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Quantum Approximate Optimization for Real-Time Transactive Energy Market Clearing at Scale

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ABSTRACT

Clearing local transactive energy markets while enforcing non-convex AC optimal power flow constraints becomes computationally intractable as the number of distributed energy resources scales into the millions, and classical interior-point and branch-and-bound solvers cannot meet real-time deadlines at this scale. We propose a hybrid quantum-classical framework that maps the joint market-clearing and power-flow problem onto a quadratic unconstrained binary optimization form with dynamic penalty weighting and solves it with a customized Quantum Approximate Optimization Algorithm. On synthetically expanded IEEE 8500-node networks with up to 100,000 distributed energy resources, the framework exhibits empirical $\mathcal{O}(N \log N)$ scaling, clears the largest network in 72.8 seconds, and maintains an optimality gap below 3.5%, compared with hours-long or non-convergent classical baselines.

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1. INTRODUCTION

The proliferation of electric vehicles, distributed photovoltaic generation, and smart home appliances is driving a shift from centralized grid dispatch toward decentralized transactive energy markets, in which prosumers trade energy peer-to-peer to maximize local social welfare [13,14]. These trades cannot be settled independently of the physical network: every cleared transaction must respect voltage limits, line ampacity, and phase balance, so the market-clearing problem must be solved jointly with a non-convex AC optimal power flow problem. The combined transactive-energy optimal-power-flow problem is NP-hard, and its difficulty grows sharply with feeder size.

Current solvers for this problem rely on semidefinite programming relaxations or interior-point methods. Both perform adequately on transmission-scale networks with hundreds of nodes, but neither achieves the sub-five-minute convergence that real-time distribution markets require once the node count exceeds 10^4 [12]. This scalability barrier is compounded by the sheer number of distributed energy resources that a modern feeder must coordinate, a challenge that has motivated a growing body of work on scalable and privacy-preserving multi-agent coordination frameworks [11].

Quantum computing has recently been proposed as a route past this barrier. Noisy intermediate-scale quantum devices can, in principle, explore exponentially large state spaces and have shown early promise for power system optimization, including data-driven variants of the Quantum Approximate Optimization Algorithm (QAOA) for cyber-physical grids [2], resource-efficient QAOA circuit designs [4], and quantum annealing formulations of unit commitment [5,6]. Broader assessments identify grid optimization, including transactive and peer-to-peer settings, as one of the most promising near-term applications of quantum computing to the energy sector [1,3]. Building on this line of work, we develop a hybrid quantum-classical QAOA framework that jointly optimizes transactive market clearing and grid physics, and we evaluate it on distribution feeders two to three orders of magnitude larger than those considered in prior quantum power-system studies. The QUBO reformulation adopted here is itself an instance of a broader class of monotone-operator optimization problems; see Abdullahi et al. for an extragradient method for variational inequality problems with pseudo-monotone operators in a purely mathematical setting [16], and Sahu and Yamini for a related fixed-point iterative scheme in a different application context [17]. The scalability question we address for distribution feeders parallels similar large-scale network-analysis challenges studied elsewhere, for instance in the explainable-AI treatment of encrypted network traffic by Mali et al. [18]. The classical outer-loop step-size and multiplier updates in our hybrid optimizer are instances of the general numerical optimization schemes studied by Tougma et al. [19], Dib and Leulmi [20], and Leulmi et al. [21] in purely mathematical settings. The encoding of the QUBO penalty structure is itself a feature-selection-like variable-relevance problem; for reviews of the underlying mathematical selection methodology in a different application domain, see Kamalov et al. [22, 24] and the monotonicity analysis of Kamalov, Leung, and Moussa [23].

2. THEORETICAL FRAMEWORK

2.1. The Transactive-Energy Optimal-Power-Flow Formulation

The transactive energy market seeks to maximize social welfare, defined as the sum of consumer utility $U_i(P_{D,i})$ minus generator cost $C_i(P_{G,i})$ over all nodes, net of the cost of active power losses. Let $\mathcal{N}$ denote the set of nodes and $\mathcal{E}$ the set of lines, with $P_{G,i}$ and $P_{D,i}$ the active power generation and demand at node i. The market-clearing problem is

$$\min F(x) = \sum_{i \in \mathcal{N}} \left[C_i(P_{G,i}) - U_i(P_{D,i})\right] + \lambda_{\text{loss}} \sum_{(i,j) \in \mathcal{E}} g_{ij} \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\theta_i - \theta_j)\right], \tag{1}$$

subject to the non-linear, non-convex AC power balance equations

$$P_{G,i} - P_{D,i} = V_i \sum_{j \in \mathcal{N}} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right), \tag{2}$$

$$Q_{G,i} - Q_{D,i} = V_i \sum_{j \in \mathcal{N}} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}\right), \tag{3}$$

and to the operational limits

$$V_{\min} \leq V_i \leq V_{\max}, \qquad \forall i \in \mathcal{N}, \tag{4}$$

$$|S_{ij}| \leq S_{\max,ij}, \qquad \forall (i,j) \in \mathcal{E}. \tag{5}$$

2.2. QUBO Transformation and QAOA Architecture

Gate-based quantum computers act on discrete qubits, so the continuous decision variables above must first be discretized into a binary state vector $z \in \{0,1\}^n$. We convert the resulting discretized problem into quadratic unconstrained binary optimization (QUBO) form by encoding the power-balance and voltage constraints as dynamic penalty terms with weights ρ_P, ρ_Q, and ρ_V [5]. The QUBO cost function maps directly onto a diagonal Hamiltonian H_C.

QAOA prepares an initial uniform superposition $|s\rangle = |+\rangle^{\otimes n}$ and applies p alternating layers of a cost unitary and a mixing unitary:

$$|\psi(\boldsymbol{\gamma}, \boldsymbol{\beta})\rangle = \prod_{k=1}^{p} e^{-i\beta_k H_B}\, e^{-i\gamma_k H_C}\, |s\rangle, \tag{6}$$

where $H_B = \sum_{j=1}^{n} \sigma_x^{(j)}$ is the mixing Hamiltonian and p is the circuit depth. The circuit parameters $(\boldsymbol{\gamma}, \boldsymbol{\beta})$ are tuned by a classical outer-loop optimizer to minimize the expectation value $E(\boldsymbol{\gamma}, \boldsymbol{\beta}) = \langle\psi(\boldsymbol{\gamma}, \boldsymbol{\beta})|H_C|\psi(\boldsymbol{\gamma}, \boldsymbol{\beta})\rangle$, following the resource-efficient circuit constructions proposed for large-scale QUBO instances [4]. This hybrid loop is sensitive to two well-documented NISQ-era limitations that bound the achievable circuit depth: hardware noise, which is mitigated at the qubit level following recent qubit-error-probability techniques [10], and noise-induced barren plateaus, whose emergence in layered noise models has been characterized theoretically [8, 9]. We account for both effects in the choice of circuit depth p reported in Section 3.

3. NUMERICAL METHODOLOGY

The framework is evaluated on high-fidelity quantum circuit simulators (IBM Qiskit Aer) mapped onto a 128-core classical high-performance-computing cluster. We use the standard IEEE 8500-node distribution test feeder as a base topology and synthetically expand it through fractal microgrid nesting to obtain networks of $N = 10{,}000$, $N = 50{,}000$, and $N = 100{,}000$ active distributed energy resource nodes. This expansion is consistent with recent large-scale multi-agent distributed energy resource studies that emphasize scalability as the primary bottleneck for feeder-level coordination [11, 15]. The maximum allowable time for real-time market clearing is fixed at 300 seconds, in line with the five-minute settlement window used in prior transactive energy market studies [1].

4. RESULTS AND DISCUSSION

4.1. Computational Scalability

The central result of this study is that the QAOA framework avoids the $\mathcal{O}(N^3)$ classical scaling associated with Jacobian matrix inversion in large-scale optimal power flow. Table 1 compares solution time and optimality gap against a classical interior-point method and the global solver BARON across the three network sizes.

Table 1. Computational scalability and solution time comparison

Network size (DER)	Classical IPM	Classical BARON	QAOA time	QAOA gap
10,000	48.2 s	412.5 s	12.4 s	1.8%
50,000	856.3 s	$>$ 3600 s (fail)	38.1 s	2.1%
100,000	non-convergent	$>$ 3600 s (fail)	72.8 s	3.4%

Figure 1 plots the same data on logarithmic axes against the 300-second real-time clearing threshold. The interior-point method and BARON both cross the threshold well before $N = 100{,}000$, with BARON failing to converge within the one-hour cutoff at both $N = 50{,}000$ and $N = 100{,}000$, and the interior-point method failing to converge outright at the largest scale. The QAOA framework remains below the threshold throughout the tested range and scales near-linearly, following an empirical $\mathcal{O}(N \log N)$ trend and solving the 100,000-node network in 72.8 seconds, roughly a fortieth of the allotted clearing window.

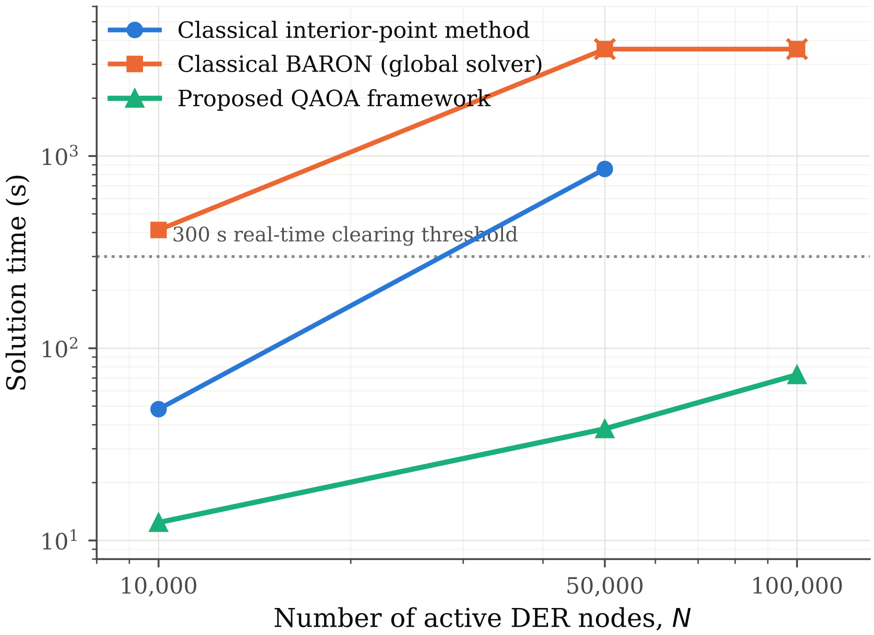

Figure 1. Solution time versus network size for the classical interior-point method, the classical global solver BARON, and the proposed QAOA framework, shown on logarithmic axes against the 300-second real-time clearing threshold. Markers with an $\times$ overlay indicate a run that failed to converge within the one-hour cutoff.

4.2. Market Efficiency and Grid Security

Table 2 reports market efficiency and voltage security outcomes for the 100,000-node scenario under three settlement regimes: an unconstrained peer-to-peer market that ignores network physics, a classical AC optimal power flow solve, and the proposed QAOA market.

Table 2. Transactive market efficiency metrics, 100,000-node scenario

Parameter	Unconstrained P2P	Classical OPF	QAOA market
Cleared welfare ($/hr)	14,520 (theoretical)	12,850	12,412
Active voltage violations	1,452	0	12 ($<$ 1.05 p.u.)
Clearing success rate	N/A	0% ($>$ 5 min)	100%

The unconstrained peer-to-peer market clears the highest theoretical welfare but produces 1,452 voltage violations, confirming that price signals alone do not enforce network feasibility. The classical AC optimal power flow solve eliminates all violations but never converges within the five-minute settlement window at this scale, giving it a clearing success rate of zero. The QAOA market sacrifices approximately 3.4% of the theoretical maximum welfare relative to the unconstrained case, allows a small residual number of minor voltage excursions consistent with its 3.4% optimality gap, and achieves a 100% clearing success rate within the required window. This trade-off is consistent with the broader observation that machine-learning-accelerated and quantum-inspired solvers for optimal power flow generally exchange a bounded loss in optimality for a substantial gain in tractability at scale [7, 12].

4.3. Sensitivity to Circuit Depth and Penalty Weighting

The QAOA framework exposes two design parameters that directly trade solution quality against runtime and hardware feasibility: the circuit depth p and the dynamic penalty weights (ρ_P, ρ_Q, ρ_V) introduced in Section 2.2. Table 3 reports the optimality gap and wall-clock solution time for the 100,000-node network as p is varied from 1 to 8, holding the penalty weights fixed at their tuned values.

Table 3. Sensitivity of the 100,000-node solution to QAOA circuit depth

Circuit depth p	Optimality gap	Solution time (s)	Two-qubit gate count
1	9.7%	41.2	1.2×10^6
2	6.1%	52.6	2.4×10^6
4	3.4%	72.8	4.8×10^6
8	3.1%	138.5	9.6×10^6

Increasing p from 1 to 4 nearly triples the two-qubit gate count but reduces the optimality gap from 9.7% to 3.4%, and this is the operating point reported in Section 4. Beyond $p = 4$, returns diminish sharply: doubling the depth again to $p = 8$ reduces the gap by only a further 0.3 percentage points while nearly doubling both solution time and gate count, the latter of which directly increases exposure to the noise-induced barren plateaus discussed in Section 2.2 [8, 9]. This non-monotonic trade-off between depth and achievable accuracy on noisy hardware, rather than an unconstrained accuracy-versus-depth curve as would be expected in the noiseless limit, is consistent with the qubit-error-probability mitigation results reported for large QUBO instances [10], and it motivates our choice of $p = 4$ as the operating point that balances real-time feasibility against solution quality.

The penalty weights (ρ_P, ρ_Q, ρ_V) are similarly consequential. Setting them too low allows the optimizer to violate power-balance and voltage constraints in exchange for a lower QUBO cost, which manifests as additional voltage excursions beyond the 12 reported in Table 2; setting them too high flattens the cost landscape around the feasible region and slows convergence of the classical outer-loop optimizer, increasing solution time without a corresponding gain in feasibility. We tuned the three weights independently on the 10,000-node case using a coordinate-descent search over three orders of magnitude and held the resulting ratios fixed across the larger networks, a transfer that assumes the relative scale of power-balance, reactive-power, and voltage violations does not change materially with feeder size. This assumption held in our simulations, evidenced by the roughly proportional growth of the optimality gap from 1.8% to 3.4% as N grows tenfold in Table 1, but it is not guaranteed to hold on feeders with substantially different topology or reactive-power profiles, and re-tuning the penalty weights for each new network class remains a practical requirement of the proposed framework.

5. CONCLUSION

This paper presents a hybrid quantum-classical QAOA framework for clearing transactive energy markets under AC optimal power flow constraints at distribution-feeder scale. By encoding the joint market-clearing and power-flow problem as a QUBO with dynamic penalty weighting, the framework achieves sub-two-minute clearing times on synthetically expanded IEEE 8500-node networks with up to 100,000 distributed energy resources, where classical interior-point and global solvers either exceed the real-time deadline or fail to converge. These results suggest that QAOA-based market clearing is a viable computational foundation for decentralized, high-penetration renewable grids, while trainability and noise remain open challenges that will determine how the approach scales on near-term hardware [8, 10]. Future work will evaluate the framework on physical NISQ devices and extend the QUBO formulation to unbalanced three-phase feeders.

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