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A Review of Quantum Computing Technologies in Power System Optimization

March, 2025

Yousu Chen

Long Vu

U.S. DEPARTMENT OF ENERGY

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Summary

As modern power grids increasingly integrate variable renewable generation, distributed energy resources, and energy storage systems, classical optimization techniques are facing unprecedented challenges. This review examines the emerging application of quantum computing to overcome these challenges in power system optimization, including optimal power flow (OPF), unit commitment (UC), economic dispatch (ED), and intelligent switching and topology optimization (IS-TO).

Recent research has introduced various quantum methodologies—such as gate-based, annealing-based, and quantum-inspired algorithms—to address the combinatorial complexity inherent in grid reconfiguration and energy management. The review summaries the application of these quantum algorithms, along with quantum devices and power system test cases, to power system optimization, highlighting hybrid quantum–classical strategies that leverage the complementary strengths of both paradigms. Some quantum advantages have been observed, including theoretical speedup, accurate simulation results, scalable qubit usage, efficient QUBO mapping. In particular, the review emphasizes the importance of integrating quantum optimization techniques with classical control frameworks, these hybrid approaches demonstrate the potential to improve real-time grid management and operational reliability.

A major focus of the analysis is devoted to the practical limitations imposed by today's quantum devices. In the noisy intermediate-scale quantum (NISQ) era, current hardware remains highly sensitive to noise and limited in qubit connectivity, which constrains the scale and accuracy of implemented algorithms. The review delves into specific challenges such as the need for qubit-efficient encoding techniques and error mitigation strategies that are critical for handling real-world grid optimization problems. In addition, the work draws attention to the performance discrepancies between theoretical quantum speedups and experimental validations, underscoring the importance of rigorous benchmark studies using representative power grid test cases.

In summary, this review highlights both the promise and limitations of quantum computing for power system optimization. It provides a rigorous overview of the state-of-the-art technologies, categorizes recent advancements in algorithm design, and discusses practical considerations for implementation, and serves as an informative resource on current research. Future research directions include developing robust hybrid frameworks, advancing qubit-efficient formulations, and scaling up experimental demonstrations to confirm the theoretical advantages of quantum methods in large-scale power system operations.

Acronyms and Abbreviations

ACOPF	Alternative Current Optimal Power Flow
ACPF	Alternative Current Power Flow
AQC	Adiabatic Quantum Computing
BQM	Binary Quadratic Model
COPF	Combinatorial OPF
CPU	Central Processing Unit
CQM	Constrained Quadratic Model
D-QSLR	Distributed Quantum Surrogate Lagrangian Relaxation
DCOPF	Direct Current Optimal Power Flow
DCPF	Direct Current Power Flow
DER	Distributed Energy Resources
DM	Differential Mutation
ED	Economic Dispatch
ELD	Economic Load Dispatch
HHL	Harrow-Hassidim-Lloyd
IPM	Interior Point Method
IS-TO	Intelligent Switching and Topology Optimization
LDRD	Laboratory Directed Research and Development
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MIP	Mixed-Integer Programming
NISQ	Noisy Intermediate-Scale Quantum
NRPF	Newton Raphson Power Flow
NT-QIPM	Noise-Tolerant Quantum Interior-Point Method
OTS	Optimal Transmission Switching
OPF	Optimal Power Flow
qMGF	quantum MicroGrid Formation
Q-ADMM	Quantum version for Alternate Direction Method of Multipliers
QA	Quantum Annealing
QAOA	Quantum Approximate Optimization Algorithm
QAS	Quantum Annealing Simulator
QC	Quantum Computing
Q-CTO	Quantum Class Topper Optimization
QNN	Quantum Neural Networks
QPHR-ADMM	Quantum-based Powell–Hestenes–Rockafellar Alternating Direction Method of Multipliers
QPSO	Quantum-behaved Particle Swarm Optimization
QPSO-DM	QPSO algorithm with Differential Mutation
QGA	Quantum Genetic Algorithm
QPU	Quantum Processing Unit
QUBO	Quadratic Unconstrained Binary Optimization

QuAADS	Quantum Algorithms and Architecture for Domain Science
PDIPM	Primal-Dual Interior Point Method
PQC	Parameterized Quantum Computers
RCQIEA	Real Coded Quantum Inspired Evolutionary Algorithm
SCED	Security-Constrained Economic Dispatch
SC-PDIPM	Step-Controlled Primal-Dual Interior Point Method
UC	Unit Commitment
UQAE	Unified Quantum Amplitude Estimation
VQA	Variational Quantum Algorithms
VQLS	Variational Quantum Linear Solver

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1.0 Introduction

Power systems are highly complex, involving numerous components, complicated interactions and highly non-linear behaviors. With the rapid evolution of power grid, an increasing number of variable energy sources and emerging technologies are being integrated into the grid. As a result, it becomes increasing challenging to maintain reliable, efficient energy delivery across interconnected networks that face a range of disturbances. Solving power system optimization is one of the biggest challenging tasks in maintaining the efficiency and reliability of power systems operations.

Common problems in power system optimization encompass optimal power flow (OPF), unit commitment (UC), economic dispatch (ED), and intelligent switching and topology optimization (IS-TO). These optimization problems are nonlinear, often non-convex, and involve both equality and inequality constraints, with discrete and continuous variables. They are NP-hard, mixed-integer optimization problems, which are difficult to solve accurately and timely for large scale power systems, while accurate solutions of these problems lead to efficient and secure operations that save billions of dollars every year.

The increasing complexity of power system leads to a higher number of constraints in optimization problems, consequently extending the computational time required for solutions. As an example, the security-constrained economic dispatch (SCED) problem of US Eastern Interconnection grid, with around 70,000 buses and 5,000–10,000 generators, contains more than 100,000 decision variables to be optimized over a vast number of possible constraints, making it computationally difficult using most classical optimization solvers commercially available. On the other hand, quantum processors exhibit potential to offer higher computational power to solve large-scale problems much faster.

Unlike classical computing, which uses binary bits for information encoding, quantum computing (QC) employs qubits to represent superpositions of states. This allows QC to use properties such as entanglement and tunneling to explore many state combinations at once. Recent advances in quantum computing offer new alternatives to traditional optimization methods. As a result, several quantum computing paradigms are being applied to power system optimization, see below:

1. **Gate-Based Quantum Computing**. Gate-based approaches like Quantum Approximate Optimization Algorithm (QAOA) have shown potential for addressing combinatorial optimization problems in power systems. These methods translate optimization problems into Quadratic Unconstrained Binary Optimization (QUBO) or Ising model formats suitable for quantum processing.

2. **Quantum Annealing**. Quantum annealing is a form of adiabatic quantum computing that exploits quantum tunneling and thermal fluctuations to escape local minima, facilitating the search for global optima in challenging combinatorial problems. Its capacity to directly solve QUBO formulations makes it a promising approach for addressing optimization challenges in large-scale power systems.

3. **Hybrid Quantum-Classical Approaches**. Hybrid quantum-classical strategies integrate the strengths of quantum and classical processing to overcome current hardware limitations. These methods typically delegate computationally intensive subproblems to quantum processors while employing classical algorithms for problem pre-processing and post-processing, thereby enhancing scalability and solution accuracy in complex power system optimization.

4. **Quantum-Inspired Algorithms**. Quantum-inspired algorithms leverage principles from quantum mechanics to design innovative heuristics and optimization techniques that run on clas-

sical hardware. By emulating quantum phenomena—such as superposition, interference, and tunneling—these methods enhance the exploration of large solution spaces and provide alternative strategies for tackling complex power system optimization problems.

Quantum optimization that utilizes quantum mechanisms is anticipated to provide a super-polynomial advantage in addressing complex NP-hard combinatorial optimization problems. Therefore, quantum optimization is expected to solve large-scale grid optimization problems with promises of improved accuracy and timely resolution in comparison to existing approaches. Following this promise, extensive research has been undertaken in recent literature to investigate the capability of quantum optimization algorithms in solving grid optimization problems.

To better bridge the gap between quantum computing experts and power system engineers, Table 1.0 describes the functionality of the four selected representative power system optimization applications, their mathematical properties, and their relevance to quantum computing.

Before proceeding, it should be noted that several reviews and tutorials on quantum computing for solving different problems in power systems have been published in the literature [1, 2, 3]. This report distinguishes itself by focusing on a rigorous review of QC algorithms to address power grid optimization problems including optimal power flow (OPF), unit commitment, economic dispatch, and intelligent switching and topology optimization. A primary emphasis is placed on recent, representative works with particular attention to their quantum advantages and practical limitations within in each category.

Power grid optimization is a critical challenge in modern energy systems. This review assesses the potential of quantum speedup by thoroughly examining the largest-scale demonstration systems and the quantum environment required for implementing QC algorithms in each work. Through a rigorous analysis, promising quantum advantages have been identified, including theoretical speedups, more accurate optimal solutions, scalable qubit usage, and efficient QUBO mapping. Vice versa, practical limitations on scalability and accuracy have been uncovered, stemming from sensitivity to noises and remarkable quantum circuit depth. In addition, the review highlights the importance of integrating quantum optimization techniques with classical frameworks to effectively demonstrate the quantum advantages in various grid optimization problems.

The rest of this technical report is organized as follows: Section 2.0 reviews the application of various quantum computing algorithms to solve representative power grid optimization problems, including optimal power flow in Section 2.1, unit commitment in Section 2.2, economic dispatch in Section 2.3, and intelligent switching and topology optimization in Section 2.4. A table summarizing the quantum computing algorithms, the size of power systems, the computing environments, the advantages and limitations is provided for each application. Finally, a summary and recommendations for future work are presented in Section 3.0.

Table 1. The Selected Power System Optimization Problems and their Relevance to Quantum Computing

Optimization Problem	**Functionality**	**Mathematical Properties**	**Relevance to Quantum Computing**
Optimal Power Flow (OPF)	Determine optimal operating conditions (e.g., generation levels, voltage profiles, and power flows) for the grid while satisfying physical and operational constraints.	Typically a nonlinear, nonconvex optimization problem due to the AC power flow equations; may involve both continuous and discrete variables.	Can benefit from hybrid quantum-classical strategies and quantum-inspired methods to address non-convexities and high-dimensional continuous spaces.
Unit Commitment (UC)	Decide the on/off status and schedule of generation units to meet demand at minimum cost, while considering constraints like start-up/shut-down costs and minimum up/down times.	A mixed-integer programming (MIP) problem with binary (on/off) decisions and continuous dispatch variables; inherently NP-hard due to the combinatorial nature of scheduling.	Well-suited for quantum annealing and other combinatorial optimization approaches that can help tackle NP-hard scheduling challenges.
Economic Dispatch (ED)	Determine the optimal output of committed generation units to supply the required load at the lowest cost while meeting operational limits.	Generally a continuous optimization problem formulated as linear or quadratic programming; typically convex when nonconvexities are ignored.	May be addressed using quantum optimization frameworks; can complement classical solvers by efficiently exploring large solution spaces.
Intelligent Switching and Topology Optimization	Optimize the configuration of network elements (e.g., switches and breakers) to improve performance, reduce losses, or enhance reliability of the power system.	A combinatorial optimization problem on graphs with discrete decision variables; NP-hard due to the complex interactions and network reconfiguration choices.	Ideal for quantum-inspired algorithms and QUBO formulations, as well as quantum annealing, to efficiently search through vast combinations of network configurations.

2.0 Quantum Computing for Grid Optimizations

Optimization plays an essential role in power system analysis and operations. Various power system tasks, such as optimal power flow analysis, unit commitment, economic dispatch, intelligent switching and topology optimization can be formulated as optimization problems. Many of these problems involve complex combinatorial decisions that become computationally intractable for large-scale systems using classical methods. In the following, we will introduce the functionality of these representative power system optimization problems, their mathematic formulations, and their connection to quantum computing. We will review the application of various quantum computing algorithms that have been explored to solve these optimization problems.

2.1 Optimal Power Flow

Optimal power flow (OPF) is a fundamental nonlinear constrained optimization problem to the operation, control, planning, optimization, and security analysis of power systems. It aims to determine the optimal operating state of the power system by adjusting generator outputs and voltage profiles while satisfying the network's physical and operational constraints.

A simplified OPF formulation is given by:

$$\min_{x,u} \quad f(x,u)$$

$$\text{s.t.} \quad g(x,u)=0, \quad h(x,u)\leq 0,$$

where x represents the state variables (e.g., voltages, angles) and u denotes the control variables (e.g., generator outputs).

It has long been a challenging computational task due to its nonconvexity, especially for large-scale systems. In recent years, quantum computing has been explored as a promising approach to accelerate OPF solution process.

Several papers have utilized Harrow-Hassidim-Lloyd (HHL) algorithm to solve OPF problems, with a typical quantum circuit showed in Figure 1. The HHL algorithm is usually considered to be an algorithm that could only work in the fault-tolerant regime with quantum error correction codes. For example, [4, 5] applied HHL algorithm to the DC power flow using both hybrid classical-quantum approach [4] and direct implementations on different quantum computer platforms [5]. Although these demonstrations on small-scale systems (e.g., 3- or 9-bus systems) have shown the feasibility of executing quantum circuits for OPF, they have not yet achieved the high accuracy or the exponential acceleration that theoretical analyses predict. In particular, the inherent limitations of current fault-intolerant quantum devices–such as error accumulation and circuit depth–hinder the performance of HHL-based methods,

Further studies, such as [6] and [7], extended the use of HHL to solve Newton Raphson Power Flow (NRPF). While simulations on IBM's Qiskit simulator and experimental tests on real quantum computers confirm that HHL can compute NRPF, they also highlight scalability issues due to noises and an increase in the depth of the circuit needed for the implementation of HHL. In [8], a detailed theoretical study revealed that when factoring in read-out requirements and the growth of condition number, the asymptotic complexity of solving DCPF using HHL scales as $O(n^{4.62} \log n)$ where n is the number of the buses. This is much higher than the $O(n^{1.9} \log n)$ complexity of leading classical methods.

To overcome the limitations of HHL on noisy intermediate-scale quantum (NISQ) devices, variational quantum algorithms have been proposed as alternatives. These algorithms–such as those employing the Variational Quantum Linear Solver (VQLS) within a Step-Controlled

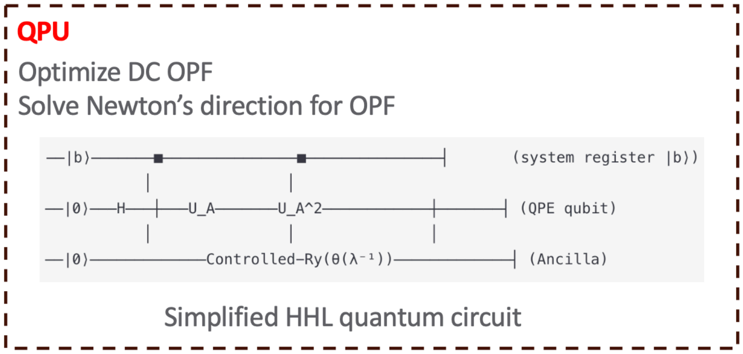

Figure 1. A typical and simplified HHL quantum circuit to solve the OPF problem.

Primal-Dual Interior Point Method (SC-PDIPM) framework, as in [9, 10]–typically demand a shallower circuit depth and are more amenable to current hardware. Variational quantum algorithms work within a hybrid quantum-classical framework, where quantum circuits evaluate the loss function and classical algorithms optimize the circuit parameters. Although some specialized variational quantum ansätze have been reported to offer exponential speedup with respect to matrix size, the overall scalability and formal performance guarantees remain unproven.

Another promising direction is the use of hybrid quantum neural networks (QNNs), as proposed in [11]. In this approach, a small 4-qubit parameterized quantum computers (PQC) is integrated as an intermediate layer within a classical neural network to solve an AC OPF problem on a 162-bus system. This method has shown high accuracy and robust generalization despite employing only a few quibts, though training costs and sensitivity to quantum noise remain challenging.

In addition, quantum annealing (QA) has been explored to leverage the current availability of large numbers of qubits. In the QA method, by encoding grid optimization problems into the energy levels of a quantum system, the system can evolve towards the global energy minimum. The system starts in the ground state of a simple Hamiltonian and evolves towards the ground state of the final Hamiltonian, which represents the problem's solution. Currently, quantum annealing is the only computing paradigm offering a large enough number of qubits for real-world problems in various fields. In [12], an annealing-based algorithm reformulated the combinatorial OPF (COPF) problem–integrating elements such as multiphase network modeling, the placement and sizing of variable energy generation, discrete sources of energy flexibility, and decisions regarding network upgrades–into a Quadratic Unconstrained Binary Optimization (QUBO) problem. Case studies on a power system with 3 PV units, 30 EVs, 55 loads, and 2 network upgrade plans were performed utilizing D-Wave Systems' Advantage quantum processing unit, featuring 5,760 qubits, along with a hybrid quantum-classical solver. The results suggest that QA scales linearly with the number of EVs and the network voltage constraints. However, this approach remains heuristic and its performance relative to classical methods requires further investigation.

Table 2 summarizes the key advantages and limitations of various QC algorithms applied to OPF problems. While QC algorithms are theoretically faster than classical methods, current hardware and simulator result do not yet provide clear evidence of a computational quantum speedup for OPF.

The *state-of-the-art* QC approach for solving OPF is presented in [13], where a noise-tolerant quantum interior-point method (NT-QIPM) was proposed to improve the scalability on noisy intermediate-scale quantum devices. In this study, the optimization model was

Table 2. QC Algorithms for Optimal Power Flow

Problem	Algorithm	Quantum Device	Size	Advantage	Limitation	Quantum Speedup	Ref.
DCPF	HHL	IBM (4q)	3-bus	Real hardware demonstration; theoretical speedup for large systems	Accuracy issues; limited scalability	Theoretically exponential	[4]
DCPF	HHL	IBMQ	9-bus	Feasible real quantum computation	Data encoding challenges; accuracy issues	Theoretical speedup	[5]
NRPF	HHL	IBM Qiskit	5-bus	Accurate simulation results	Exponential circuit depth; simulation limitations	Comparable to classical	[6]
NRPF	HHL	Real Quantum (7q)	5-bus	Validated on real hardware	Noise; deep circuits	Noise-free simulation similar to classical	[7]
DCPF	HHL (theor.)	–	–	Complexity analysis	High runtime; large condition number	$O(n^{4.62}\log n)$ vs. $O(n^{1.9}\log n)$	[8]
AC/DCPF	IPM + VQLS	6q	9-bus or 14-bus	Shallower hybrid circuit	Lacks formal guarantees; scalability concerns	Unclear advantage or worse than classical method	[9, 10]
AC OPF	Hybrid QNN	4q PQC	162-bus	High accuracy; robust generalization	Sensitive to noise; high training cost	Not directly compared	[11]
COPF	QA	D-Wave (5760q)	<100 units	Scalable qubit usage; QUBO-based formulation	Heuristic solver; no rigorous speedup analysis	Not available	[12]
AC/DCPF	NT-QIPM + HHL	IBM Qiskit	Up to 2869	Excellent scalability; per-iteration $O(\log(n)) + O(n/\epsilon)$	Sensitive to HHL errors and quantum noise; convergence issues if error threshold exceeded	Theoretical vs. $O(n^3)$	[13]

reformulated as a quadratic optimization problem with linear constraints. By integrating the HHL algorithm within the interior-point framework, Newton's direction was established by solving systems of linear equations. To address the effects of HHL errors and quantum noise on Newton's direction, as discussed in [7], a noise-resistant QIPM variant was introduced. This algorithm was demonstrated to accurately solve both ACOPF and DCOPF for systems with up to 2869 buses. While the DCOPF was solved smoothly by NT-QIPM, and the ACOPF by a classically augmented NT-QIPM, a direct comparison with classical methods was not provide. Nevertheless, the NT-QIPM method holds great potential for computational advantage. Its theoretical per-iteration runtime is $O(\log(n)) + O(n/\epsilon)$, which contrasts with the $O(n^3)$ runtime per iteration of state-of-the-art classical interior-point methods.

While the NT-QIPM approach in [13] has shown both accurateness and scalability, one limitation is its dependence on HHL. If the HHL error exceeds a certain threshold, or if such errors accumulate, NT-QIPM may fail to converge. Moreover, HHL itself has inherent inaccuracies, is inefficient on current quantum hardware, and faces significant scalability challenges on current NISQ devices because of the deep quantum circuit requirements. To improve the resilience of NT-QIPM for near-term quantum applications, future research could investigate alternative quantum linear solvers with lower error rates, such as VQLS or Quantum block encoding. In summary, although NT-QIPM offers promising theoretical advantages in terms of runtime and scalability, practical issues related to quantum noise and limited hardware capabilities must be addressed to make quantum computing more robust and efficient for solving OPF problems.

2.2 Unit Commitment

Unit commitment (UC) is one of the most popular and critical optimization problems in power system operations. It addresses the scheduling problem of determining the optimal on/off scheduling and dispatch of generating units to meet forecasted electricity demand at the lowest possible cost, while adhering to operational constraints like ramping limits, minimum up/down times, and generation bounds. Mathematically, UC is formulated as a large-scale mixed-integer nonlinear programming (MINLP) problem, which poses significant computational challenges for resolution due to the nonlinear cost function and the combinatorial characteristics of the feasible solution sets. A basic UC formulation is:

$$\min_{u,P} \quad \sum_{t=1}^{T}\sum_{i=1}^{N}\left(C_i(P_{i,t})\,u_{i,t} + S_i(u_{i,t} - u_{i,t-1})\right)$$

$$\text{s.t.} \quad \sum_{i=1}^{N} u_{i,t}P_{i,t} \geq D_t, \quad u_{i,t} \in \{0,1\}, \quad \forall\, t,$$

where $u_{i,t}$ is a binary variable indicating the status (on/off) of unit i at time t, $P_{i,t}$ is the power output, and D_t is the demand at time t.

The complexity of the UC problem is anticipated to rise with the growing integration of intermittent variable energy sources. UC is known as NP-complete, meaning that any proposed solutions are verifiable in polynomial time (i.e., it is in-NP) and every in-NP problem can be reduced to it in polynomial time (i.e., NP-hard), which indicates that no polynomial-time algorithm is likely to exist for solving UC optimally.

The hybrid quantum–classical approach has emerged as a promising candidate for addressing the computational complexity of the UC problem. In this hybrid approach, classical central processing units (CPUs) tackle the quadratic and continuous subproblems, while quantum processing units (QPUs) are utilized to optimize the binary or combinatorial aspects of the problem. For instance, the work in [14] proposed using a hybrid quantum-classical algorithm to solve mixed-integer linear programming (MILP) problems. This hybrid approach was extended to solve mixed-integer convex optimization problems in [15]. Furthermore, the authors advanced this hybrid Benders' decomposition approach using QAOA in [16].

Figure 2 illustrates a typical hybrid quantum-classical architecture for solving UC. In this framework, quantum algorithms—most commonly the QAOA—are employed to handle the binary decision variables after reformulating the UC problem as a quadratic unconstrained binary optimization (QUBO) instance. Early work in [17] presented a hybrid quantum–classical method in which QAOA was enhanced by incorporating a classical minimizer, thereby enabling the resolution of mixed binary optimization problems. This enhancement effectively transforms a

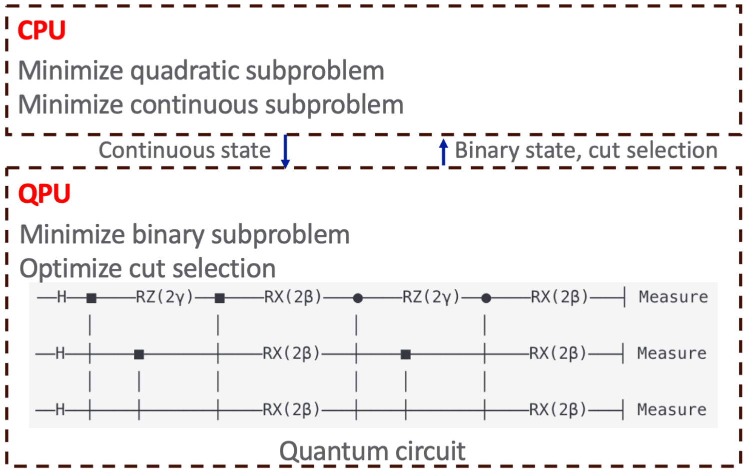

Figure 2. A typical quantum–classical hybrid approach to solve the UC problem.

QUBO instance into a continuous optimization problem defined over variational parameters. Given that each QAOA circuit has a logical depth of $O(N^2P)$, the hybrid quantum-classical approach retains potential efficacy even for larger system sizes. However, the study in [17] provides only numerical examples on an emulator for systems with up to 10 units, rather than on an actual quantum computer, thereby limiting evidence of the exponential speedup typically associated to quantum computing. Similarly, [18] introduced another hybrid quantum–classical algorithm in which UC was decomposed into three subproblems–a quadratic subproblem, a QUBO subproblem, and an unconstrained quadratic subproblem–that are iteratively coordinated through a three-block alternating direction method of multipliers algorithm. In this approach, the initial and final subproblems are solved using a conventional optimization solver, while the QUBO subproblem is tackled using QAOA. However, the case study in [18] is also limited in scale (with only 10 units) and relies on classical simulation, which does not effectively showcase the potential computational advantages of quantum computing. In addition, a hybrid quantum–classical algorithm, based on the Benders decomposition framework, was developed to solve the energy-management problem for a data center with nine cooling units and battery energy storage systems [19].

To enhance scalability, [20] employed a multi-cut Benders decomposition strategy. In their approach, multiple feasible solutions from the master problem generate several valid cuts that are then processed by a hybrid quantum-classical solver. The classical CPU is responsible for managing MILP master problems, while the QPU focuses on the cut selection tasks. This algorithm was tested on systems with up to 30 buses using the D-Wave Advantage 4.1 quantum annealer. It is noted that the implementation of this hybrid algorithm is complex and presents several challenges. First, the size of the binary indicator matrix is dependent on the number of complicating variables, thereby constraining the scalability of the problem. Second, minor embedding must be performed at each iteration, adding additional computational overhead. Third, selecting appropriate hyperparameters and weights for quadratic penalty functions is a non-trivial task, as it is crucial to ensure the lowest-energy state while simultaneously minimizing logical chain breakage. Consequently, in order to apply this method effectively to large-scale problem instances, further advancements in minor embedding techniques and improvements in current hardware capabilities are necessary.

To address these challenges, [21] proposed a distributed quantum surrogate Lagrangian relaxation (D-QSLR) framework. This method decomposes the UC problem into binary subproblems–solved via QAOA–and continuous subproblems–handled classically–with coordination achieved through iterative updates of Lagrangian multipliers. The D-QSLR framework has been demonstrated on systems with up to 1020 units over a 24-hour period, showing enhanced convergence performance through the incorporation of contraction-mapping stepsizes. In a representative test case, the QSLR approach converged in only 2 iterations, significantly outperforming the quantum version for the decomposition and coordination alternate direction method of multipliers (Q-ADMM) method, proposed in [22], which required 19 iterations for convergence. Moreover, the D-QSLR method has shown the capability to achieve high accuracy even in a noisy quantum environment.

Additional hybrid approaches have been developed to improve the integration of continuous and binary variables. For instance, [22] further explored scalability improvements for QAOA by decomposing the UC problem into individual subproblems through the relaxation of coupling constraints, with coordination via Lagrangian multiplier updates. Nevertheless, the practical realization of the exponential speedup offered by quantum computing remains unverified. An alternative approach in [1] utilizes encoding to convert continuous variables into a discrete format, which, however, requires $N(l+2)$ qubits for an $N-$unit system with l discretization partitions–substantially escalating qubit requirements even for smaller-scale systems (e.g. 12 units). Recently, the hybrid annealing method in [23] applied Lagrangian decomposition and Benders decomposition to partition the UC problem into multiple smaller optimization sub-problems.By optimizing qubit usage through analysis of the maximum reachability limits of the inequality constraints, this work reduces the number of variables in the QUBO formulation and avoids unnecessary qubit consumption. Experiments performed on the D-Wave Advantage ^{TM} adiabatic quantum computing (AQC) platform, involving systems with up to 54 units, demonstrate a significant advantage of AQC in terms of computation time, achieving an acceleration factor of at least five times compared to quantum annealing simulator (QAS).

Table 3 summarizes the advanced quantum computing algorithms for solving the UC problem discussed above. Overall, hybrid quantum–classical methods dominante the literature and demonstrate the best potential for scalability in solving UC. Computationally, it can be concluded from Table 3 that QC methods can enable speedup in comparison to classical methods or quantum simulators, especially for large-scale systems; however, most demonstrations to date have been restrcted to small-scale systems. A common limitation among these methods, which typically use Benders cuts to leverage quantum advantages at different steps, is the reliance on slack variables to convert the inequality constraints into equalities. Handling these slack variables on QPUs requires a substantial allocation of qubits for binary encoding, leading to significant qubit overhead, reduced computational efficiency, or even chain break–a catastrophic failure in QC. Among the approaches discussed, the *state-of-the-art* approach is the D-QSLR algorithm [21], which has been demonstrated on systems up to 1020 units, outperforms the Q-ADMM method, and obtains high accuracy even in a noisy environment. Unfortunately, this scalable quantum approach has not yet been compared directly with classical methods.

In future research, a qubit-efficient QA approach can be pursued to address the above-mentioned limitations in current hybrid quantum-classical methods and facilitate implementation on various available quantum annealers. In particular, recent work in [24] theoretically proved that the qubit-efficient QPHR-ADMM (Quantum-based Powell–Hestenes–Rockafellar Alternating Direction Method of Multipliers) algorithm can reduce the total QPU qubit overhead to max$\{T, J\}$ where T is number of blocks partitioning the binary variable and J is the precision level in binary encoding, compared to at least $(NT+J)$ qubits overhead required by other methods. This combination of Lagrangian Multiplier and quantum ADMM offers a promising strategy to handle qubit allocation issues in binary encoding, thereby enhancing the solutions of the UC problem. Furthermore, due to its scalability and high accuracy even in noisy environments, the D-QSLR approach is recommended as a promising

Table 3. QC Algorithms for Unit Commitment

Algorithm	Quantum device	Size	Advantage	Limitation	Quantum Speedup	Ref.
Hybrid QAOA	10 qbits and IBM Qiskit	10 units	Low circuit depth; supports mixed binary optimization	Limited optimality evidence	None reported	[17, 18]
Multi-cut, Hybrid QA, Benders'	D-Wave 5000	9 cooling units	Multi-cut at each iteration	More qubits consumption due to slack variables	Less iterations	[19]
Benders Cut, Hybrid QA	D-Wave (5000)	30-bus	Effective QUBO mapping for cut selection	Scalability issues; heuristic cuts, embedding overhead	Faster than classical method for cut selection	[20]
D-QSLR, Hybrid QAOA	IBM Qiskit / Terra / IBMQ	up to 1020 units, 24-h	High scalability, high accuracy in noisy devices	Requires precise measurements	No speed comparison	[21]
Q-ADMM	IBMQ / D-Wave 2000	9 DERs–12 units	Achieves operation cost optimality	Scalability and circuit depth limitations	Fewer iterations than classical	[22, 1]
Benders Cut, QA	D-Wave (5627)	54 units	Efficient QUBO mapping	Limited qubit connectivity	AQC at least 5 times faster than QAS	[23]
QPHR-ADMM	D-Wave (5000-qubit)	5 units, 24-h	Qubit-efficient and fast	Hardware embedding challenges	Theoretically faster for large systems	[24]

approach to solve the UC problem on real quantum computers, despite ongoing challenges such as limited qubit counts, short coherence times, and inherent quantum noises.

2.3 Economic Dispatch

Economic dispatch (ED) problem determines the optimal power output levels of committed generating unit so as to minimize the overall possible cost while satisfying the system load and various operational constraints. In power systems, ED is critical for achieving cost-effective generation and reliable operation. A typical ED problem can be expressed as:

$$\min_{P} \quad \sum_{i=1}^{N} C_i(P_i)$$

$$\text{s.t.} \quad \sum_{i=1}^{N} P_i = D, \quad P_i^{\text{min}} \leq P_i \leq P_i^{\text{max}},$$

where P_i is the output of generator i, D is the total demand, and $C_i(P_i)$ is the cost function (often quadratic) associated with generator i.

Early work in [25] introduced the Real Coded Quantum Inspired Evolution Algorithm (RCQIEA) to solve security-constrained economic dispatch problems. This algorithm employs a population-based strategy that incorporates elements of quantum computing to encode and evolve sets of candidate solutions, aiming to achieve optimal results through a partially directed random methodology. Although the RCQIEA demonstrated a reduced operational cost relative to alternative methods, its convergence time of 5.88 seconds on a small system comprising seven machines raises concerns regarding scalability.

In [26], a quantum-behaved particle swarm optimization algorithm (QPSO) was applied to the economic load dispatch (ELD) problem. By integrating the superposition feature and probabilistic representation inherent in quantum methods with traditional PSO, QPSO allowed a single particle to represent multiple states simultaneously, while quantum rotation gates facilitate the update process. Through simulations of two ELD scenarios involving 3 and 13 generating units, it was found that the QPSO provided a more optimal solution compared to both the enhanced particle swarm optimization algorithm and evolutionary programming techniques. This capacity was further enhanced in [27], through the introduction of differential mutation (QPSO-DM), which integrates the QPSO algorithm with a differential mutation (DM) operation to improve the algorithm's global search capabilities, robustness, and convergence properties when handling nonlinear generator characteristics, such as ramp rate limits, prohibited operating zones, and nonsmooth cost functions. Simulation results for systems with up to 40 generation units demonstrated that the QPSO-DM method outperformed enhanced PSO and evolutionary programming techniques in obtaining high-quality solutions.

Another method, the quantum genetic algorithm (QGA), presented in [28, 29] exploits quantum-inspired encoding to represent chromosomes in a superposition state, thereby enhancing the genetic algorithm;s exploration of the solution space. QGA demonstrated high accuracy and convergence on test systems comprising up to 90 units, though it still requires significant CPU computation time. A chaotic QGA was also applied to tackle the environmental economic dispatch in a smart microgrid featuring distributed generation. The accuracy and effectiveness of the mathematical model were validated, and the demonstrations were performed on a system with 6 generation resources—again, often requiring substantial CPU time.

The Quantum Class Topper Optimization (Q-CTO) algorithm, as introduced in [30, 31], addressed ED by minimizing the total generation cost including transmission losses. Despite its effective search capability, Q-CTO has so far been demonstrated only on small systems with up to 14 generators.

All the above are quantum-inspired algorithms, instead of traditional quantum computing approaches. More recently, a hybrid quantum–classical approach was proposed in [32] that combines Unified Quantum Amplitude Estimation (UQAE) with the Quantum Approximate Optimization Algorithm (QAOA) (hereafter referred to as UQAE-QAOA) to solve stochastic ED problem by leveraging quantum advantages to generate numerous uncertain scenarios with a limited number of qubits. This method expedites the associated NP-hard optimization process to polynomial time complexity while maintaining accuracy. In this study, a QAE algorithm characterizes the prediction errors of variable energy sources, integrating these errors into a two-stage stochastic optimization framework with fewer qubits and reduced estimation errors. A multi-cut Benders decomposition method was then applied with both the NP-hard feasible cut selection problem and the master problem reformulated into quantum-compatible forms and solved using a tailored QAOA. Using IBM's Qiskit, the findings of this paper illustrate that, on a 6-bus system over a 4-hour horizon, QAE generates massive scenarios in 0.11 seconds and the QAOA-based Bender cut reduces the number of possible cuts from 782 to 16, and solves the cut selection problem in 2.23 seconds–all while preserving high accuracy.

Table 4. QC Algorithms for Economic Dispatch

Algorithm	Device	Size	Advantage	Limitation	Ref.
RCQIEA	CPU implementation	Up to 7 units	Lower cost	Scalability	[25]
QPSO	CPU implementation	13-40 units	High-quality solutions, robustness, convergence	Parameterization tuning needed	[26, 27]
QGA chaotic QGA	CPU implementation	Up to 90 units	Accuracy; scalability	High CPU computation time	[28, 29]
Q-CTO	CPU implementation	6-14 units	Searching capability	Scalability	[30, 31]
UQAE-QAOA	IBM Qiskit	Stochastic ED, 6-bus, 4-h	Cost accuracy	Hardware noise	[32]

Table 4 summarizes various quantum computing methods for solving the ED problem. Overall, quantum-inspired algorithms have been implemented on CPUs and demonstrated only on relatively small-scale systems (with the largest involving 90 units in [28]), yet typically requiring a long computation time. The hybrid QPU-CPU implementation in [32] is one of the few approaches that leverage actual quantum hardware; however, it requires a similar number of iterations as the CPU-only quantum-inspired implementation, and no significant quantum speedup has yet been observed. Moreover, the inclusion of security constraints and uncertainties from variable energy resources contributes to the NP-hard nature of the problem, making it challenging for current quantum methods to outperform classical techniques.

In future research, the hybrid quantum-classical approach leveraging the strengths of both QPU and CPU is recommended for the ED problem. Such an approach could use quantum computing to generate massive uncertain scenarios and solve decomposed subproblems via techniques multi-cut Benders' decomposition. Similar to the UC problem, addressing the significant qubit overhead associated with binary encoding–possibly through qubit-efficient methods–will be critical for enhancing scalability and computational efficiency.

2.4 Intelligent Switching and Topology Optimization

The integration of distributed energy resources (DERs) and the increased complexity of modern power systems have created significant challenges for grid operation, control, and optimization. Intelligent switching and network optimization have become critical components in addressing these challenges, enabling more efficient and resilient grid operation. In this context, the operational status of switchable elements—such as breakers, tie-lines, and sectionalizing switches—is dynamically adjusted to reconfigure grid topology to improve system performance, reduce losses, or enhance reliability.

A simplified formulation is:

$$\min_{s} \quad f(s)$$

$$\text{s.t.} \quad \text{network operational constraints,}$$

where $s_{ij} \in \{0, 1\}$ represents the state (open/closed) of the switch between nodes i and j. This formulation typically leads to a combinatorial optimization problem, which is well-suited for quantum-inspired algorithms.

These optimization problems are inherently NP-hard mixed-integer problems with vast solution spaces, posing significant computational challenges for classical optimization methods. As noted by Ellinas et al. (2024) [33], ”The main issue of these formulations is the computational complexity of the solution algorithms, as they are considered NP-Hard problems.”

Several studies have demonstrated the potential of these hybrid strategies. For instance, Ellinas and colleagues developed a hybrid quantum-classical algorithm for mixed-integer optimization in power systems, focusing on optimal transmission switching (OTS) and neural network verification. Their approach leverages an accelerated version of Bender’s Decomposition to split mixed-integer linear programs (MILPs) into an Integer Master Problem (solved on a quantum processor) and a linear Subproblem (solved classically). This hybrid approach demonstrated capabilities on systems with up to 14 buses in [34]. In parallel, researchers in [35] developed a lossless QUBO formulation for microgrid formation that significantly reduces qubit requirements. Their approach was demonstrated on IEEE test feeders with up to 906 nodes, achieving substantial improvements in computational efficiency while maintaining solution quality. Additionally, Jing et al. developed a data-driven QAOA framework for networked microgrid reconfiguration, which enhances parameter tuning via transfer strategies for smart switching applications. Their approach was validated for finding the maximum sections of power and data delivery on a modified IEEE 24-bus system with 11 integrated DERs, with and without consideration of depolarizing noise on quantum gates [36].

Further reinforcing the promise of these approaches, Kaseb and collaborators proposed a novel adiabatic quantum computing approach for power flow analysis using a discrete combinatorial optimization formulation [37]. Their method converts the power flow problem into a QUBO form solvable by quantum and digital annealers. Tested on systems of varying sizes using D-Wave’s Advantage quantum annealer and Fujitsu’s digital annealer, their method demonstrated robustness for ill-conditioned cases that challenge classical solvers. Finally, Morstyn and Wang applied annealing-based quantum computing to combinatorial optimal power flow problems, achieving promising results for network optimization tasks in [38, 12].

In addition to these academic studies, a recent case study by researchers at Quantum Quants and the Netherlands Organization for Applied Scientific Research demonstrates a practical application of quantum computing for intelligent switching and network reconfiguration. Detailed in the D-Wave case study [39, 40], the researchers transformed a decentralized power grid into a graph model and applied hybrid quantum–classical solvers—specifically the Constrained Quadratic Model (CQM) and Binary Quadratic Model (BQM)—to optimize the network topology. Their approach efficiently partitioned large-scale power grids (e.g., Germany’s national grid with over 400 nodes and 500 edges) to redistribute surplus power, achieving near-optimal solutions that outperformed traditional classical solvers.

Table 5 summarizes representative quantum computing approaches for intelligent switching, network reconfiguration, and topology optimization in power systems, including insights from the recent D-Wave case study.

In summary, these emerging quantum computing approaches enable the effective exploration of vast combinatorial solution spaces for grid reconfiguration and topology optimization. While current quantum devices are still in the noisy intermediate-scale era, the integration of quantum algorithms with classical optimization frameworks paves the way for faster and more scalable solutions. Future research can focus on improving qubit connectivity, developing efficient parameter tuning techniques, and extending these hybrid methods to real-time and large-scale applications. This includes developing robust frameworks that dynamically allocate subproblems to QPUs for discrete decision-making and classical optimizers

Table 5. QC Algorithms for Intelligent Switching and Network Optimization

Algorithm	Device	Size	Advantage	Limitation	Ref.
Hybrid QAOA-OTS	IBM Qiskit / CPU+QPUs	6–14-bus	Fast exploration of combinatorial switching configurations	Susceptible to hardware noise; scalability challenges	[34]
Lossless qMGF	D-Wave (5760 qubits)	up to 906 nodes	Significant reduction in qubit requirements for topology optimization	Limited performance in densely interconnected grids	[35]
Data-Driven QAOA	IBM Qiskit	24-bus	Enhanced parameter tuning via transfer strategy for smart switching	Parameter sensitivity and noise issues	[36]
Q-Digital Annealing PF	D-Wave Hybrid	up to 14-bus	Robust handling of power flow reconfiguration challenges	Convergence sensitivity and interface complexities	[37]
Q-Assisted Topology	Hybrid QC-Classical	System-scale planning	Integrates quantum optimization with net-zero and grid decarbonization strategies	Practical deployment remains at a conceptual stage	[38, 12]
Hybrid CQM/BQM	D-Wave Advantage / Hybrid QPU	400+ nodes / 500+ edges	Demonstrated superior performance in large-scale grid partitioning and reconfiguration, reducing surplus power effectively	Requires careful hybrid integration and tuning for practical deployment	[39, 40]

for continuous constraints, and extending the methods to handle multi-objective formulations that simultaneously address loss minimization, load balancing, and resiliency enhancement.

3.0 Summary and Future Work

This report provides a rigorous overview of recent quantum computing algorithms applied to various grid optimization problems–optimal power flow (OPF), unit commitment (UC), economic dispatch (ED), and intelligent switching. The following observations and recommendations have been obtained:

- **Quantum vs. Classical Performance:** Despite significant theoretical promise, quantum computing algorithms have yet to demonstrate clear outperformance over classical methods in grid optimization.

- **HHL and Quantum Linear Solvers:** A majority of current works rely on the HHL algorithm for solving linear systems within grid optimization problems. However, its requirement for deep quantum circuits makes it highly susceptible to noise on current NISQ devices. Alternative quantum linear solvers, such as VQLS or methods based on quantum block encoding, are recommended to complement state-of-the-art noise-tolerant frameworks like NT-QIPM for large-scale OPF challenges.

- **Optimal Power flow (OPF):** While quantum algorithms like HHL and its variants offer potential exponential speedup in theory, their performance on real quantum hardware or simulators has not yet surpassed classical techniques, especially when solving tasks such as Newton-Raphson power flow.

- **Unit Commitment (UC) Algorithms:** Hybrid quantum–classical approaches dominate the literature on UC. These methods, which typically decompose the problem into binary and continuous subproblems, show promising speedups on small-scale systems. Notably, the state-of-the-art D-QSLR method scales up to over 1000 units and demonstrates high accuracy even in noisy environments; however, its performance has not been benchmarked directly against classical solvers.

- **Economic Dispatch (ED) Approaches:** There are multiple quantum-inspired algorithms, such as RCQIEA, QPSO, QGA, and Q-CTO, have been implemented on classical CPUs and tested only on small systems (up to 40 units). There is one hybrid QPU-CPU implementation combining UQAE and QAOA, which uses quantum hardware to generate large sets of uncertain scenarios; yet, no significant quantum speedup has been observed for ED so far.

- **Intelligent Switching and Topology Optimization:** Hybrid approaches—leveraging tools such as QAOA or quantum annealing in combination with classical optimization for real-time grid reconfiguration—show promise in dynamically adjusting network configurations, reducing losses, and improving system resilience under variable operating conditions. However, challenges related to efficient qubit encoding of binary switching decisions and integration with existing grid management systems persist. Future work could focus on developing qubit-efficient formulations, robust optimization frameworks that consider uncertainties in distributed generation and load fluctuations, and practical demonstrations on scaled-down test systems.

To enhance scalability and efficiency, future research direction includes: (1) developing hybrid quantum–classical methods that integrate qubit-efficient techniques to lessen the burden of binary encoding; (2) investigating alternative quantum linear solvers as potential replacements for HHL in noise-sensitive applications; and (3) scaling up demonstrations to larger systems while directly comparisons them with classical methods to confirm any theoretical quantum speedup.

In summary, while quantum computing shows considerable promise for optimizing power grids, its practical benefits still require experimental validation. Advancements in hybrid strategies, along with improvements in both quantum hardware and algorithm design, will be essential to fully harnessing quantum computing for grid optimization challenges.

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