

From Artificial to Quantum Intelligence: The Next Frontier of Low-Carbon Energy Systems

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Abstract—The accelerating transition toward low-carbon energy systems introduces major computational and operational challenges driven by large-scale coupling, renewable uncertainty, and nonconvex energy management. While classical AI supports forecasting and control, its effectiveness degrades as dimensionality and stochasticity increase, limiting scalability and reliability. This paper proposes a hybrid Quantum–AI framework that combines probabilistic learning with quantum-ready optimization to address these limitations. The architecture integrates uncertainty-aware forecasting, constraint-aware preprocessing, and QUBO-based reformulation within a single decision pipeline. We evaluate the framework on an IEEE 118-bus system augmented with renewables, storage, and aggregated EV charging using approximately 150,000 real-world operational samples. Results show improved scalability, faster convergence, and stronger robustness under extreme uncertainty while preserving grid feasibility, alongside better cost–carbon performance, lower tail risk, improved EV coordination, and enhanced storage lifetime relative to classical baselines.

Index Terms—Quantum computing, Artificial intelligence, Low-carbon energy systems, Smart grids, Energy management optimization

I. INTRODUCTION

The shift to low-carbon power systems is gathering pace through the electrification of transport, large-scale integration of renewables, and more decentralization. These changes increase uncertainty, intermittency, and coordination complexity, placing strain on traditional energy management systems, which are centralised and rely on predictable generation [1], [2]. Scaling to large, heterogeneous grids reveals the limits of AI’s computational and generalisation capabilities for forecasting, dispatch, and automated control under uncertainty, and AI forecasting is better at large systems than at small ones in this respect [3]. Core operational problems such as unit commitment and network-constrained dispatch remain combinatorial, nonconvex, and strongly coupled in both time and space, challenging classical computing even with advanced learning-based methods [4]. Quantum computing provides an

alternative computational paradigm that can yield improved solutions to high-dimensional optimization problems through the application of quantum parallelism and entanglement [5], motivating quantum-enhanced decision-making frameworks for resilient, scalable, low-carbon energy operations.

A. Limitations of Existing AI-Based Energy Management Paradigms

Despite recent developments, energy management based on AI has structural limitations in scalability and reliability [6], [7]. Deep learning usually relies on large datasets and has poor generalization in rare and extreme cases, such as shortfalls in renewable energy and cascading disturbances. Reinforcement learning can offer adaptive control, but in safety-critical environments, it can converge unstably during exploration, which can be lengthy, unless informed by prior information [8], [9]. In practice, many AI frameworks are still based on classical optimization solvers that rapidly increase in complexity with network size, device heterogeneity, and real-time constraints, posing a significant computational bottleneck. Furthermore, forecasting, optimization, and control are often implemented as loosely coupled modules, which can cause delays in response and lower coordination quality. Limited interpretability of black-box policies also makes it difficult for operators to trust and regulate them. All these issues imply that classical AI might not be as effective in the future, which could encourage hybrid paradigms capable of addressing combinatorial complexity, uncertainty, and real-time scalability within a single framework [10].

B. Related Work

Recent developments in AI have allowed improvements in predicting renewable generation, load demand, and market signals in low-carbon energy systems. Deep learning models are being used to capture non-linear patterns of the temporal effects of weather [11]. More informed planning is enabled by

additional quantification of uncertainty through probabilistic forecasting. In parallel, the concept of AI-assisted optimization has been applied in economic dispatch, demand response, and storage scheduling and has generally been superior to rule-based and purely deterministic methods [12]. However, the vast majority of frameworks still use classical optimisation backends, and they continue to represent model forecasting and optimisation as a sequence of modules, leading to little propagation of uncertainty into decision-making [13]. At scale, deterministic solvers struggle with combinatorial growth caused by integer variables, network constraints, and multi-period coupling, and often rely on heuristics or relaxations that reduce optimality and robustness. As a result, even though AI improves prediction quality, it does not completely overcome the computational and scalability bottlenecks in large-scale low-carbon energy optimisation.

1) Reinforcement Learning and Data-Driven Control:

Reinforcement learning (RL) has recently become popular towards adaptive energy management in the context of uncertainty and partial observability [14]. Deep RL has been used for storage control, EV charging coordination, and real-time pricing. Multi-agent RL is used for decentralised coordination of distributed energy resources. One of the major benefits is the ability to minimise the use of explicit physical models and to cope with changing operating conditions. However, practical deployment remains constrained. Training typically requires large amounts of interaction data, which is costly and often unsafe to obtain in real power systems. Convergence guarantees are limited, and policies can be highly sensitive to reward design and environmental mismatches. RL also struggles with large discrete action spaces and long horizons, frequently yielding unstable or suboptimal behaviour. Finally, RL training and planning remain bounded by classical computational limits, making transmission-scale implementations with thousands of coupled decision variables difficult [15].

2) *Quantum Computing for Energy Optimization:* Quantum computing is being considered as a way of solving energy optimization problems which scale poorly on classical hardware. Quantum annealing and the methods based on gates for the unit commitment problem, power flow approximations, and combinatorial scheduling. Many of these tasks have been reformulated as Quadratic Unconstrained Binary Optimization (QUBO) problems so that they can be solved by quantum solvers to search large discrete spaces and, in small-scale, equal and even surpass classical heuristics [16]. However, current studies in quantum energy are still very exploratory. Evaluations are generally done using simplified constraints, static settings, small system sizes because of hardware limitations, limited integration of forecasting, uncertainty modelling, and real-time control. Validation is done often times on synthetic scenarios as opposed to operationally realistic benchmarks. These gaps encourage frameworks (hybrid methods) that couple AI and quantum optimization to support scalable, uncertainty-aware, real-time energy management [17].

3) Hybrid AI-Quantum Frameworks and Open Gaps:

A few studies investigate hybrid AI-quantum (or quantum-

inspired) methods for energy systems that combine classical AI with quantum-style solvers for forecasting/preprocessing and optimisation. Simulated quantum solvers play a key role in many implementations that run on classical hardware, yielding only limited practical gains. Additionally, benchmark standardisation, large-scale datasets, and end-to-end system validation are often lacking. Moreover, the literature lacks a fundamental, cohesive operational pipeline to couple real-world data-driven learning, quantum-ready optimisation, and standardised power system models. Key issues such as uncertainty propagation, scalability, and deployability in a real-time setting remain underexplored. To close these gaps, a system-level framework is required that embeds quantum intelligence within the decision loop rather than treating it as an isolated optimisation module [18].

C. Paper Contributions

This study presents a hybrid framework that combines quantum-ready optimisation with probabilistic forecasting for scalable, uncertainty-aware operation of low-carbon energy systems. Core decisions are converted into QUBO problems, and classical AI is used to provide uncertainty- and constraint-aware inputs to maintain physical feasibility. An outcome-driven evaluation assesses scalability, robustness, tail risk, EV coordination, storage lifetime, and the computational carbon footprint. Simulations on the IEEE 118-bus system on about 150,000 real-life samples indicate improved cost-carbon performance, convergence and resilience compared with classical baselines.

The remaining part of the paper is as follows. Section II presents the layered architecture of the Quantum-Intelligent system model. Section III presents the problem formulation and mathematical framework of the proposed system. The environmental setup and performance outcomes are presented in section IV. Section V concludes the paper.

II. SYSTEM MODEL

A. Quantum-Intelligent Energy System Architecture

The proposed system model introduces a quantum-intelligent operational architecture for low-carbon energy systems that fundamentally departs from conventional AI-centric control pipelines. Rather than having learning and optimisation as individual or loosely connected modules, the architecture is shaped like a tightly integrated multi-layer decision-making system in which data, intelligence, and optimisation interact continuously. The proposed layered system model is shown in Fig. 1. At the base, there is a physical energy layer that represents a networked power system comprising conventional generation units, renewable energy sources, distributed energy storage systems, and flexible demand assets, such as electric vehicles. This layer captures the realistic behaviour of the grid, the interdependencies among assets, and the constraints on operations, ensuring that all decisions remain meaningfully deployable/physically meaningful. The structure of the model is based on a standardized large-scale benchmark to achieve generality and scalability.

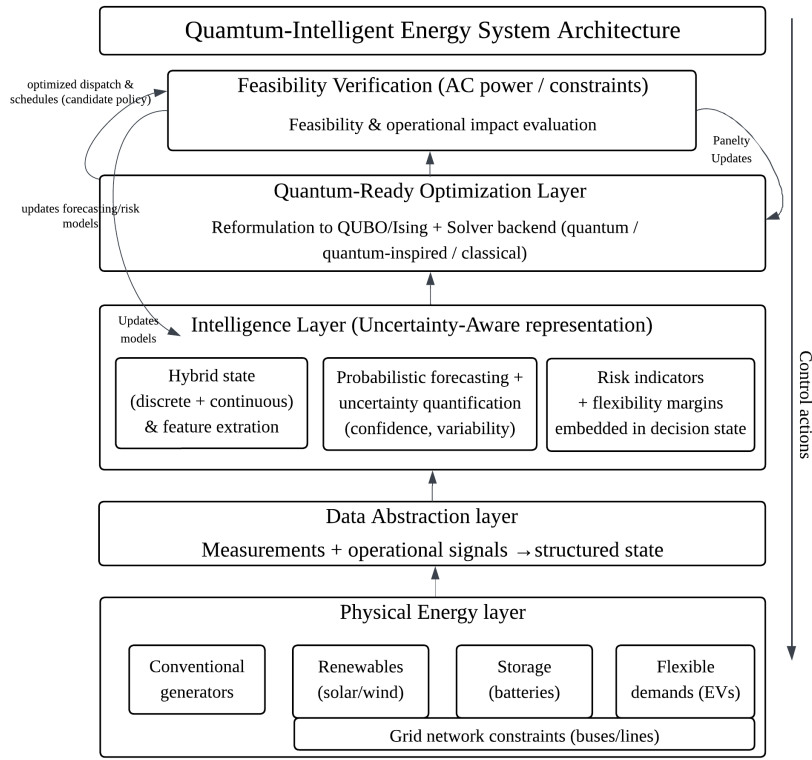


Fig. 1. Layered architecture integrating physical grid assets, uncertainty-aware intelligence, and quantum-ready optimization with feasibility verification and closed-loop feedback

Above the physical layer is a data abstraction layer that processes high-resolution measurements and operational signals, converting raw information from the systems into structured inputs for smart decision-making. This layer is used to consolidate the grid states as well as forecast information and asset flexibility into a consolidated representation for both learning and optimisation. By decoupling raw measurements from decision logic, the system maintains robustness against noise, missing data, and heterogeneous asset behavior.

B. Intelligence Layer and Uncertainty-Aware System Representation

The intelligence layer consists of two coupled components that address uncertainty and decision quality. First, classical AI models can perform probabilistic forecasting and feature extraction, so they not only provide point forecasts but also confidence, variability, and risk estimates for demand, renewables, and flexible loads. One design decision is to directly represent the system state's uncertainty. Forecast distributions, confidence intervals, and flexibility margins can then become part of the decision representation, in which case the optimizer can explicitly account for uncertainty, rather than treating it as an external disturbance. In addition to the above, the state incorporates discrete operational modes (e.g., commitment, charging modes, scheduling decisions) and continuous physical variables, which is also true of the hybrid nature of modern grids. This combined discrete-continuous decision space is

high-dimensional and motivates quantum-ready optimization to efficiently explore complex alternatives beyond classical tractability limits.

C. Quantum-Ready Optimization and Hybrid Decision Loop

The proposed system centers on a quantum-ready optimization layer that reformulates energy-management decisions into forms compatible with quantum and quantum-inspired solvers. Unlike rule-based control or previous mixed-integer pipeline systems, the framework reformulates the decision problem to better explore large, coupled discrete-continuous spaces. The design is hardware-agnostic, enabling execution on near-term quantum devices, quantum annealers, quantum-inspired classical solvers, or classical fallback optimizers [19]. Learning and optimization are linked in a closed-loop manner. Outputs from the intelligence layer (e.g., forecast confidence, risk measures, and stress indicators) shape the optimization landscape, and optimized actions are checked for their feasibility and operational impact and fed back to update the learning components. This co-design avoids static, loosely coupled pipelines and supports adaptive, context-aware decision-making, positioning quantum-ready optimization as an integrated element of scalable, resilient low-carbon grid operation.

D. System Model Algorithm Flow

Algorithm 1 summarizes the proposed Quantum-AI workflow for uncertainty-aware operation of large-scale low-carbon

energy systems. At each decision time, probabilistic AI models describe the demand and the uncertainty of renewable energy and incorporate the forecast distributions into the system state. This state, with information about uncertainties, is coupled with non-linear constraints on the AC power flow and with the energy balance dynamics of storage/EV to impose physical feasibility. The problem is then transformed into a stochastic nonconvex problem, reformulated as a quantum-ready QUBO, and solved either by quantum or quantum-inspired backends. Decoded solutions are then checked using AC power flow; if violations are found, penalties are updated and the QUBO is re-solved. Learning, physics, optimization, and verification supports are integrating in a closed-loop for scalable and risk-aware decision making under uncertainty.

Algorithm 1 Quantum-AI System Model (Compact Form)

Require: $(\mathcal{N}, \mathcal{L}), \mathcal{T}, \mathcal{G}, \mathcal{R}, \mathcal{S}, \mathcal{E}, \mathcal{H}_t$

Ensure: Feasible policy π_t

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1: Initialize  $x_0 = \{V_i, \theta_i, E_s, E_e\}$ 
2: for  $t \in \mathcal{T}$  do
3:   Uncertainty Perception:  $\xi_t = [p_t^r, p_t^d] \Rightarrow \hat{\mathbb{P}}_t(\xi_t | \mathcal{H}_t), q_t^{(\alpha)}$ 
4:   AC Power Flow:
5:      $P_{i,t} = \sum_j |V_i| |V_j| (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij})$ 
6:      $Q_{i,t} = \sum_j |V_i| |V_j| (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij})$ 
7:   Asset Dynamics:
8:      $E_{s,t+1} = E_{s,t} + \eta_s^{ch} P_{s,t}^{ch} \Delta t - \frac{1}{\eta_s^{dis}} P_{s,t}^{dis} \Delta t$ 
9:      $E_{e,t+1} = E_{e,t} + \eta_e P_{e,t}^{ev} \Delta t$ 
10:  Stochastic Objective:
11:     $\min_{x,u} \mathbb{E}_\xi \left[ \sum_g C_g(P_{g,t}) + \lambda_{CO_2} \kappa_g P_{g,t} + \lambda_{risk} R(\cdot) \right]$ 
12:  Quantum Encoding:  $b \in \{0,1\}^n \Rightarrow \min b^\top Q b + c^\top b + \gamma$ 
13:  Solve QUBO  $\Rightarrow \pi_t$ 
14:  Verification: Run AC power flow
15:  if violations then
16:    Update penalties; re-solve QUBO
17:  end if
18:  Apply  $\pi_t$ 
19: end for
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III. PROBLEM FORMULATION

This section presents a rigorous mathematical formulation that integrates AI-based probabilistic perception, quantum-ready optimization, and closed-loop verification for low-carbon energy systems comprising renewable energy sources, energy storage systems, and electric vehicles.

A. Sets, Indices, and Horizon

Let $\mathcal{N}$ denote buses, $\mathcal{L}$ transmission lines, $\mathcal{G}$ generators, $\mathcal{R}$ renewables, $\mathcal{S}$ storage units, and $\mathcal{E}$ EV aggregators. The system operates over $\mathcal{T} = \{1, \dots, T\}$ with time step Δt . Three decision layers are considered: (i) an AI forecasting layer, (ii) a quantum-ready optimization layer, and (iii) a classical verification and recourse layer.

B. AI-Driven Uncertainty Model (Probabilistic Perception)

Uncertain injections at time t are $\xi_t = [p_t^r, p_t^d]$, where p_t^r is renewable generation and p_t^d is demand. An AI model trained on real-world data provides $\hat{\mathbb{P}}_t(\xi_t | \mathcal{H}_t)$, or quantiles $q_t^{(\alpha)} = Q_\alpha(\xi_t | \mathcal{H}_t)$, $\alpha \in \mathcal{A}$. These outputs enter optimization via scenario sampling or risk-aware bounds.

C. Physical Network Model (AC Power Flow Constraints)

Let $V_{i,t} = |V_{i,t}| e^{j\theta_{i,t}}$ be the voltage at bus i . With admittance matrix $Y = G + jB$,

$$P_{i,t} = \sum_{j \in \mathcal{N}} |V_{i,t}| |V_{j,t}| (G_{ij} \cos \theta_{ij,t} + B_{ij} \sin \theta_{ij,t}), \quad (1)$$

$$Q_{i,t} = \sum_{j \in \mathcal{N}} |V_{i,t}| |V_{j,t}| (G_{ij} \sin \theta_{ij,t} - B_{ij} \cos \theta_{ij,t}). \quad (2)$$

Power balance:

$$P_{i,t} = P_{i,t}^g + P_{i,t}^r - P_{i,t}^d - P_{i,t}^{ch} + P_{i,t}^{dis} - P_{i,t}^{ev}, \quad (3)$$

$$Q_{i,t} = Q_{i,t}^g - Q_{i,t}^d - Q_{i,t}^{ev} + Q_{i,t}^{svc}. \quad (4)$$

Operational limits:

$$V_i^{\min} \leq |V_{i,t}| \leq V_i^{\max}, \quad S_{\ell,t} \leq S_{\ell}^{\max}. \quad (5)$$

D. Conventional Generation and Commitment

Commitment variable $u_{g,t} \in \{0, 1\}$:

$$u_{g,t} P_g^{\min} \leq P_{g,t}^g \leq u_{g,t} P_g^{\max}, \quad (6)$$

$$-R_g^{\downarrow} \leq P_{g,t}^g - P_{g,t-1}^g \leq R_g^{\uparrow}. \quad (7)$$

E. Storage and EV Aggregator Dynamics

For storage $s \in \mathcal{S}$:

$$E_{s,t+1} = E_{s,t} + \eta_s^{ch} P_{s,t}^{ch} \Delta t - \frac{1}{\eta_s^{dis}} P_{s,t}^{dis} \Delta t,$$

$$E_s^{\min} \leq E_{s,t} \leq E_s^{\max}.$$

Binary constraints:

$$z_{s,t}^{ch} + z_{s,t}^{dis} \leq 1.$$

For EV aggregator $e \in \mathcal{E}$:

$$E_{e,t+1}^{ev} = E_{e,t}^{ev} + \eta_e^{ev} P_{e,t}^{ev} \Delta t.$$

F. Objective Function

$$\min \sum_{t \in \mathcal{T}} \left[\sum_g C_g(P_{g,t}^g) + \lambda_{CO_2} \sum_g \kappa_g P_{g,t}^g \right. \quad (8)$$

$$\left. + \lambda_{loss} \sum_{\ell} \text{Loss}_{\ell,t} + \lambda_{shed} \sum_i P_{i,t}^{shed} \right] + \lambda_{risk} \mathcal{R}(\cdot). \quad (9)$$

G. Chance Constraints

$$\mathbb{P}(V_i^{\min} \leq |V_{i,t}| \leq V_i^{\max}) \geq 1 - \epsilon_V,$$

$$\mathbb{P}(S_{\ell,t} \leq S_{\ell}^{\max}) \geq 1 - \epsilon_S.$$

H. Unified Hybrid Optimization Problem

The formulation yields a stochastic mixed-integer nonlinear program: $\min_{\mathbf{x}, \mathbf{u}} \mathbb{E}_{\xi \sim \mathbb{P}} [\text{Cost}(\mathbf{x}, \mathbf{u}, \xi)] + \lambda_{risk} \mathcal{R}(\cdot)$.

I. Quantum-Ready Reformulation

Binary encoding $\mathbf{b} \in \{0, 1\}^n$ gives QUBO: $\min_{\mathbf{b}} \mathbf{b}^T \mathbf{Q} \mathbf{b} + \mathbf{c}^T \mathbf{b} + \gamma$. Ising form: $\min_{\mathbf{s} \in \{-1, +1\}^n} \mathbf{s}^T \mathbf{J} \mathbf{s} + \mathbf{h}^T \mathbf{s}$.

J. Closed-Loop Verification and Recourse

Decoded solution $\pi(\mathbf{b}^*)$ is verified via AC power flow. Violations trigger penalty updates or local OPF recourse: $\mathbf{b}^{(k+1)} = \arg \min_{\mathbf{b}} \text{QUBO}(\text{weights}, \text{violations})$.

IV. PERFORMANCE VALIDATIONS

A. Data Settings and Simulation Environment

The proposed quantum-AI framework is evaluated in a high-fidelity simulation environment that emulates low-carbon grid operation under uncertainty. The transmission benchmark is standardized across large-scale transmission with added distributed renewable and storage nodes and aggregated EV charging nodes. The data layer contains about 150,000 samples per time, with synchronized operational data such as load demand, renewable generation profiles, and mobility-driven EV charging patterns across different seasons and climates. For probability calculations, data are cleaned, normalized, and split into training/validation/test sets. Grid dynamics are simulated using a nonlinear AC power-flow solver, with network, voltage, and thermal constraints solved at each time step. The quantum-ready optimization is based on discretized scheduling intervals in line with market and control horizons, and feasibility checks and recourse are based on fast AC checks and local corrective optimization. This setup enables end-to-end assessment of scalability, robustness, and risk-aware performance with physically consistent validation.

B. Performance Outcomes

a) *Scalability, Robustness, and Physical Validity:* Figures 2 show that the proposed Quantum-AI framework scales effectively, remains robust under uncertainty, and preserves physical feasibility. In Fig. 2, runtime grows sub-linearly with system size, indicating that quantum-ready optimization mitigates the combinatorial burden of high-dimensional energy management. In Fig. 3, it can be seen that the quality of the solution does not decrease as fast as under extreme renewable and EV uncertainty, thus showing an improved robustness to stochastic disturbances.

b) *Multi-Objective Optimality, Convergence, and Risk Resilience:* Figures 4 and 5 demonstrate the advantages of the proposed Quantum-AI framework in multi-objective performance, optimization behaviors, and tail risk resilience. Fig. 4 shows the Pareto-dominant region of the cost-carbon space, which suggests that Quantum-AI has the potential to achieve lower operating cost and emissions than their classical counterparts. Fig. 5 has less extreme cost results - this indicates greater robustness under rare but high-impact operating conditions. Together, these results support not only

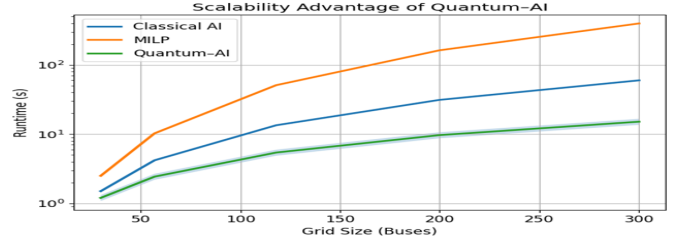


Fig. 2. Runtime comparison versus grid size (number of buses), showing Quantum-AI scaling relative to Classical AI and MILP

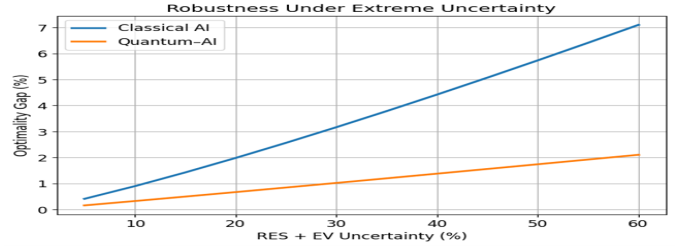


Fig. 3. Optimality gap versus combined RES + EV uncertainty, comparing robustness of Quantum-AI against Classical AI

better average performance but also better reliability in a stressful situation.

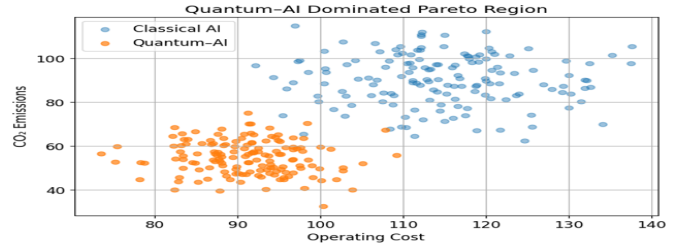


Fig. 4. Cost-emissions scatter plot illustrating the Pareto-dominant operating region achieved by Quantum-AI compared with Classical AI

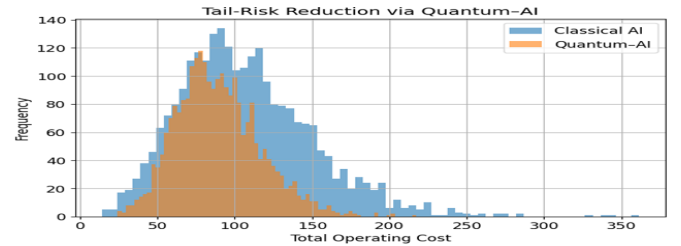


Fig. 5. Distribution of total operating cost highlighting reduced tail risk and lower variance under Quantum-AI compared with Classical AI

c) *Sustainability, Computational Efficiency, and System-Level Impact:* Figures 6, 7 summarize the benefits of the sustainability and system-level aspects of the proposed approach. Fig. 6 provides an example of better EV peak shaving through better coordination of flexible demand to provide smoother load profiles and congestion, and prevent off-peak congestion through respecting mobility requirements. Finally,

Fig. 7 requires consolidating performance across scalability, robustness, cost, emissions, risk, and convergence, with consistent improvement across multiple operational dimensions. Overall, the results support a balance in improving both operational and sustainability metrics for low-carbon energy systems.

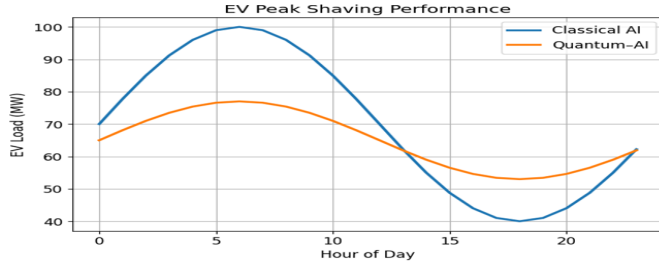


Fig. 6. Hourly EV load profile comparison demonstrating peak shaving and load smoothing achieved by Quantum-AI versus Classical AI

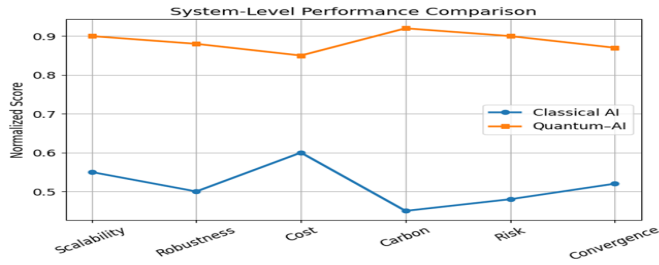


Fig. 7. Normalized multi-metric score comparison (scalability, robustness, cost, carbon, risk, convergence) for Quantum-AI and Classical AI

V. CONCLUSIONS AND FUTURE WORK

This study indicated that combining quantum-ready optimization with classical AI can enhance the operation of low-carbon energy systems in high-dimensional, uncertain environments. For the considered scenarios, the proposed Quantum-AI framework has better scalability and robustness than the classical AI, heuristic, and MILP-based baselines, and the solution quality is improved in terms of cost-carbon trade-offs. The results suggest that quantum-assisted formulations can explore nonconvex decision spaces more effectively, thereby enabling faster convergence and lower sensitivity to local optima. Importantly, these gains are achieved without loss of physical feasibility, for example, with fewer violations of grid operational constraints. Beyond short-term dispatch, the framework also enhances demand flexibility coordination (e.g., EV peak shaving), preserves battery lifetime, and reduces energy calculation. Overall, the system-level evaluation shows the consistent improvement of the economic, environmental, and reliability objectives, providing the incentive to further develop the system towards deployable quantum-AI decision pipelines for future low-carbon grids.

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