefit three major challenges when integrating bioenergy: (i) bio-economy models introducing new cascaded down feedstocks, (ii) improved anaerobic digestion models to 'program' bioenergy production and (iii) demand management models to compensate fluctuation of other renewables and/or to maximise profit.

Quantum computing for power systems

Recent developments in this field can be categorised into three key areas. First, computational blocks in power systems analysis are directly brought to quantum. Corresponding classical algorithms often involve solving linear or nonlinear systems of equations and are replaced by quantum subroutines, e.g., the Harrow-Hassidim-Lloyd (HHL) algorithm for the solution of DC and AC power flow equations[34,35]. To address some of the issues with HHL, variational quantum circuits have been designed for power flow[36] and electromagnetic transient program[37]. Second, fundamental power system problems are being reformulated to fit quantum optimisation frameworks. The UC problem has been reformulated to fit quantum optimisation frameworks, e.g., QA[38] and QAOA[39]. Due to the current limitations of quantum hardware, only small-scale problems can be addressed, leading to increased interest in decomposing larger UC problem instances into smaller, quantum-solvable instances[40–42]. Other proposed applications for QA are network reconfiguration in distribution grids[43] and optimal power flow[44,45]. Third, quantum computation is employed to enhance classical simulation and optimisation methods. For instance, quantum algorithms are used to find optimal cuts in Benders decompositions, enabling the solution of large-scale unit commitment problems[46] or for graph partitioning to optimise parallelised dynamic simulation. (Figure source: [47])



Quantum computing for unit commitment and battery scheduling in power systems

In the recent few years, a plethora of quantum computing approaches have been proposed to address variations of the UC problem across varying types of quantum computer hardware and algorithmic approaches.

These include quantum annealing optimisation, gate-based variational algorithms like QAOA, and oracle-based methods such as Grover search. While the literature is vast, we provide a quick overview of a few selected solution approaches that demonstrate the variety of ways researchers are attempting to use quantum computers to solve the problem.

In[46], the authors present a hybrid optimisation strategy that combines classical multi-cut Benders decomposition with quantum computing to solve the UC problem. Rather than solving the entire master problem via quantum hardware, the approach uses a quantum annealing approach to select an optimal subset of Benders' cuts—generated from multiple feasible solutions of the master problem. Numerical experiments demonstrate that this hybrid method accelerates convergence compared to classical Benders, though current hardware limitations—like embedding overhead and limited qubit connectivity—still restrict scalability.

In[39], the authors instead apply the gate-based QAOA and integrate it with a classical optimiser, enabling a division of labor for the UC problem—QAOA handles binary decisions (e.g., on/off generator status), while the classical component optimises continuous variables. Their architecture avoids encoding continuous variables into qubits, thereby reducing quantum gate complexity while preserving accuracy.

In[48], the authors propose to apply the well-known Grover search algorithm to the UC problem. Namely, the authors design an efficient quantum oracle tailored to the UC problem that learns to highlight good candidate solutions. This oracle enables a quantum algorithm that, when paired with classical methods, reduces the number of linear programming subproblems needed in solving UC. The approach is validated through experiments on both quantum hardware and simulators, demonstrating the feasibility of searching for quasi-optimal UC solutions in the Grover model.

Lastly, in[49], the UC problem was generalised for electric Vehicle-2-Grid bidirectional charging. In this work, the authors apply a quantum machine learning approach that learns to predict how much to discharge a fleet of plugged in electric vehicles to meet the pre-defined energy demand. The authors suggest using the quantum kernel classifier to discretise the discharge "unit" amounts and demonstrate considerable scaling advantage at solving this UC problem variant relative to classical optimisations and approximate dynamic programming techniques.

These works, and others like them, have demonstrated that the quantum applications community has established the UC problem as a compelling use-case for quantum-based solution approaches. The problem and its generalisations are structurally rich in its variations, highly relevant to global energy operations, and flexible enough to admit multiple quantum formulations, while simultaneously being classically challenging at scale.

Quantum-assisted coalition formation for renewable energy management

Given its combinatorial nature, CF can be reformulated as a Quadratic Unconstrained Binary Optimisation (QUBO) problem, as demonstrated by the BILP-Q algorithm[50], enabling the use of quantum routines, such as QA and QAOA, to efficiently explore large solution spaces. However, due to current limitations in quantum hardware, scaling these approaches to larger problem instances remains a challenge.

Hybrid quantum-classical methodologies mitigate these limitations by optimising the interplay between quantum and classical resources. For instance, GCS-Q[51] employs a top-down approach, iteratively splitting the grand coalition into smaller sub-coalitions. In this process, quantum annealing is leveraged to solve the computationally expensive bipartitioning problem, formulated as a QUBO instance, while classical computing orchestrates the overall coalition structure and ensures efficient recursion. This hybrid strategy balances potential quantum benefits with classical robustness, making it a promising approach for scalable coalition formation.

Despite these advances, exploring alternative quantum approaches beyond QUBO formulations is crucial for further improvements in coalition formation.

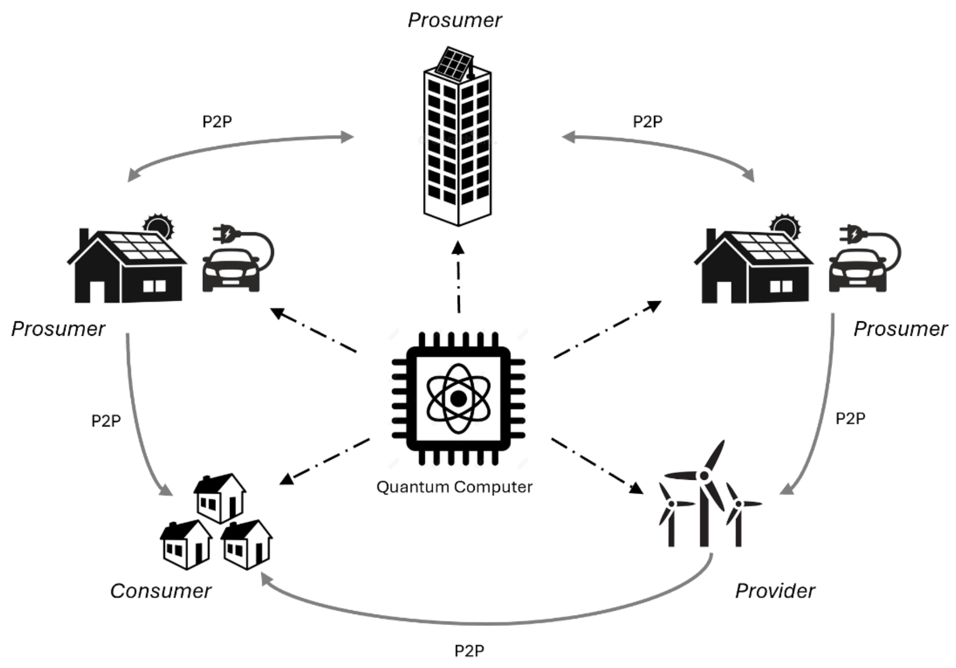
One promising direction involves Grover-based search algorithms[52], which can offer quadratic speed-ups in searching for optimal coalition structures within large solution spaces. Instead of relying on QUBO formulations, Grover's search can efficiently navigate complex coalition landscapes by encoding coalition evaluation functions as quantum oracles.

Another research avenue includes quantum-enhanced combinatorial optimisation techniques that leverage fault-tolerant quantum algorithms, such as quantum dynamic programming or tensor-network-inspired quantum methods, to improve efficiency in CF problems.

Ultimately, integrating these novel quantum techniques with domain-specific heuristics and adaptive hybrid architectures will be key to unlocking the full potential of quantum computing in real-world CF applications for renewable energy management.

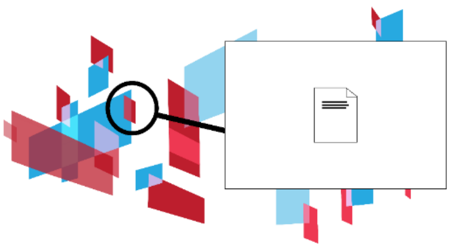
Concrete Applications of Quantum Coalition Formation in Renewable Energy Management:

- **Dynamic coalition formation for energy trading**: Optimisation of peer-to-peer energy trading among renewable energy producers and consumers.
- **Decentralised scheduling of distributed assets:** Efficient scheduling of energy resources, such as EVs and battery storage, to balance local supply and demand.
- **Grid stability and demand response optimisation**: Adaptive coalition strategies to mitigate fluctuations in energy supply from renewable sources.
- **Multi-agent coordination for microgrid optimisation**: Enhanced cooperation among distributed energy nodes to improve overall grid efficiency.



Quantum computing for bioenergy

While solar and wind depend on irregular environmental factors, bioenergy can be regulated to supply demands, especially peak demands. In particular, anaerobic digestion plants are well suited for demand-oriented regulation rather than bio-methane storage and its on-demand energy conversion. Anaerobic digestion plants provide power and heat from biogenic feedstocks and can be controlled by optimised feeding[53]. For example,[54] studied optimal mixing of biomass in co-digestion tanks using quantum annealing in collaboration with Nature Energy, Odense, Denmark. The proposed Quantum Annealing Continuous Optimisation algorithm outperformed traditional ones, especially when considering the most complex scenarios[54,55], which may also hold when tackling the widely established Anaerobic Digestion Models[55–58].



However, a net-zero transition must also promote a circular (bio-) economy introducing competition in usage for biomass – both for cascades of material use and ultimately energy use[59]. In consequence, the complexity of bioenergy in terms of localisation, availability, and degree of processing of biomasses increases tremendously. One could address this escalating complexity of the bio-economy with quantum parallelism, investigating multiple parameter sets at once[60]. On the other hand, gate-based quantum algorithms, unlike annealers, could be advantageous when considering multi-objective optimisation[61]; e.g., possibly long cascades of use for material before the final energy conversion.

Energy efficiency

Increasing energy efficiency and reducing energy consumption with the aim of fighting climate change require innovative solutions, and quantum computing offers a promising path towards energy efficiency across diverse domains in two ways: solving computational problems of energy efficiency, and providing a greener technology to reduce energy consumption in data centres and supercomputing facilities.

For energy efficiency problems, there is a vast literature in quantum computing regarding applications of QML to their solution. The techniques utilised are diverse, spanning from quantum reinforcement learning to quantum supervised and unsupervised learning, and are used for important tasks such as optimisation and forecasting. The fundamental motivation behind all studies is that quantum computers, leveraging principles of superposition and entanglement could in theory overcome limitations of classical computers, typically related to the complexity or the numerosity involved in machine learning computations.

Regarding the energy consumption of data and supercomputing centers, these facilities are among the world's most energy-intensive infrastructures. In 2022, they accounted for approximately 1–2% of global electricity consumption (~240–540 TWh), with projections suggesting this could rise to 3.5% by 2026, driven by AI and simulation workloads[62]. This trajectory is environmentally unsustainable, particularly as classical computing reaches thermodynamic efficiency limits. While the appeal of quantum computing generally lies in the prospect of a vastly superior runtime performance, a view that maps to the concept of quantum advantage, stakeholders begin to contemplate the possibility of obtaining high performances in computing that are less dependent on energy consumption as well. Clearly, a thorough approach to the comparison of quantum and classical solutions must account for the energy consumed by the computation. This broader view raises some fundamental questions, which are also of eminently practical importance, such as the relation between quantum advantage and a potential corresponding green advantage, resulting in energy savings, how to quantify energy consumption in quantum computations, and how to integrate quantum and classical hardware to minimise it.

QML applications and energy efficiency

Quantum reinforcement learning in different energy-efficiency scenarios shows promising results and an enhancement with respect to its classical counterpart.

As shown in[63], a quantum-based reinforcement learning approach proves the feasibility of implementing decision-making scenarios with less complexity than its classic counterpart, obtaining better results than classical neural networks in a suite of use cases, such as heating, ventilation, and air conditioning (HVAC) control in buildings, the energy management in an electrical vehicle simulator, and the optimisation of profit of charging stations for electrical cars. Indeed, variational quantum circuits (VQC) at the foundation of quantum machine learning algorithms require fewer parameters and achieve better results, but they need more time to converge, and their computing time is higher. The main problem is that the barren plateau phenomenon, which refers to gradients that vanish exponentially, is more frequent for VQC than for classical neural networks. Moreover, the reduced availability of real quantum hardware even at the noisy-intermediate scale forces experimenters to use classical hardware and quantum simulators, which have very poor performance.

In the domain of quantum supervised learning, forecasting different energy sources is one of the most interesting topics. As the review[64] shows, the introduction of entanglement and superposition in diverse machine learning algorithms provides significant improvements. For example, quantum neural networks (QNN) and quantum support vector machines (QSVM) offer great enhancement in solar irradiation forecasting, and quantum long short-term memory cells (QLSTM) have overall performance better than the baseline models in terms of forecasting annual average energy coming from renewable sources. Analogous results are obtained for load forecasting in energy grids and carbon price forecasting.

In the domain of quantum unsupervised learning, cluster analysis and anomaly detection play a crucial role in energy efficiency. In[65], the relevance of quantum artificial intelligence methods for fault detection in energy systems is stressed. Moreover, the authors show how cluster analysis with quantum circuits in the field of quantum chemistry can be beneficial for the design of new materials for energy storage. As noted also in their recent paper about AI data center energy control[66], VQCs show at least in theory a great advantage with respect to their classical counterparts.

In general, quantum circuits improve accuracy and have fewer parameters, but they are reported as slower. In fact, hybrid algorithms can introduce overhead and additional operations. Moreover, NISQ devices will work at extremely low temperatures, which require significant energy for cooling. As technology advances, it is hoped that more energy efficient quantum computers will emerge. As stressed before, even if QML has in theory a great potential, the challenges that remain are mainly related to the need for fault-tolerant quantum hardware and to the ability to develop algorithms that can tackle energy efficiency problems with a complete quantum approach, overcoming current hybrid approaches.

Energy efficiency of quantum computing

Quantum Energy Advantage. Thanks to its computing model, its large internal data space and efficient parallelisation, quantum computation offers the potential for better energetic performance in information processing than classical computing.

In the standard model of quantum computation, quantum operations are reversible, in contrast to classical computation, where logical operations, like AND or OR are completely irreversible. According to Landauer's principle[67], there is a minimum amount of energy dissipated required for every irreversible operation on information. Quantum computation is thus, in theory, dissipation-free. However, driving qubit operations is classical and non reversible. With fault-tolerant quantum computing using quantum error correction, a significant physical qubits overhead is needed to fight against the noise generating qubit decoherence and damaging algorithms output. This reinforces the need to account for all energetic costs when assessing the power and energy needs of quantum computers. Depending on the qubit type, the energetic cost is spread over qubit control (electronics signals generation, lasers, photonics), cryogenics (between 4K and 10 mK depending on the qubit type), and classical computing (quantum circuit preparation, compilation and optimisation, error correction). Most of this cost scales linearly with the number of physical qubits in the system.

Early demonstrations pointed to a potential "quantum energy advantage". Google's 2019 Sycamore and 2024 Willow processors completed quantum sampling tasks with orders of magnitude less energy than the best-known classical simulation methods, although these were not computational tasks in the classical meaning since they didn't use any input data[68,69]. Similarly, quantum factoring using Shor's integer factoring algorithm could, in theory, require significantly less energy than classical approaches as integer size is growing in number of storage bits[70,71].

While exact numbers vary, the trend suggests that as quantum systems scale, their energy-per-solution could outperform classical high-performance computers, especially in simulation, optimisation, and cryptographic tasks. This is corroborated by a recent work[72] which analysed the energy consumption of an ideal trapped-ion quantum computer performing the Quantum Fourier Transform and estimated how this consumption would scale with the number of qubits, identifying a threshold for a quantum energy advantage against classical supercomputers performing the discrete Fourier transform. Transferring quantum information within different parts of a quantum computer also comes at a cost, and in this respect another work studied the optimisation of energy efficiency in a quantum data bus[73]. This will be extended to evaluating and optimising the cost of quantum processor interconnect technologies that will be necessary for the implementation of large scale fault-tolerant quantum computers[74].

This potential quantum energy advantage is especially relevant at a time when the energetic footprint of classical information and communication technologies has reached an all-time high[75]. In this regard, exploratory research has been carried out on the use of quantum gates for classical computation, specifically trapped ions[76] and semiconductor quantum dots[77], as more energy-efficient alternatives to current semiconductor-based computing platforms.

Engineering and Infrastructure Challenges. Realising this potential at scale requires overcoming key barriers:

- Hardware maturity: NISQ devices remain noisy and small-scale. To overcome these limitations, quantum error correction and fault-tolerance will be required, implying, however, a significant overhead in physical qubits and their related classical control costs[74,78].
- Control electronics optimisation: it can come from tuning the balance between room temperature and cryogenic temperature electronics, improving cabling density and signals multiplexing, and using more efficient cryoelectronic circuits.
- Cryogenics optimisation: innovations in high-yield cryocooling solutions are expected for large scale FTQC systems, like the usage of liquid helium factories. It may drastically reduce baseline consumption for these systems. Neutral atoms platform may require some 4K cryogenics to cool their vacuum chamber and ion ultra-vacuum pumps, but this is a near fixed cost against the number of physical qubits. Their own cooling relies on laser-based cooling, which is less energy-intensive.
- System integration: Hybrid HPC-QC architectures can exploit quantum accelerators for subroutines, as currently done with GPUs. Colocation and orchestration of quantum processing unit (QPU) clusters will be critical.
- Algorithms: fault-tolerant quantum computing will require massive resources, but energy-aware algorithms and optimised compilation chains may reduce energy-per-task.

The operation of several quantum computing platforms, namely photonic as well as solid-state based platforms, such as superconducting qubits, requires cryogenic systems. Since cryogenic systems have very high power requirements, they account for a significant part of energy consumption in these platforms. As the number of physical qubits grows, the share of energy consumption by control electronics grows, accounting to 80% of the total energy consumptions for upcoming FTQC systems like IBM Starling, planned in 2029, with 200 logical qubits and the support for 100 million gate operations. A quantum computer's power consumption is nearly constant whether it is executing a circuit or being idle[79]. Its total energy consumption is measured against a given algorithm task and depends on the circuit depth and the overhead of quantum error correction.

Qubits are extremely sensitive to noise, decoherence, and even imperfect operations or defects in semiconductor circuits. This is why quantum error correction mechanisms are needed. However, the codes used to correct this error require a larger number of qubits (to encode the information, plus many more auxiliary ones) and a greater number of operations (often involving approximations to match the operations to those we can implement). These methods are expected to increase the energy consumption of quantum computation. These costs can be mitigated by improving the non-local connectivity between physical qubits, improving their fidelities and using more efficient error correction codes.

Sustainability and Policy Outlook. There are efforts towards standardised optimisation frameworks, like the Metric-Noise-Resource (MNR) approach[80], which allow for a comparison of performance vs. energy cost across platforms[62]. Initiatives like the Quantum Energy Initiative (QEI) launched in 2022 aim to define sustainable quantum technologies as a formal R&D field[78,81]. It also initiated the IEEE Quantum Energy Initiative working group to standardise the way to measure and evaluate the energy consumption of quantum computers[82].

The European Union, via Horizon Europe, EERA, and Quantum Flagship, supports benchmarking efforts to evaluate environmental impact. One such initiative, involving EDF, CNRS, Alice&Bob (cat-qubits) and Quandela (photonic qubits), aims at optimising the energetic cost of quantum computing using a full-stack approach, covering qubit energetics at the fundamental level, systems engineering, and with EDF's own selected applications as use-case references[83].

Conclusion. Although today's quantum systems are still few in number and their absolute energy consumption remains very small compared to the ~200 TWh consumed annually by classical data centres[62], now is the time to design the quantum revolution with sustainability in mind. Every additional qubit, every new quantum lab or center, should advance not only in computational power but also in operational efficiency. The potential benefits go beyond reducing electricity bills: more energy-efficient quantum computing could enable the scaling of previously unfeasible algorithms (due to lower heat dissipation), democratise access in energy-constrained environments, and reduce the climate footprint of the information age.

Quantum computing could transform how we measure energy efficiency in computation. While the technology is still maturing, foundational experiments, energy scaling trends, and coordinated European initiatives indicate that QC could play a central role in future green digital infrastructures. Aligning energy-aware hardware, algorithms, and policy now will help build a quantum future that is not only powerful, but sustainable.

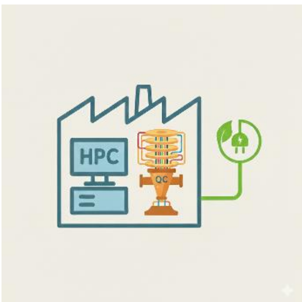
Quantum computing energy consumption

Quantum computing promises to achieve significant computational speedup, particularly in solving problems that are intractable with classical computing methods, even within HPC facilities. This capability is defined by the concept of computational quantum advantage, which establishes the threshold at which a quantum computer surpasses classical hardware in terms of computing time to solve some given problem. However, beyond computational speed improvements, quantum computing may also offer a **green quantum advantage**—

a comparative measure of energy efficiency between quantum and classical systems—by significantly reducing the energy consumption of specific tasks, when these tasks are still possible with classical means. This advantage will be crucial in evaluating the performance of quantum versus classical hardware. Its well-defined characterisation would enable more informed decisions regarding energy-efficient strategies, such as optimising workload distribution in hybrid quantum-classical algorithms. Determining this advantage remains a complex challenge that has recently gained significant attention, particularly with the emergence of the **Quantum Energy Initiative**[84], which aims to drive the development of energy-efficient and sustainable quantum technologies[85].

The quantum advantage is expected to naturally extend to a green quantum advantage, as bounded-error quantum polynomial time problem solutions (BQP) scale more efficiently than classical equivalent NP problem solutions and require less energy at sufficiently large problem sizes. However, it remains to be determined whether quantum algorithms without a clear computational speedup can still achieve energy savings and to what extent this advantage is observable with current and future quantum hardware devices, which are now progressing beyond the noisy intermediate-scale quantum (NISQ) regime[86].

A crucial first step in validating green quantum advantage is developing robust metrics to quantify energy consumption in quantum computing. Significant progress has been made in this direction. The **Equality of Fidelity and Energy Point (EFEP)** defines the threshold where a classical quantum emulator and quantum hardware achieve the same fidelity at equal energy cost. In[70], this metric was employed to compare the energy consumption of a quantum hardware with that of a classical emulator based on tensor networks, a state-of-the-art approach for handling quantum many-body problems and emulating quantum computers with classical ones. The study highlights that green quantum advantage critically depends on the quality of experimental quantum gates and the level of entanglement generated within the quantum processing unit. Importantly, for current NISQ devices, classical emulation can be more energy-efficient than quantum computation while maintaining the same final state fidelity. Another key metric, the **Metric Noise Resource (MNR)**, measures resource efficiency as a performance-to-cost ratio. In[80], it was shown that, under some conditions related to future advancements in the design of FTQC systems, a quantum energy advantage could emerge before a computational speedup, reinforcing the practical benefits of quantum technologies. With these tools, it is possible to assess and enhance quantum energy efficiency by optimising the whole quantum computing system, including its classical computing components and quantum circuits. Along this direction, a recent study analysed the computational efficiency and thermodynamic cost of D-Wave quantum annealers[87], while in[88], it was shown that hybrid quantum-classical approaches, such as parametrised quantum circuits, could offer practical energy advantages.



These results suggest that, in the long term, **integrating quantum computing with classical HPC systems** will be essential to minimise overall energy consumption while maximising computational benefits. In this hybrid framework, quantum-classical workflows must be carefully designed to allocate computational tasks between quantum and classical processors based on energy efficiency considerations. Additionally, developing scheduling algorithms that dynamically optimise resource usage and enhancing cloud-based quantum computing platforms will be crucial to ensuring energy-efficient remote access and computation. Further improvements in quantum energy efficiency also depend on advancements in enabling technologies. Key areas of focus include developing low-energy quantum optimal control mechanisms to manipulate qubits efficiently, implementing noise mitigation strategies to extend computation times while minimising additional energy costs, and refining error correction protocols to balance fault tolerance with energy efficiency, ensuring that corrections do not introduce excessive computational overhead. These technological advancements will play a critical role in making quantum computing not only viable but also scalable and energy-efficient.

In conclusion, while quantum computing holds significant promise for solving more efficiently computationally challenging intractable problems, it also presents the potential for a green quantum advantage, which could emerge independently of computational speedup. Assessing the energy efficiency of quantum systems requires the development of robust energy metrics for quantum computing, enabling direct comparisons with classical methods. Although current quantum hardware, particularly in the NISQ era, may not yet surpass classical emulation in energy efficiency, ongoing advancements in quantum algorithms and hybrid quantum-classical approaches offer promising pathways for energy savings. In the long term, the integration of fault-tolerant quantum computers with classical HPC systems, along with optimised resource allocation and technological innovations, will be essential for realising a quantum computing economic environment that is not only powerful but also sustainable[89].

Concrete applications of energy-aware quantum computing:

- **Quantum chemistry applications:** use quantum–classical hybrid workflows to reduce the energy cost of molecular-simulation.
- **Optimising transportation and logistics networks:** leverage energy-aware quantum scheduling to minimise routing and planning overhead.
- **Climate and materials modelling:** HPC–quantum platforms could dynamically allocate simulations between quantum and classical processors to lower total energy consumption.

Energy efficiency and sustainability issue: supercomputing vs quantum computing

While quantum computers have the potential to revolutionise many sectors, their current implementations result in expensive, specialised hardware requiring ad-hoc infrastructure and installation, which cannot realise personal, or even departmental, computing platforms. Therefore, current quantum computers must be remote-accessible computing resources, which are administered and owned by third parties. Currently, such infrastructure for quantum computing is limited, in both hardware and software, which makes it challenging to fully utilise the technology.

A promising solution to make quantum computing widely accessible is through cloud computing. In this model, quantum calculations will be performed in data centers, and the results will be delivered via the cloud. This approach enables the general public to benefit from quantum computing without the need for personal devices to handle complex quantum processes. The integration of quantum computing and classical computing in the cloud represents an exciting frontier in technology, with the potential to tackle problems that are currently beyond our capabilities and drive future innovation.

The convergence of quantum and classical computing in the cloud is expected to enhance computational power and the use of computing resources, and thus energy consumption. However, at least four mitigating factors can limit such an increase.

- This integration will allow software to determine the most efficient computing method—whether classical, AI, or quantum—for various parts of a computation. Users will benefit from this combined power without needing to engage directly in the intricate processes involved.

- In the long term, replacing supercomputers with quantum computers could help reduce the electricity demand in the sector, especially if quantum computing technology advances steadily in the direction of achieving a green advantage.
- Data centers are evolving to become more sustainable and efficient, including the transition to Hyperscale Data Centers. These facilities can support large-scale operations without a significant increase in electricity consumption. This shift is also financially beneficial, with the global market for Hyperscale Data Centers expected to double in size by 2026, compared to 2023, reaching a value of USD 212 billion.
- Finally, another area of promising research for decarbonising data center operations involves shifting electricity demand in time and location. Software developments are enabling operators to temporarily move power loads based on carbon-aware models, relocating data center workloads to regions with lower carbon intensity during selected times. This approach has the potential to improve operational affordability by reducing the costs associated with consuming low-emission energy by up to 34% around the clock. According to Google's 2023 Environmental Report, combining this methodology with other energy efficiency measures and on-site low-emission energy production has shown that data centers can achieve a 64% share of carbon-free energy in their total electricity consumption[90].

Digitalisation in Europe

Digitalisation is changing, and, in its broadest meaning, has always changed the way society faces its coming challenges. Although we are accustomed to viewing digitalisation as necessarily intertwined with computerised resources and workflows, in reality the present, mechanised form of digitalisation is the continuation of a centuries-long process which existed prior to computing devices and the Internet[91]. In this process, society repeatedly found in digitalisation the necessary support to evolve and control existing technologies, and to meet new demands and the additional challenges posed by them.

The Clean Energy Transition (CET)[92] requires an energy generation model in which many non-centralised sources will feed the energy mix and the producer-consumer (*prosumer*) concept will become a reality. Indeed, adopting the model entails managing distributed energy resources (DER), including distributed sources and storage systems, load variability and source availability, and enabling control and communication at the level of consumers. It thereby incentivises the broad diffusion of prosumers which schedule load, production and storage with a degree of autonomy[93] and contribute to the overall capacity as long as optimisation, e. g., to minimise capacity requirements, is feasible. In such a complex environment, prosumer-level optimisation, as well as the optimisation of DER placement and network flow, will only be possible via digital capabilities. Europe is reinforcing this vision at the highest level with the Letta's and Draghi's reports[94-96], which place digitalisation among the enabling transformations for Europe's decarbonisation and transition to net-zero by 2050, and for the enhancement of Europe's energy market's resiliency, besides emphasising its importance to the competitiveness of all sectors. The European Commission has launched a series of initiatives in which digitalisation is paramount for the CET, such as the Action Plan for the Digitalisation of the Energy Sector[97], the Pact for skills and their Large Scale Partnerships[98], or the Revamp of the SET Plan[99]. In all of them, digitalisation has emerged as a fully needed cross-cutting enabler and counts on specific task forces. Other major European actors, such as ENTSO-e, also count on specific actions for pushing digital developments. Notably, in the SET Plan, the European Technology and Innovation Platform Smart Networks for Energy Transition (ETIP SNET), in its R&I Implementation Plan 2025+[100], allocates resources to support research spanning multiple areas and facets of digitalisation, and mainly focusing on HPC and simulation techniques, Internet of Things (IoT) and sensorised environments, data science, artificial intelligence, cybersecurity, protocols, peer-to-peer interactions and blockchain. One of the ultimate goals is to develop a digital twin of the European energy grid, but the complexity and number of parameters that it will need pose significant challenges. The integration of the different digital capabilities in data-driven workflows is also a challenge itself. In this scenario, quantum computing can be a crucial step beyond to model this grid with the required accuracy, and to tackle the most computationally intensive challenges for its optimisation.

Research actions: What needs to be done

Cutting-edge research infrastructure to carry out extensive experimental work is an absolute necessity for research in both quantum computing and energy production and management. While such a necessity is indisputable in energy research, the dependence of quantum science and computing on an international, jointly developed, quantum computing research and development infrastructure becomes apparent if one analyses the unique features of the technology. Despite its enormous potential, quantum computing has seen limited adoption, its restricted use being due partly to the present limits of its technological state of advancement, partly also to its peculiar characteristics, which require a complex dedicated infrastructure and the concurrent evaluation of multiple quantum hardware architectures. To build momentum in applied quantum research, we must guarantee that quantum hardware is accessible to the widest possible range of private and public research communities, to enable the comparison of results, avoid redundancy, extend experimentation to diverse hardware architectures, and provide computational resources to higher TRL projects involving both academia and industry.

Significant initiatives have already been and are being undertaken to start addressing the needs of quantum computing as a whole, e. g., HPCQS, OpenSuperQ and OpenSuperQPlus, Quantum Flagship and QUCATS, EuroQCI, and EuroQHPC-Integration[101]. However, as with any new technology, additional initiatives and steps are required to make it effectively usable by application domain experts.

Interdisciplinarity and coordination are key to the success of research and development in energy production and management with quantum computing. The development of net-zero energy grids can be successful only if coordinated efforts are undertaken in multiple disciplines, such as chemistry, materials science, computer and information science and engineering, which are essential to face the challenges of the mass use of renewable sources of energy. Quantum computing itself is an intrinsically multidisciplinary research and innovation area, spanning physics, computational physics, and computer science, which requires a combination of actions across a wide range of technology readiness levels. In this paper, the opportunities for the solution through quantum computing of a variety of problems emerging in the development of net-zero grids have been highlighted. It is our belief that these opportunities can be seized only if coordinated research and development actions are carried out on a larger scale than is feasible for individual research institutions.

Fundamental interdisciplinary research

Any research on quantum solutions for computational problems in energy production and management can and will encompass applied components. However, the inherent complexity of energy-related challenges makes fundamental research essential to closely align the nature of these problems, the characteristics of the different quantum architectures, and the development of quantum algorithms capable of addressing them effectively. Consequently, adequate funding should be allocated to fundamental research projects of varying scale that promote interdisciplinary collaboration among specialists in the energy domain, quantum science, quantum computing, and computer science.

Pilot projects

For concrete applications of quantum computing to a sector as complex, specialised, and technical as the energy sector to be successful, the full involvement of a community of industrial partners is mandatory. Actions at the EU level could assign budget to fund larger projects that support the growth of small and medium companies of the quantum sector, through their involvement as providers of quantum computing in pilot projects and use cases, involving providers of energy technology and system operators. The projects could aim at slightly higher TRLs, e. g., aligned with the TRL range of a Horizon research and innovation action.

Training projects

Quantum computing is a computing paradigm totally different from the paradigms of classical computation. Thus, proficiency in the design, implementation, maintenance, and update of quantum computing applications requires a radically different set of skills. In applicative domains, a lack thereof would have very negative consequences on fairly assessing the technology and its returns, comparing it with classical approaches, building an open and objective mindset towards it, as well as keeping the pace with its rapid advancements. Actions at the national and European level could support educational activities that develop competences and skills in quantum computing the needed workforce must acquire.

Quantum software projects

From a user perspective, the success of classical computing in applications lies in the stunning multitude of known algorithms as much as in the power of the software abstraction layers that have been constantly developed and improved over more than six decades. This is the case even for numerical calculus applications, where the conceptual distance to the hardware level is smaller. In comparison, software engineering research in quantum computing is underdeveloped, both in absolute terms and in relation to the complexity of the hardware. European funding initiatives could dedicate resources to support the development of a quantum software stack that allows abstraction, specifically designed for engineering problems.

HPC-QC integration

Quantum hardware, in all its architectural variants, is prospectively viewed as a component of a set of complementary computational accelerators, which will be at the disposal of science and industry in the future. Current high-performance computing centres are already, and will continue, integrating quantum devices in their array of computing machines. Classical high-performance computing and quantum computing are not complementary only at the application level, where different applications can be implemented as either purely classical or purely quantum solutions. The structure of a complex application, such as the ones supporting energy grid management, is likely to be comprised of blocks that cannot be all implemented optimally in a single technology – resulting in a hybrid, integrated, HPC-QC application. EU projects could provide funding to research in HPC-QC integration, i. e., in the engineering and infrastructural support for the realisation of computational flows utilising both technologies in the most transparent way possible. This integration could involve using the modular supercomputing architecture in the first EU exascale supercomputer, which incorporates both quantum and neuromorphic modules.

Large-scale testbeds

Energy grids powered by fossil and renewable sources have generated a large amount of data in the last decade, much of which is now becoming available to energy research projects, to the purpose of virtually testing new materials, new energy production mechanisms, and assessing life cycles. Software applications as components of an energy grid can be tested on such data as well, deriving performance measures, both in runtime and in accuracy, in a variety of scenarios and operating conditions. The adoption of quantum computing in applications, as an alternative, or as an accelerator, calls for accurate testing and comparisons with classical counterparts, and adds multiple degrees of freedom to the design of experiments. Thus, there will be an urgent need for large-scale curated test datasets, specifically collected to test quantum and hybrid solutions to energy production and management problems.

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