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An overview of recent advances

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Review article

Quantum computation in power systems: An overview of recent advances

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ABSTRACT

Quantum mechanics (QM) can be understood as a set of rules that forms the basis for developing all quantum theories. One of these theories is quantum computation (QC), i.e., computation based on QM logic. It is believed that QC provides paths to the problem solution that may not be possible for classical computers. Therefore, it has received attention to solve complex computational problems in different areas. Most of the research efforts, however, have concentrated on problems in theoretical physics and computer science, leaving little attention to solve practical problems in industrial applications. This is particularly true in power system applications where QC is mostly unknown. This paper mainly aims to attract the attention of power system researchers/engineers to QC as a potential solution to address emerging computational challenges of power systems. To this end, the historical development of QC and its fundamental concepts are first described. Then, recent contributions to solving computationally-demanding power system problems such as AC and DC power flow (PF), contingency analysis, state estimation, electromagnetic transients simulation (EMT), fault diagnosis, unit commitment (UC), and facility location–allocation (FLA) problems are discussed. Unfortunately, power system researchers have not yet been able to convincingly demonstrate a quantum advantage in solving large-scale power system problems mainly because we are in the noisy intermediate-scale quantum (NISQ) era, where quantum devices are noisy and have limited quantum resources. However, it may be demonstrated in the future with technological advances and increased research efforts in the area.

Contents

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1. Historical development of QC

In the late 19th century and the early 20th century, classical physics theories were found to be incapable of explaining several phenomena, such as black-body radiation and the photoelectric effect, among others. The efforts that have been made for around a quarter-century to resolve these problems resulted in creating a revolutionary theory in the early 1920s, known as the modern theory of QM (Nielsen and Chuang, 2011).

The QM can be understood as a set of rules that forms the basis for developing all quantum theories. These rules are simple but counter-intuitive as they are not analogous to what humans often experience in everyday life. Two examples of such counter-intuitive properties are quantum superposition (i.e., an object has always an unknown state until measured) and quantum entanglement (i.e, two paired particles, regardless of their distance, have always opposite spines). Such properties are key principles of QC, i.e., computation based on QM logic.

The idea of QC was introduced in the 1970s. However, it received little attention until 1982, when Feynman (1982) reasoned in a conference that classical computers (two-state systems) may not tractably process computations involving quantum phenomena and conjectured the feasibility of using quantum systems to simulate other quantum systems. Around the same time, Benioff (1980) proposed the viability of quantum computers, i.e., computers that operate under established laws of QM.

By opening the doors to the quantum information world, researchers started to explore characteristics of algorithms that could be executed by quantum computers. For example, in his pioneering 1985 paper (Deutsch, 1985), David Deutsch explained how would a quantum algorithm (QA) look like, and developed one of the first QAs in collaboration with Richard Jozsa (Deutsch and Jozsa, 1992). This algorithm, called the Deutsch–Jozsa algorithm, could solve a computational problem (Deutsch's problem) more *efficiently*[1] than its classical solutions. Later, inspired by the work of Deutsch and some other researchers and by incorporating both entanglement and superposition, Peter Shor developed a QA that could efficiently determine prime factors of large integers (Shor, 1994). The significance of this discovery becomes clear when we consider that the security of many cryptographic protocols relies on the factoring problem's intractability to classical solutions. Further contributions to prove the potential power of quantum computers were made by Grover (1996), who demonstrated that a quadratic speedup in solving an unstructured search problem could be achieved by a QA.

In parallel with Shor, Grover, and other researchers who were trying to develop QAs, many scientists were working on developing Feynman's idea, i.e., the physical implementation of quantum computers. A few examples come in what follows. In 1998, for instance, a two quantum bit (qubit)[2] quantum computer based on nuclear magnetic resonance was invented to solve Deutsch's problem (Jones and Mosca, 1998). In 1999, Nakamura demonstrated that a qubit can be implemented using a superconducting circuit (Nakamura et al., 1999). Introducing the first experimental implementation of quantum error-correction (QEC)[3] in 1998 (Cory et al., 1998), demonstrating the first five photon entanglement in 2004 (Zhao et al., 2004), offering the first commercial quantum computer based on quantum annealing processors (known as D-Wave One) by D-wave in 2011 (Merali et al., 2011), and reaching quantum supremacy[4] by Google in a specific calculation in 2019 (Arute et al., 2019) are some other major milestones in the evolution of QC. The timeline of QC evolution is shown in Fig. 1.

All in all, QC is believed to be much more efficient than its classical counterpart in solving some problems. However, despite all developments in this area, QC is still in its early stages of evolution. While there is no consensus about the reasons behind this rather slow development, researchers often attribute it to one or more of the following reasons:

- QM rules, which form the basis for designing QC algorithms, are counter-intuitive. If we regard human intuition as an aid for the algorithm design, we are deprived of this aid in the QA design (at least in a part of the design procedure) as the human intuition is rooted in the classical world (Nielsen and Chuang, 2011).
- Some scientists hold pessimistic views on QC either because they believe useful fault-tolerant quantum computers may never be built (due to the enormous technical challenges), or because they think improvements in classical software and hardware will reduce/eliminate the potential computational advantage of QC (Dyakonov, 2019). This has probably discouraged some researchers from entering the field and caused a shortage of highly qualified personnel and researchers as we have in classical computing disciplines. However, this is changing.
- To be really interesting, QAs are often expected to be more efficient than their classical counterparts. It is, however, hard to achieve as it is not clear in what sort of problems they are more efficient.

Today, QC has received some attention in different applications, such as information security, simulation of quantum systems, machine learning, artificial intelligence, computational biology, drug design, battery chemistry, and power systems. The

[1] "Efficiently" here means in a practically relevant time that is not achievable by most advanced classical algorithms (CAs).

[2] Qubit is the basic unit of quantum information.

[3] QEC is a set of methods to protect quantum information from errors caused by quantum decoherence (loss of quantum coherence) and other quantum noise.

[4] Quantum supremacy means that a quantum computer may solve a problem (regardless of its usefulness) that is not solvable by any classical device within a reasonable time.

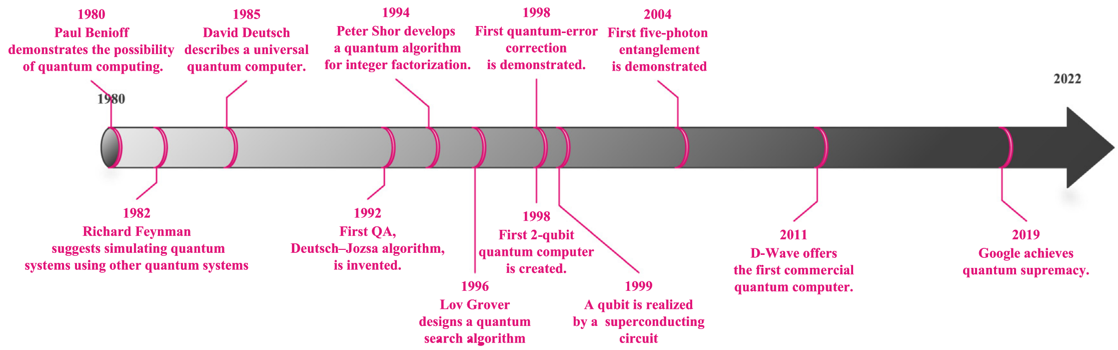

Fig. 1. Timeline of QC evolution.

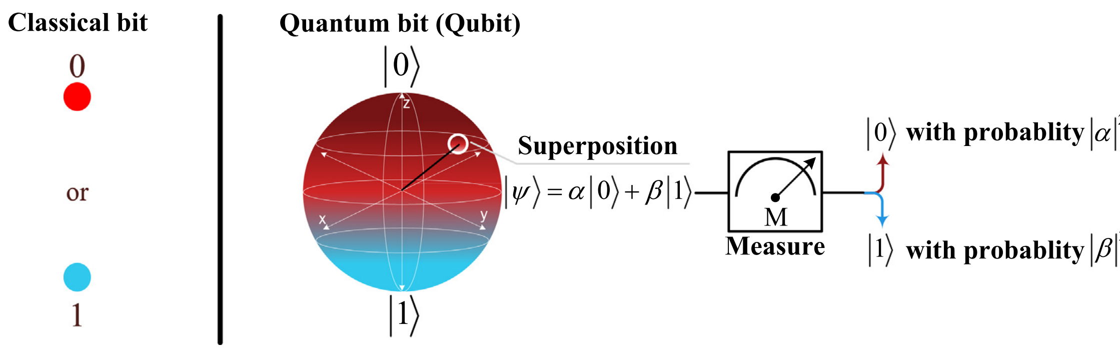

Fig. 2. Classical bit vs qubit.

main objective of this paper is to provide an overview of the recent progress of QC in solving power systems problems. To better understand all these, a brief study of the fundamentals of QC is necessary first.

2. Fundamental of QC

2.1. Central concepts

In classical systems, the bit is the most basic information unit for computations. It shows a logic state with two possibilities-either 0 or 1 at a time. Quantum information is based on a comparable concept, called a qubit. The difference is that a qubit, in addition to quantum states $|1\rangle$ and $|0\rangle$, which are corresponding to classical states 1 and 0, respectively, may also exist in a linear combination of them, i.e.,

$$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle\,. \qquad (1)$$

This is often called the superposition, which is a central concept in QC (Nielsen and Chuang, 2011) (see Fig. 2). Note that α and β are complex numbers, which determine the probability of having the quantum states $|0\rangle$ and $|1\rangle$, respectively. Therefore, $|\alpha|^2 + |\beta|^2 = 1$. Fig. 2 shows a visual representation of the qubit state space, which is a unit 2-sphere known as the Bloch sphere. Note that any state of a qubit corresponds to a point on the surface of the Bloch sphere. Note also that the state of a qubit is its private world access to which is strictly limited. The only way to acquire some information is through a measurement process, which gives the result $|0\rangle$ or $|1\rangle$ with the probability $|\alpha|^2$ and $|\beta|^2$, respectively. It means that the measurement disturbs the superposition state of qubits (see Fig. 2).

Another central concept in QC is quantum entanglement, which means quantum states of two or more particles/qubits are correlated. It implies that performing any action/manipulation on one of them affects the state of the others. Quantum entanglement is believed to be a unique resource in developing very fast QAs.

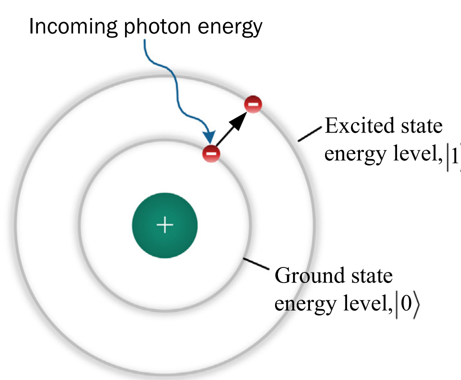

Fig. 3. A representation of qubit by two energy levels for an electron spinning around the nucleus.

Despite their counter-intuitive behavior, qubits are real and practically realizable. A good example is considering the ground and excited energy levels of an electron (orbiting around the nucleus of an atom) as the quantum states $|0\rangle$ and $|1\rangle$, respectively, and moving the electron between these energy levels by, for example, shining light on atom (see Fig. 3). Note that the light needs to have a suitable energy, and should be shinned for an appropriate time. Considering that the atom energy levels are discrete, shining light for a reduced length of time is likely to move the electron (initially at the ground state) to halfway of the energy levels $|0\rangle$ and $|1\rangle$, i.e., to a superposition state.

A natural question that may arise here is: how can QC lead to potentially extraordinary computing abilities? A reason possibly lies in quantum parallelism, which is a hypothetical concept. It is

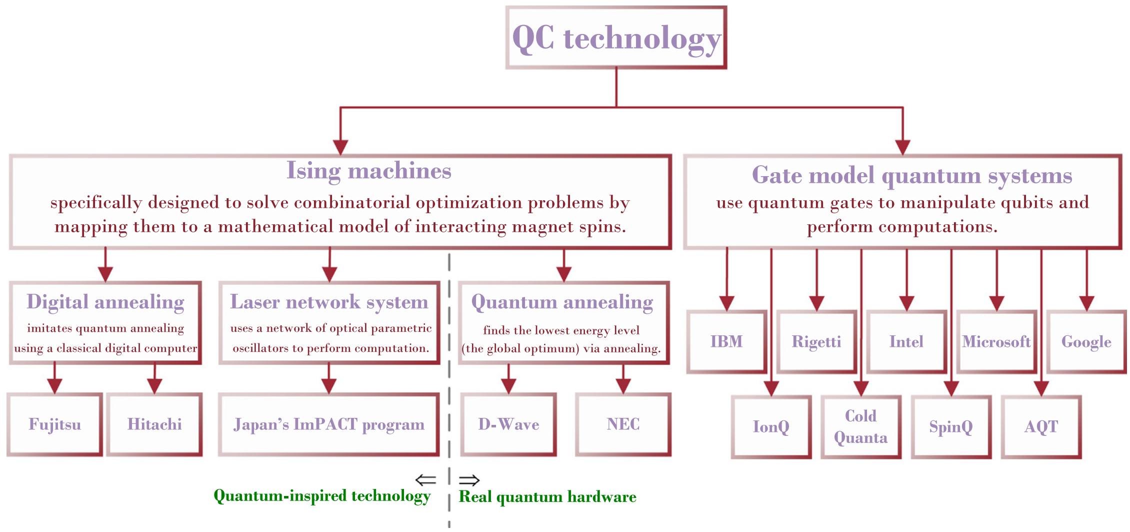

Fig. 4. QC technology.

speculated that the effect of applying an operator to a quantum superposition of states is equivalent to apply it to all states in parallel. Considering that an m-particles quantum system has 2^m quantum states, it is hypothesized that a small quantum device may act similar to a classic parallel device with 2^m processors in solving some problems. It should be mentioned here that some articles have questioned the reality of computational quantum parallelism (Lanzagorta and Uhlmann, 2008).

An alternative reason can possibly be the flexibility that QC may sometimes provide. For instance, we have no single-bit operation in classical computers that flips a bit when applied only twice. However, such an operation exists in quantum computers. When extend to a quantum system of many particles, such flexibilities are likely to provide paths to the problem solution that may not be possible for classical devices.

Interested readers are referred to Nielsen and Chuang (2011) for a more in-depth discussion of QC's central concepts and its computational potentials.

2.2. Hardware

Here, it may be interesting to briefly discuss different quantum architectures. As shown in Fig. 4, there are two main technologies: Gate model quantum systems and Ising machine systems. The gate model relies on quantum gates (as the building block of quantum circuits) to control the state of qubits and solve computational problems. The main challenge in this technology is building stable qubits and incorporating them into microchips. For instance, IBM and Google, which are pioneers in quantum gate technology, have made qubits of tiny superconducting metal resonator circuits. By having two distinct energy levels, which may be regarded as the quantum states $|0\rangle$ and $|1\rangle$, these circuits may ease into a quantum superposition state using microwaves. Such a state, however, is stable for a very short amount of time.

The second technology is Ising-machine systems (named after Ernst Ising), which are physical devices uniquely designed to solve complex combinatorial optimization problems (i.e., to find the best of many possible combinations). The basic idea behind these systems is mapping the optimization problem to an Ising problem (a mathematical model of interacting magnet spins), and using a physical device that can solve such problems (at least, a wide range of them). A pioneer in this technology is Canadian company D-Wave, which uses a process called quantum annealing to return low-energy solutions.

Quantum annealers, similar to gate-model quantum computers, rely on qubits. It means that they both need a cryogenic environment as thermal energy and its succeeding oscillations may disturb states of qubits and, therefore, adversely affect quantum operations. These technologies, however, have their own advantages/restrictions. For instance, quantum annealers are likely to show more robustness to noise than gate-based models. However, as mentioned before, they are restricted to combinatorial optimization problems and may not replicate the universality of gate-based architectures.

An alternative to real quantum technology is quantum-inspired technology. A notable example of this technology is the digital quantum annealer, which imitates quantum annealing using classical digital computers. Fig. 4 provides a brief description of this technology and shows companies/research programs active in this area.

All in all, we are still in the NISQ era, where the number of qubits on quantum devices (especially on the gate-model ones) is limited, and they are not stable enough and advanced enough to achieve fault-tolerance and sustainable quantum supremacy. Recent progress in terms of quantum computing hardware, however, is amazing. For instance, IBM has recently introduced its 127-qubit quantum processor named Eagle, which has twice the qubits of the previous flagship of IBM, i.e., the 65-qubit Hummingbird. Interested readers are referred to IBM's road-map for scaling quantum technology (Gambetta, 2020).

It should also be emphasized here that in addition to the companies highlighted in Fig. 4, there are many other hardware-focused companies working actively on developing QC technology, especially gate-model technology. Interested readers are referred to Dargan (2022) for a complete list of major players in hardware-focused QC technology as well as important start-ups in the area with promising intellectual properties.

2.3. Design aspects

As shown in Fig. 5, QC involves three main parts, i.e., quantum encoding, quantum processing, and quantum decoding. In what follows, these aspects are briefly described.

2.3.1. Quantum encoding

Executing any algorithm requires loading some input data in a format required for processing them. Therefore, executing QAs requires encoding classical data in qubits (Eskandarpour et al.,

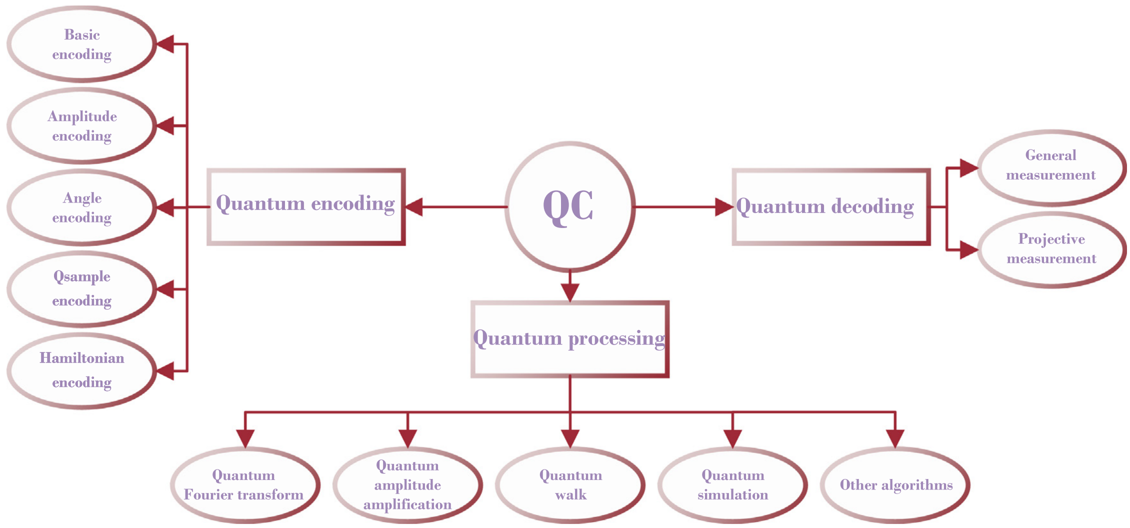

Fig. 5. Design aspects of QC.

2020a). To this end, the common trend is to initialize all qubits to $|0\rangle$ and apply a state preparation routine to change the initial state to the target one. Basic encoding, amplitude encoding, angle encoding, Hamiltonian encoding, and qsample encoding are some of the available methods for this purpose. Note that depending on the type of data encoding, a pre-processing in a classic computer may be required. Interested readers are referred to Weigold et al. (2020) to capture knowledge about different quantum encodings.

It needs to be emphasized here that quantum encoding is not trivial at all because, as mentioned before, qubits are stable for a short time. Therefore, operations required for the quantum encoding must be small. It implies that one has to find a satisfactory compromise between the loading process run-time complexity and qubits number. This fact limits the number of qubits that can be loaded for QC.

2.3.2. Quantum processing

Once the classical data is encoded in qubits, it needs to be processed. To this end, a QA is needed (Montanaro, 2016). Designing QAs has been an area of research for over 25 years. Therefore, a comprehensive overview of all existing QAs may not be possible in this paper. However, they can be divided into some major categories and briefly explained.

- Quantum Fourier Transform (QFT)-based Algorithms: QFT, which is the quantum counterpart of the discrete FT in classical systems, is a QA for computing the FT of a vector of amplitudes of a quantum state. The QFT may not provide a computational speedup over the classic FT. However, it is the key to quantum phase estimation (QPE), which makes us able to efficiently solve some problems. For instance, it is the core of the Harrow–Hassidim–Lloyd (HHL) algorithm, which is a QA to solve a set of linear equations (SLE) exponentially faster than CAs under certain conditions. In addition to solving an SLE, the QPE may also be used to efficiently solve the factoring, order-finding, period-finding, and discrete logarithm problems, which have no classical solution in polynomial order time (Montanaro, 2016; Nielsen and Chuang, 2011).
- Quantum Amplitude Amplification-based Algorithms: A quantum amplitude amplification algorithm (Brassard et al., 2002) is the quantum counterpart of classical probability amplification, and a generalization of Grover's quantum search algorithm, proposed for solving an unstructured search problem (Grover, 1996). It can be understood as a process that starts with a balanced superposition of states and amplifies the probability amplitude associated with the desired search element and simultaneously reduces all other probability amplitudes in every step, leading to a quadratic quantum speedup over classical search algorithms. It is a powerful subroutine that can be used in more complex QAs to efficiently solve some problems such as finding the minimum of a function, determining graph connectivity, pattern matching, quantum counting, and searching for crypto keys, among others.
- Quantum Walks-based Algorithms: A quantum walk can be understood as the quantum counterpart of the concept of random walk, in which a walker takes up particular states in some mathematical space and, due to the stochastic nature of transiting between states, a sort of randomness happen. In quantum walks, however, the randomness happens because of QM properties such as the superposition, and collapse of superposed quantum states by the measurement process. Quantum walks provide a powerful framework for designing fast QAs. For example, it can be applied for the fast evaluation of boolean formulae and achieving a computational speedup over CAs based on Markov chains (Montanaro, 2016).
- Quantum Simulation Algorithms: This class includes those algorithms developed for addressing the problem of computing dynamical properties of a quantum system, where no efficient CA for that exists. Note that simulating quantum mechanical systems using CAs involves exponential complexity. Quantum simulation has attracted attention in solving some problems, especially in low-temperature physics, quantum chemistry, and quantum field theory (Montanaro, 2016).

2.3.3. Quantum decoding

Once the quantum processing is finished, some useful information from quantum states needs to be extracted. It is, however, challenging because according to QM laws, when a quantum state is measured, a part of the information encoded in the quantum state is lost. Therefore, one has to design/use the right measurement method to extract the maximum possible information from quantum states.

It needs to be emphasized at the end of this section that the promised speedup of many QAs, including the HHL algorithm and quantum search algorithm, among others, relies on having access to a functional quantum random access memory (QRAM) (Giovannetti et al., 2008), which is a quantum counterpart of the classical RAM. A classical RAM includes a memory array, where each memory cell has a unique numerical address, and address and output registers. Initializing the address register with a cell's address returns the content of that memory cell to the output register. QRAM has the same functionality. The difference is that its address and output registers are quantum registers. It means they can be in a superposition of states, which allows accessing multiple memory locations simultaneously and processing data in parallel. Unfortunately, despite proposing different theoretical models for a QRAM, its physical implementation has not yet been achieved (Eskandarpour et al., 2020a; Weigold et al., 2021). Covering this gap in knowledge would be a great step towards achieving quantum advantage in solving complex computational problems.

3. Why QC in power systems?

Roughly speaking, electric grids are huge cyber/physical networks that connect thousands of electricity generation systems to millions of customers. Today, electrical grids are facing some serious challenges, which are expected to exponentially grow in the next two decades. One of these emerging challenges is the expansion of distributed and large-scale renewable energy-based power generation systems (especially based on PV and wind systems) in electrical grids to address environmental concerns of fossil-fuel-based electricity generators as well as the shortage of energy in the future. A second challenge is the ever-increasing growth in the electrification of new sectors because of its economical and environmental benefits. This is especially true in the transportation sector, where electric vehicles (EVs) with bi-directional PF capability are expected to support the electric grid during contingencies. The intermittent nature of renewable energy resources, which makes the electric grid more nonlinear and stochastic, and deploying a large number of EVs (acting as energy storage systems) suggest that extremely more measurement and data processing efforts are needed to maintain, process, and optimize the future grid (Eskandarpour et al., 2020a). The current computational algorithms/devices, however, may not be able to handle such an unprecedented stream of data. A solution to address this challenge is accelerating big data analytics by developing reduced-complexity mathematical models of electrical grids using techniques such as averaging, aggregating degrees of freedom, separating time scales, and linearization, among others. Such models, however, may not be very suitable for the next generation grid which, as mentioned before, is expected to be much more nonlinear and stochastic than today's grid. An alternative solution could be developing classical digital computers with much more processing power. Such supercomputers, however, consume huge amounts of electricity, nearly all of which are transformed to heat. For instance, Tianhe-2, a Chinese supercomputer with the peak performance of 54.9 petaflops, consumes around 18 MW of electrical power, causing a several million dollars annual energy cost. All this suggests that to maintain and process the future grid, new computational algorithms/models/platforms are needed. It is speculated that QC could be a key to satisfying this need. Note that quantum processors operate at near absolute zero temperature, where a superconducting state happens and, therefore, conduction losses and heat generation are nearly zero. Therefore, their energy consumption would be much lower than their classical counterparts (Brownell, 2019). For example, see Smelyanskiy et al. (2012, Fig. 12) for a summary of energy consumption and dissipation sources in 128-qubit and 512-qubit quantum computers by D-wave.

4. Recent advances of QC in power systems

Generally speaking, QC has received little attention in power systems. This section overviews recent advances in this area. It needs to be emphasized here that recent works have mainly focused on designing QAs and/or modifying available QAs to solve power systems problems.

4.1. Grid analytics

Power system analysis is important for planning and expansion purposes, understanding how the system operates under different conditions, and determining the best operating condition for the system (Li et al., 2022). Power flow (PF) studies, contingency analysis, state estimation, electromagnetic transients (EMT) simulation and analysis, and fault diagnosis are some key elements of power system analysis.

4.1.1. AC PF

An AC PF study is the investigation of the steady-state flow of active and reactive powers in various transmission/distribution lines of an interconnected network through numerically solving a set of nonlinear equations. This problem has been extensively solved using CAs in the literature (Nair et al., 2022). Among available classical options, the fast decoupled PF (FDPF) is particularly popular as it adopts constant Jacobian matrices and offers good computational efficiency. However, research efforts to speed up its solution for large-scale power systems are still required. To this end, the concept of AC quantum PF (QPF) algorithm has been presented by Feng et al. (2021). This concept mainly includes developing a quantum-state PF model based on the FDPF approach and using the HHL algorithm (Harrow et al., 2009) to solve it. The quantum circuit for the HHL algorithm can be observed in Fig. 6. The circuit includes five main parts (i.e., state preparation, QPE, ancilla qubit rotation, inverse QPE (IQPE), and measurement) and adopts three registers (a-register, c-register, and b-register), all initialized to $|0\rangle$. In the state preparation, the $N_b = 2^{n_b}$ components of the vector b are encoded as the amplitudes of basis states of n_b qubits in the b-register. Then, by using the QPE, a binary estimation of eigenvalues of the coefficient matrix A is provided and stored in n qubits of the c-register. Note that using more qubits in the c-register leads to a more accurate approximation of eigenvalues. The next step is the rotation of the ancilla qubit conditioned on eigenvalues stored in the c-register. When the ancilla qubit is measured, it collapses to either $|0\rangle$ or $|1\rangle$. $|0\rangle$ means that the solution may not be trusted and the process is repeated until we get $|1\rangle$ in the ancilla qubit output. This measurement is often carried out after the IQPE, as shown in Fig. 6. Note that the IQPE unentangles the b- and c-registers. Therefore, c-register sets back to $|0\rangle^{\otimes n}$ and b-register gives the solution $|x\rangle$. It is worth mentioning here that the run-time of the HHL algorithm is $\mathcal{O}(\frac{s^2\kappa^2}{\varepsilon}\log(N_b))$, where N_b is the number of linear equations, κ and s are the system condition number and sparsity, respectively, and ε denotes the accuracy of solution. Therefore, it is exponentially faster than the best-known CA for solving an SLE (i.e., the conjugate gradient algorithm), which runs in $\mathcal{O}(s\kappa\log(1/\varepsilon)N_b)$.

Through implementation on a noise-free quantum simulator, it is shown by Feng et al. (2021) that the HHL-based AC QPF may converge to the same solution as the classical FDPF in the same number of iterations (see Table I in Feng et al. (2021)). Unfortunately, no implementation on a real quantum device and no detailed discussion about possible challenges of the HHL-based AC QPF on NISQ devices are provided in Feng et al. (2021). However, the iterative nature of the QPF algorithm (see **Algorithm 1** and Fig. 1 in Feng et al. (2021)) and the lack of a quantum

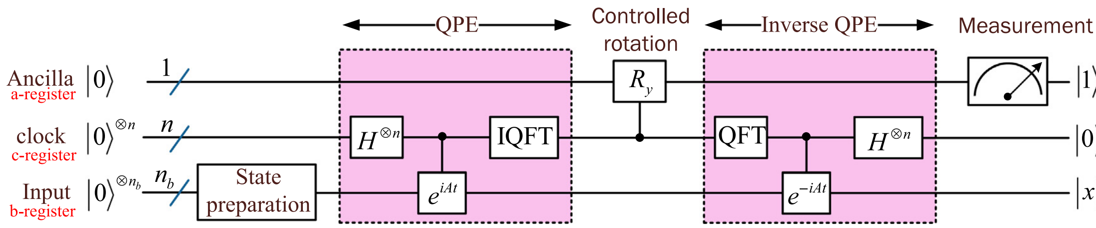

Fig. 6. Quantum circuit for the HHL algorithm to solve $A|x\rangle = |b\rangle$, which is the quantum-state representation of a classical SLE, $Ax = b$. A and b are both known. A is a Hermitian $N_b \times N_b$ matrix, and b is a N_b-dimensional vector. $N_b = 2^{n_b}$.

memory to store quantum states at the end of each iteration and perform logical operations prevents executing the whole HHL-based AC QPF within QC algorithm (see Feng et al. (2021, Fig. 1)) and achieving quantum advantage. Note that in this situation the full solution vector needs to be extracted in every iteration, which requires a running-time of at least $\mathcal{O}(N_b)$ (Aaronson, 2015; Sævarsson et al., 2022), eliminating computational advantages of the HHL-based QPF over classical solutions.

To provide a better understanding of its challenges, a careful investigation of the HHL-based AC QPF algorithm on real IBM quantum computers is conducted in Sævarsson et al. (2022). It is verified that the HHL-based AC QPF may converge to the same solution as the classical FDPF on noisy quantum hardware. The challenge is that it requires a much larger number of iterations to converge. It means that the presence of noise adversely impacts the convergence speed of the HHL-based AC QPF. An inaccurate estimation of eigenvalues by the HHL algorithm (for example, due to having a limited number of qubits for storing eigenvalues in the c-register) may cause further convergence delay. The above observations suggest that the HHL-based AC QPF is facing serious scalability issues on current noisy quantum hardware mainly because the quantum circuit depth and, therefore, the impact from the noise considerably increases with the system size. Note that even for small-size problems, the HHL algorithm requires deep quantum circuits. A possible solution to deal with this challenge could be removing unnecessary quantum parts of the HHL algorithm and processing a part of information with a classical computer to achieve a shallow-depth quantum circuit and, therefore, mitigate quantum noise on NISQ hardware (Lee et al., 2019). However, further investigations to ensure efficiency of such hybrid schemes are required.

4.1.2. DC PF

A classical solution to speed up AC PF calculations is neglecting transmission losses and reactive PF, and considering only active PF in the network. In this way, a simplified AC PF problem (known as the DC PF problem) is obtained, which its solution is less accurate, but non-iterative and always convergent. The DC PF problem has been extensively solved using CAs in the literature. However, to deal with its growing size and time sensitiveness, research efforts to speed up its solution are still ongoing. To this end, an HHL-based QA is designed by Eskandarpour et al. (2021, 2020b), and verified on a small test system using a gate-model quantum simulator and a practical quantum computer. It is shown that the noise-free quantum simulation promises finding an accurate solution. However, the implementation on a practical quantum hardware fails to achieve the same accuracy because of the noise impact. Considering that the number of quantum gates (the quantum circuit depth) and, therefore, the noise impact exponentially grows with the system size, it can be concluded that the HHL-based DC QPF algorithm has serious scalability issues on noisy quantum computers. An imperfect QPE (for instance due to an ill-conditioned admittance matrix) may aggravate the situation. Note that an ill-conditioned coefficient matrix has a large condition number, i.e., a large difference between the largest and smallest eigenvalues. Therefore, with limited qubit resources in current quantum hardware, an accurate QPE (eigenvalue calculation) is hard to achieve. A possible solution to deal with this challenge is transforming the original SLE to a new set with a smaller condition number (Saad and Van Der Vorst, 2000; Chen, 2005). An alternative solution could be using a modified QPE scheme in the HHL algorithm to get rid of the influence caused by the ill-conditioned part of the admittance matrix (Harrow et al., 2009). A hybrid quantum–classical algorithm (HQCA) with a reduced quantum circuit depth and a reduced number of qubits could also sometimes be beneficial (Gao et al., 2022).

4.1.3. $N - k$ Contingency analysis

Another vital study in power system analysis is contingency analysis. It is a "what-if" scenario that investigates the effect of any contingency, e.g., lines/generators outages, on the power system and provides information about the grid security (Khaitan and McCalley, 2014). Currently, the grid contingency analysis mostly relies on the $N - 1$ criterion, which states that the grid security should be guaranteed if one grid component is intentionally/unintentionally disconnected (Yang and Nagarajan, 2020). However, by growing the number of natural disasters as well as the movement toward a lower-carbon future grid, a higher-order ($N - k$, $k > 1$) criterion in the grid security analysis is needed (Javanbakht and Mohagheghi, 2014). Such a criterion involves considering $\binom{N}{k} = \frac{N!}{k!(N-k)!}$ contingency scenarios which, depending on the value of k and the power system size, may be extremely computationally demanding and, therefore, not possible to solve in a reasonable time using classical algorithms/computers. Note that, for any possible contingency scenario, solving a DC or AC PF problem is often needed. For instance, considering $N - 3$ criterion in a power system with 500 transmission lines and generators ($N = 500$) is corresponding to 20,708,500 contingency scenarios. To deal with this challenge, solving PF problems using an HHL algorithm is suggested by Eskandarpour et al. (2020c). No simulation/experimental results are provided by Eskandarpour et al. (2020c). As discussed above, the HHL-based DC and AC QPF in the NISQ era are already facing several challenges to achieve quantum advantage mainly because the depth of HHL quantum circuit (and therefore the noise impact) grows significantly with the system size. Therefore, their application to analyze and enhance grid security is only attractive in future noise-free quantum computers.

4.1.4. State estimation

The static-state estimation is a vital element in all energy management systems, and a basic tool to ensure power system reliable operation. It is often defined as a signal processing effort to transform noisy metering measurements and pseudo-measurements to an estimate of the power system's static-state, i.e., the steady-state vector of phase angles and magnitudes of voltages at all network buses (Abur and Exposito, 2004).

Probably, the most popular algorithm for the power system state estimation is the weighted least squared algorithm, which minimizes weighted quadratic distances between a set of measurements and power system's states. This algorithm involves the iterative solution of an SLE, which is very computationally demanding in large-scale power systems. To deal with this computational challenge, using the HHL algorithm is proposed by Feng et al. (2022b). A preconditioner is also presented by Feng et al. (2022b) to tackle the ill-conditioned coefficient matrix issue. The challenges of applying the HHL algorithm and their possible solutions were discussed before.

4.1.5. EMT simulation

In recent years, especially with the proliferation of power converter interfaced renewable energy resources in power systems, which results in a so-called low-inertia power system, EMT simulation and analysis have become increasingly more important to understand how power electronic-based power systems operate, explain equipment failures, and test protection devices. A full EMT simulation of large power systems, however, is a great computational challenge even for powerful commercial simulators with multi-core processors. To better understand this challenge, let us take a quick look at the basic formulation of the Electromagnetic Transient Program (EMTP). In this formulation, differential equations of each component (e.g., an RLC load or an electrical machine) is discretized at each time step and transformed to an equivalent resistance as (2), where k denotes the current sample, v and i are respectively the nodal voltage and current, g is the equivalent conductance, and i_h denotes history terms represented by a current source.

$$i(k) = g v(k) - i_h(k) \tag{2}$$

For instance, consider an ideal inductor, which is described in the continuous-time domain as $v(t) = L\frac{di(t)}{dt}$. If we discretize this differential equation using the trapezoidal method, we get

$$i(k) = \underbrace{\frac{T_s}{2L}}_{g} v(k) + \underbrace{\frac{T_s}{2L} v(k-1) + i(k-1)}_{-i_h(k)} \tag{3}$$

where T_s is the sampling time. Consequently, at each time step, a power system described by a set of nonlinear differential–algebraic equations may be represented by a network of equivalent resistors described by

$$\boldsymbol{G}(k)\boldsymbol{v}(k) = \boldsymbol{i}(k) \tag{4}$$

where $\boldsymbol{v}$ and $\boldsymbol{i}$ are the nodal voltage and current vectors, respectively, and $\boldsymbol{G}$ denotes the equivalent conductance matrix. (4) is an SLE, called discrete-time nodal equations, which needs to be solved iteratively at each time step by EMTP to determine the nodal voltage vector. However, it is a challenging task in large power systems as the computational complexity scales polynomially with the system size. To deal with this challenge, the concept of quantum EMTP (QEMTP), which is based on using the HHL algorithm to iteratively solve linear nodal equations, is proposed by Zhou et al. (2021). A proof of concept using noise-free quantum simulations is also provided by Zhou et al. (2021). The QEMTP concept, however, is facing several challenges as those discussed for the AC QPF on noisy quantum hardware. To enable a quantum EMT simulation on NISQ devices, the concept of noisy intermediate-scale QEMTP is presented by Zhou et al. (2022). The key idea is to use a shallow-depth variational quantum linear solver (VQLS) (Bravo-Prieto et al., 2019) instead of the HHL algorithm to solve nodal equations. Generally, variational QAs (VQAs) are the practical embodiment of this idea that quantum computers may be trained in a similar way as we train neural networks. Therefore, they can be seen as quantum counterparts of classical machine-learning (CML) techniques (Cerezo et al., 2021). A VQA basically includes a fixed-architecture parametrized quantum circuit (often called ansatz, which means an educated guess), a quantum measurement used to estimate a cost function, and a classical optimizer that aids to minimize the cost function by adjusting the parameters of ansatz. This process is repeated many times so that the cost function value is minimized. Hence, a VQA is basically an iterative HQCA. The VQLS works based on the same concept described above to solve the quantum representation of (4), i.e., $\boldsymbol{G}\left|\boldsymbol{v}\right\rangle = \left|\boldsymbol{i}\right\rangle$. Basically, it looks for variationally prepared $\left|\boldsymbol{v}\right\rangle$ so that $\boldsymbol{G}\left|\boldsymbol{v}\right\rangle$ is proportional to $\left|\boldsymbol{i}\right\rangle$. To this end, it uses a cost function that quantifies the distance between $\boldsymbol{G}\left|\boldsymbol{v}\right\rangle$ and $\left|\boldsymbol{i}\right\rangle$ at each time step and penalizes us when $\boldsymbol{G}\left|\boldsymbol{v}\right\rangle$ has a component orthogonal to $\left|\boldsymbol{i}\right\rangle$ because we need $\boldsymbol{G}\left|\boldsymbol{v}\right\rangle \propto \left|\boldsymbol{i}\right\rangle$.

The variational nature of the VQLS and its shallow quantum depth may mitigate error on noisy quantum circuits and, therefore, allow the implementation on NISQ devices. The verification of the noisy intermediate-scale QEMTP concept presented by Zhou et al. (2022) on a real IBM quantum hardware supports this fact. However, theoretically speaking, the VQLS offers a much less computational speedup in solving an SLE compared to the HHL algorithm.

4.1.6. Transient stability assessment (TSA)

Transient stability is often described as the ability of a power system to return to a stable condition after occurring a large disturbance. It implies that interconnected power systems rely on TSA for a resilient and reliable operation. Classical TSA methods are mostly based on explicit/implicit integration of a set of differential–algebraic equations, which model the dynamics of interconnected power systems. This task, however, is very computational demanding in large-scale power systems. The intermittent nature of renewable energy resources and unknown models caused by data privacy issues even make it more computationally expensive. To deal with these challenges, artificial intelligence-based TSA methods have received attention these years. The application of quantum machine learning (QML) could contribute to this trend (Zhou and Zhang, 2022).

Generally speaking, QML explores the interaction between QC and ML to see how findings/techniques of one area could be employed to address the computational challenges of the other. In recent years, considerable developments in both directions have been reported in the literature (Dunjko and Briegel, 2018). For instance, QC could be efficient to improve the time complexity of classical ML (CML) tasks as they often involve computationally-demanding subroutines which may be solved faster using QAs. Conversely, cutting-edge technologies of CML may be helpful in quantum experiments and advanced quantum technologies. QML is believed to be one of the most promising applications of QC for forecasting, classification, and clustering. However, its development is still facing many technical challenges and the majority of research in this new area is still theoretical and conceptual. In power systems applications, QML mainly aims to achieve quantum speed-up in data analysis.

In Zhou and Zhang (2022), a confluence of ML and QC to *potentially* address TSA issues in bulk power systems is proposed. A distinguishing feature of the quantum TSA (QTSA) compared to CML algorithms is that it embeds transient stability features into quantum states through a trained shallow-depth variational quantum circuit (VQC), where stable/unstable samples are explicitly separated in the Hilbert space. A quantum natural gradient algorithm, which is able to search the steepest descent direction in the output space, is deployed to efficiently train the VQC. Thanks to its variational nature and its shallow quantum depth, QTSA exhibits resilience to noisy quantum environments. This fact was demonstrated by Zhou and Zhang (2022) by running QTSA on real IBM quantum computers and noise-free quantum simulators and comparing their results. It was also demonstrated that QTSA provides a comparable accuracy compared to CML-based TSA methods. The authors, however, could not demonstrate quantum advantage compared to classical ML-based TSA methods.

4.1.7. Fault diagnosis

Because of the ever-increasing energy demand without sufficient investments to increase generation, transmission, and distribution capacities, power systems often operate near to their limits. Therefore, fault detection and analysis plays an important role to detect the source and cause of damaging disturbances and prevent failures and blackouts in power systems. To this end, extensive research efforts have been made in the literature to develop fast and accurate fault detection and classification algorithms. Among different options, hybrid approaches are particularly interesting as they combine state-of-the-art feature extraction models (such as the restricted Boltzmann machine (RBM) and conditional RBM (CRBM)) with efficient classification space. A challenge of such hybrid models is developing fast and efficient training methodologies with possibly limited data volume for training. To deal with this challenge, a hybrid quantum–classical deep learning framework to identify faults in power systems is proposed by Ajagekar and You (2021b,a). This framework uses a CRBM network to extract desired features from input data. To avoid the large computational cost of classical training methodologies, a QC-assisted training strategy is then developed to train the CRBM network. The reliability and efficiency of this QC-assisted deep learning framework are demonstrated by applying it to a standard IEEE test system. The obtained results demonstrate that the QC-assisted fault diagnosis framework could often outperform its state-of-the-art classical counterparts (like artificial neural networks and decision trees with low missed detection rate) by providing much lower false alarm rates and shorter response time.

4.2. Grid optimization

In power applications, optimization problems are widespread as without optimal use of available resources, many new technologies may not be cost-effective. In classical systems, metaheuristics algorithms are popular for solving these problems. However, with fast-growing the complexity and size of optimization problems, more efficient algorithms to speed up calculations are needed. To this end, some quantum-inspired algorithms (QIAs) have been developed (Arrazola et al., 2019; Montiel Ross, 2020; Chung et al., 2011). These algorithms are basically some intelligent algorithms that run on a classical computer, and solve optimization problems by emulating QM concepts/principles. Lacking implementation on a real quantum computer implies that achieving a quantum advantage using these algorithms is unlikely. However, some degrees of speedup under stringent conditions may be achieved (Arrazola et al., 2019).

Recently, QC has attracted attention to solve some power system optimization problems. These applications are briefly discussed in what follows.

4.2.1. Unit commitment (UC) problem

Power systems need to decide how to meet varying electricity demand so that the total profit from electricity production is maximized while all physical and operating constraints are satisfied. To this end, we are facing some optimization problems. One of them is the UC problem, which is the process of deciding the schedule of generating units to minimize the generation cost, subject to operating constraints. Solving this problem, however, is very difficult because we may have many generation units of different types and, therefore, with different energy generation costs and operating constraints. These units may also be distributed over a large geographical area, which implies the response of the power network to generating units' start-up and shut-down also needs to be taken into account. The complexity of the UC problem is expected to considerably increase in the future with the increased penetration of intermittent renewable energy resources into power systems. To deal with its computational challenge, adapting quantum approximation optimization algorithm (QAOA) to solve the UC problem is proposed by Koretsky et al. (2021). This idea will be explained after a brief description of the QAOA.

The QAOA is a variational algorithm (i.e., a hybrid algorithm including a parametrized quantum circuit, a quantum measurement to estimate a cost function, and a classical optimizer to adjust/optimize the quantum circuit's variational parameters) designed for solving quadratic unconstrained binary optimization (QUBO) problems (i.e., problems with a quadratic objective function and without any variable constraint). Note that the QAOA does not give the optimal solution. It just gives a good-enough solution characterized by a lower limit of the approximation ratio.

The key idea to solving the UC problem in Koretsky et al. (2021) is converting an UC problem (which involves some constraints) into a QUBO problem, where some penalty terms are included in the QUBO objective function to get rid of the UC problem's constraints. The QAOA is then employed to translate the QUBO instant to a continuous optimization problem over variational parameters of the quantum circuit, which is optimized simultaneously by a classical optimizer. The correctness and potential of this HQCA are demonstrated using some noise-free quantum simulation results (Koretsky et al., 2021). This work is a valuable contribution to push the frontier in solving power system optimization problems using VQAs. However, the lack of implementation on a real quantum computer suggests that it will probably face some challenges not seen in simulation studies. Besides, it is still unknown if the QAOA may actually outperform classical solutions in solving combinatorial optimization problems.

A different QA to solve the UC problem has been proposed by Ajagekar and You (2019). This algorithm, which is developed for quantum annealing machines and tested on a D-wave quantum computer, handles the mixed-integer nature of the decision variables in the UC problem by discretizing continuous ones. Note that discretizing continuous variables in this quantum annealing algorithm (QAA) is expensive from a gate-count point of view (Koretsky et al., 2021). Unfortunately, just mediocre results on a small-scale test system were obtained and quantum advantage could not be demonstrated by Ajagekar and You (2019). This issue is mainly attributed to the quantum noise, which adversely affects the solution quality.

Because of limited qubit resources, solving large-scale power systems UC problems on current NISQ devices is not possible. To deal with this challenge, a decomposition and coordination framework is proposed by Nikmehr et al. (2022), Feng et al. (2022a). The key idea of this framework is the decomposition of large-scale UC problems into some smaller subproblems solvable by NISQ hardware and the coordination of distributed subproblems to obtain feasible solutions. The QAOA is adopted to solve these subproblems. With the same motivation as Nikmehr et al. (2022) and Feng et al. (2022a), decomposing large UC problems into three subproblems (a QUBO problem and two non-QUBO problems) and using the QAOA and a classical optimizer to respectively solve QUBO and non-QUBO problems are proposed by Mahroo and Kargarian (2022).

4.2.2. Facility location–allocation (FLA) problem

FLA problems are critical parts of any energy system strategic design and planning. Generally, an FLA problem is a strategic decision problem concerned with determining the optimal number of facilities to be set up and the best location for them so that construction/operation/transportation costs are minimized and some constraints are respected. Some energy system optimization problems could also be formulated as an FLA problem. An example of such problems is the quadratic assignment problem, which is a combinatorial optimization problem subsumed under the category of facility location problems. In the context of grid optimization, a QAA to solve a quadratic assignment problem for 3 to 20 facilities and candidate locations is presented by Ajagekar and You (2019). This algorithm is implemented on a real D-Wave quantum computer (D-wave 2000Q) and its results are compared with those of a classical solver run on an Intel Core i7 CPU. It is demonstrated that the run-time of the classical solver grows exponentially with the problem size and reaches a time-out limit (12 h) without giving a solution for problems with more than 14 facilities. It is, however, not the case for the quantum solver, and a quantum advantage is observed for large problems (see Ajagekar and You (2019, Table 2)). For instance, the run-times of classical and quantum solvers for the problem with 14 facilities are approximately 42,010 and 1008 s, respectively, which makes the quantum solver almost 42 times faster than the classical solver. This quantum advantage, however, may be challenged by some classical algorithms/computers customized for the problem under study. This fact does not undermine the importance of contributions made by Ajagekar and You (2019). It just suggests that QC is at its early developmental stages.

In Jones et al. (2020), the viability of D-wave quantum hardware to solve the optimal PMU placement (OPMUP) problem has been investigated. This work will be described after a brief description of the OPMUP problem. If we have the voltage and current phasors at all buses of a power system in a GPS-synchronized manner, the entire power system state can be reconstructed. These synchronously measured phasors, called synchrophasors, are measured/estimated by PMUs. Note that there is no need to place a PMU at every bus to have full observability as PMUs can estimate synchrophasors of their adjacent buses. It implies that we face an optimization problem to minimize the number of PMUs (and therefore the cost) for a given power system topology while ensuring full observability of the entire power system (Gou, 2008; Nazari-Heris and Mohammadi-Ivatloo, 2015). In Jones et al. (2020), as mentioned above, solving the OPMUP problem using D-wave quantum annealers has been explored. To thin end, the OPMUP problem was first formulated as a dominating set problem. It was then reformulated as a quantum Hamiltonian operator and implemented for the solution on a D-wave 2000Q quantum annealer. The solution quality and time were finally benchmarked against CPLEX and simulated annealing, which are some classical optimizers. It was observed that the D-wave 2000Q quantum annealer could outperform the classical optimizer CPLEX in some instances. These observations, which are consistent with those made by Ajagekar and You (2019), do not convincingly demonstrate the quantum advantage. However, they suggest that adiabatic quantum annealing holds a great potential to outperform classical optimizers in solving complex combinatorial optimization problems.

A summary of recent QC developments to solve power system problems can be observed in Table 1.

5. Potential research areas

While developments of QC in grid analytics and optimization are in progress, there are many areas where QC may have a great potential. A few notable examples are highlighted in what follows.

5.1. Battery development

In power grids, energy storage systems (ESS) are key elements to deal with the intermittent nature of renewable energy resources (Massucco et al., 2021). Investigations show that reaching carbon neutrality by 2050 (according to the Paris agreement) demands to manufacture and install a large amount of reliable and low-cost ESSs, especially batteries, faster than ever before (Ho et al., 2018). Currently, the main challenges of using batteries in power grids are their limited capacity/charge speed and their high cost. Batteries in electric vehicles suffer from the same limitations. Considering that the performance and cost of batteries are directly related to their component materials, developing more efficient computational models to predict/reach better materials/designs for batteries are needed. Such models are mostly based on the solution of Schrödinger's equation, which is a complex computational task. Among different approaches to solve Schrödinger's equation, density functional theory (DFT) calculations are particularly popular. However, some limitations of DFT, especially its limitation to model processes/systems with large variations in electronic structure, have caused some obstacles in investigation areas crucial for battery technology advancement. It is speculated that quantum computing approaches could improve strengths and mitigate shortcomings of DFT and help the industry to develop better batteries.

5.2. Weather forecast

Movement towards a lower-carbon future grid highly depends on improving weather forecast ability (Aslam et al., 2020). The reason is that the future grid will mainly rely on wind and solar resources, which have an intermittent nature. Therefore, a continuous supply of energy involves having more accurate weather prediction, which is a very challenging task using classical computers/models as a huge amount of data needs to be analyzed/processed. It is speculated that some VQAs, called quantum neural networks in the literature, may significantly help towards addressing this difficulty (Gurwinder, 2009).

5.3. Decentralized asset management

In the grid of the future, the flow of energy will not be one-sided from centralized generating plants to customers. In fact, it is expected that domestic customers and small-scale companies will also sometimes supply the grid. In the future, electric vehicles are also expected to act as a flexible energy storage medium thanks to their batteries and support the grid during contingencies (Borray et al., 2020). The coordination and management of such a large number of generation and/or storage systems in the grid of the future demands a huge processing power. QC systems are expected to significantly contribute to address this challenge.

5.4. Customer analytics

In energy applications, customer analytics refers to the procedure for gathering customers' data, for example through smart electrical meters, and processing them to make more-informed business decisions and satisfy customers' needs/preferences in a timely manner. This process, which is very computationally demanding, requires much further development in the interdisciplinary field of quantum artificial intelligence. Quantum machine learning is speculated to be a key to solve this challenge. Considering the current development pace, adapting customer analytics to quantum is anticipated to take a decade or more.

Table 1
A summary of recent QC advances in solving power system problems. Sim.: simulator. a/o: and/or.

	Problem	Algorithm	Validation platform	Impact	Challenge
Grid analytics	AC PF (Feng et al., 2021; Sævarsson et al., 2022)	HHL	IBM-Q: Sim. a/o real devices	Potential exponential speedup in future noise-free quantum computers	1-Need for quantum memory to perform iterative HHL-based algorithms within QC and achieve computational speedup 2-Need for more shallow-depth quantum circuits to mitigate noise impact and scalability issues on NISQ devices 3-Need for a matrix preconditioning and/or filtering functions to address computational issues caused by ill-conditioned power systems
	DC PF (Eskandarpour et al., 2021, 2020b)	HHL	IBM-Q: Sim. a/o real devices		
	Contingency analysis (Eskandarpour et al., 2020c)	HHL	–		
	State estimation (Feng et al., 2022b)	HHL	IBM-Q: Simulator		
	EMT simulation (Zhou et al., 2021, 2022)	HHL	IBM-Q: Simulator		
		VQLS	IBM-Q:Sim. & real devices	Noise resilience on NISQ devices	Much less computational speedup compared to the HHL algorithm
	QTSA (Zhou and Zhang, 2022)	QML	IBM-Q: Sim. & real devices	Noise resilience on NISQ devices and comparable accuracy compared to CML algorithms	Proving quantum speedup compared to CML algorithms is challenging.
	Fault diagnosis (Ajagekar and You, 2021b,a)	QML	D-Wave 2000Q	Potential computational efficiency compared to CML algorithms	Promised computational efficiency is application-specific and hardware-dependent.
Grid optimization	UC (Chung et al., 2011; Koretsky et al., 2021; Ajagekar and You, 2019; Nikmehr et al., 2022; Feng et al., 2022a; Mahroo and Kargarian, 2022)	QIA	Classical computers	Some degrees of computational speedup under stringent conditions	Quantum advantage may not be achieved
		QAOA	IBM-Q: Simulator	Noise resilience on NISQ devices	1-QAOA does not provide the optimal solution. 2-It is unknown if QAOA may actually outperform classical optimizers.
		QAA	D-Wave 2000Q	Mediocre performance in small-scale case studies	Need for more efficient error correcting schemes to improve the algorithm performance
	FLA (Ajagekar and You, 2019)	QAA	D-Wave 2000Q	Possible exponential speedup over CAs in some instances	Reduced solution quality by increasing the problem size

6. Discussion and conclusion

After a description of the historical development of QC and its fundamental concepts, an overview of recent QC advances in solving power systems problems was provided. We made the following observations:

- The majority of recent developments are based on applying the HHL algorithm, which is theoretically able to solve an SLE exponentially faster than state-of-the-art classical solvers. However, power system researchers/engineers have not yet been able to show this quantum advantage because of one or more of the following reasons:
  (1) Most of the HHL-based QAs in power system applications (e.g., HHL-based AC QPF or HHL-based state estimation) have an iterative nature to solve an SLE. The lack of quantum memory to store quantum states at the end of each iteration and perform logical operations prevents executing the whole HHL-based algorithm within QC and achieving quantum advantage.
  (2) The HHL algorithm needs deep quantum circuits (i.e., a large number of quantum gates) even to solve small-size problems. Therefore, its performance is adversely affected because of the noise effect on current NISQ devices.
  (3) The HHL algorithm has serious scalability issues on noisy quantum hardware because its quantum circuit depth and, therefore, the noise impact considerably grow with the problem size.
  (4) An ill-conditioned coefficient matrix reduces the computational advantage of the HHL algorithm compared to its classical counterparts.
- Variational algorithms proposed to solve power system problems are noticeable. The variational nature of these algorithms gives them some noise resilience properties, making them useful for the implementation on NISQ devices. However, there are still many hardware and algorithmic limitations. For instance, to enable reliable implementation on NISQ devices, the state preparation circuit should have a shallow depth. Besides, to enable efficient energy minimization, the number of variational parameters should be small, otherwise it may lead to an intractable optimization problem. It should be emphasized here that it is still unknown if VQAs may actually outperform classical solvers. There are some examples (mostly in computer science) where a VQA designed to solve a specific problem could outperform best-known classical solvers, but it was beaten later by developing more efficient classical algorithms.
- A very few QAAs to solve power systems optimization problems may be found in the literature. In some cases, a quantum advantage is observed. However, they are mostly application-specific/hardware-dependent, meaning that they could be high-probably challenged by classical algorithms/hardware customized for the problems under study.

All in all, power system researchers/engineers have not yet been able to ***convincingly*** demonstrate the quantum advantage in solving power system problems mainly because we are in the NISQ era, where quantum hardware is noisy and have limited quantum resources. Their research efforts and outcomes, however, are still extremely valuable as they pave the way for further contributions and developments in the area.

It sounds unlikely that a major deployment of QC to solve operational power systems problems happens in the next few years because QC is still at the early development stage. However, some speculations about the timeline of availability of different QC technologies and using them to solve grid problems can be made. For example, to solve power systems optimization problems, reliable quantum annealing technology is speculated to be available in short term. However, VQAs (for example, VQLS and especially QAOA) seem to require more technological advances for deployment. Finally, deep quantum circuits (e.g., the HHL algorithm), which require fault-tolerant quantum computers for deployment, seem to be far away from the demonstration phase.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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