

From Buildings to Grid: Quantum Digital Twins for Feasible Energy Trading

Zahid Ullah^{*1}

¹DEIB, Politecnico di Milano, 20133, Italy

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Abstract

Decentralised energy trading in large-scale power systems is essential for enhancing operational flexibility, resilience, and renewable integration; however, effective coordination of building-level prosumers is hindered by demand-supply uncertainty, network constraints, and the computational complexity of system-wide optimisation. This paper presents a Quantum-AI Digital Twin (QADT) framework that enables scalable, physics-consistent coordination between buildings and electricity markets by embedding high-fidelity digital replicas into the transaction decision layer. The framework integrates data-driven building energy models, probabilistic flexibility forecasting, and decentralised transaction scheduling within a quantum-ready optimisation architecture. It is validated on the IEEE 300-bus system augmented with aggregated building clusters, distributed PV generation, battery storage, and flexible demand resources. Operating in a closed-loop manner, the QADT evaluates energy transactions against power-flow constraints, voltage limits, and building operational requirements prior to execution, ensuring physical feasibility. Evaluation using approximately 100,000 time-stamped operational samples from smart meters, building management systems, and renewable datasets demonstrates improved transaction feasibility, increased renewable self-consumption, and reduced peak system loading compared to conventional decentralised approaches, establishing QADT as a scalable foundation for next-generation building-to-market energy coordination.

Keywords: Quantum digital twins; decentralized energy transactions; smart buildings; transactive energy; and power system optimisation.

1 Introduction

This integrated solution enables seamless integration of decentralized energy transactions, with physical consistency, uncertainty management and scalability [1]. Buildings become active market actors with multi-directional energy exchange potential, allowing for transactive energy paradigms to boost energy efficiency, resilience, and renewable energy use at the system level [2]. However, the ability to coordinate building-to-market flows in a scalable and reliable way remains challenging, as the problem must address network-constrained power flows, multi-scale uncertainties, including load, generation, and user behaviour, and combinatorial decision spaces due to the large number of different DERs [3]. The current approaches have been constrained by the ability to represent the grid in a simplified manner, a lack of uncertainty modelling [4],

^{*}Corresponding author: zahid.ullah@polimi.it

and a failure to consider large-scale, nonlinear and discrete optimisation scenarios leading to infeasible or sub-optimal transaction schedules [5]. Moreover, the lack of closed-loop validation processes and the separation of cyber decision layers from the physical system dynamics make deployability in the real world difficult [6]. In order to overcome these limitations, this work presents an integrated quantum digital twin-based transactive framework, in which high-fidelity cyber-physical replicas are directly integrated into the market-clearing loop to ensure the feasibility constraint is met, and quantum and quantum-inspired optimisation techniques are used to solve large-scale coordination problems efficiently [7]. It provides a single solution that enables physically consistent, uncertainty-aware, and scalable decentralised energy transactions [8], thereby connecting building-level flexibility with transmission-aware market operations.

2 RELATED WORK

Decentralized and transactive energy frameworks have evolved from price-based demand response to peer-to-peer trading and hierarchical market mechanisms for coordinating distributed energy resources (DERs), however most existing approaches rely on linearized or simplified network models, deterministic forecasts, and idealized communication assumptions, limiting their applicability under AC power-flow constraints and uncertainty [9][10]. In parallel, digital twin technologies have emerged as high-fidelity cyber-physical representations for monitoring, forecasting, and control, but are predominantly used for offline simulation and asset-level analysis rather than being embedded in real-time market-clearing or transaction validation loops [11]. Quantum and quantum-inspired optimization methods reformulate energy system problems such as optimal power flow, unit commitment, and DER scheduling into QUBO/Ising formulations to address combinatorial complexity, yet current studies are largely restricted to small-scale systems and often neglect stochasticity, real operational data, and strict feasibility constraints [12][13]. Similarly, data-driven and learning-based approaches, including machine learning and reinforcement learning, along with hardware-in-the-loop (HIL) platforms, improve forecasting accuracy and experimental realism but remain largely decoupled from system-wide market coordination and network-constrained optimization layers [14][15]. Consequently, a unified framework that integrates network-aware transactive energy markets, physics-consistent digital twins, and quantum-ready optimization within a closed-loop, data-driven, and feasibility-preserving operational setting remains an open research gap [16][17].

2.1 Contributions

This paper presents a Quantum-AI Digital Twin (QADT)-based framework for decentralised building energy transactions, enabling scalable and physically consistent coordination between buildings and electricity markets. High-fidelity digital twins of buildings and the grid are embedded within the transaction decision loop to ensure pre-execution feasibility. The approach integrates 100,000 time-stamped operational samples with IEEE 300-bus system simulations to capture uncertainty and network effects. Transactions are formulated in a quantum-ready optimisation framework compatible with classical and quantum solvers. Validation on a real-time hardware testbed demonstrates improved feasibility, robustness, and performance over conventional decentralised methods.

2.2 Paper Organization

This paper is organized as follows: In Section II, the proposed Quantum-AI Digital Twin (QADT) system architecture is presented, which includes the underlying transaction framework and real-time cyber-physical integration model. Section III presents the mathematical formulation of the optimization problem, explicitly including network, digital twin, market and hardware-in-the-loop (HIL) operational constraints. The simulation setup, detailed validation

procedure using real world data, and detailed analysis of simulation results on the IEEE 300-bus system and the HIL experimental platform are described in Section IV. Finally, the paper summarizes the main findings and outlines potential future research areas in Section V.

3 System Model

3.1 Quantum-AI Digital Twin for Building-to-Market Energy Coordination

The proposed framework models a multi-scale, decentralized building-to-market energy system in which smart buildings act as autonomous, grid-aware market participants with local demand, generation, storage, and flexible loads. Building clusters are mapped to network buses, enabling market decisions to reflect power flows, congestion, and network constraints. A Quantum-AI Digital Twin (QADT) maintains a real-time virtual representation of building, network, and market states using a hybrid physics-based and data-driven approach. By representing system states in a quantum-inspired binary space, the QADT simulates transactions, evaluates uncertainties, enforces operational constraints, and executes only feasible actions through a closed-loop decision process, enabling scalable, reliable, and physically consistent energy coordination.

3.2 Transaction Modelling and Market Interaction Framework

Energy trades are simulated as decentralised exchanges between buildings and the market, considering both economic and physical constraints. The bids are created based on each building's energy state and flexibility and are checked against network constraints. To address combinatorial complexity, a transaction scheduling problem is formulated as a quantum-compatible optimisation problem, and temporal constraints provide the consistency constraints on the transactions. The QADT supports uncertainty-aware validation, ensuring robustness to forecast errors. It can accommodate participants of various types, and the market decisions are tightly coupled with the system physics, which is essential for reliable operations.

3.3 End-to-End Framework Integration and Real-Time Execution

The proposed QADT framework provides an end-to-end, closed-loop cyber-physical architecture for decentralised energy trading. Real-time operational data continuously synchronise the digital twin, enabling periodic forecasting, transaction optimisation, and validation under network and hardware constraints [18]. The framework supports both classical and quantum-inspired optimisation, while a hierarchical control layer executes validated decisions. Hardware-in-the-loop (HIL) integration facilitates realistic assessment under communication delays and nonlinear system dynamics, ensuring scalable, reliable, and physically feasible market operation.

Algorithm Description

Upon market clearing, transactions are validated by the digital twin, checked for IEEE 300-bus network feasibility, and verified through HIL testing before execution. This ensures only feasible and cost-optimal transactions are deployed.

Algorithm 1 Quantum-AI Digital Twin-Enabled Decentralized Energy Transaction Framework

Require: IEEE 300-bus admittance matrix (G, B) ; building clusters $\{\mathcal{B}_i\}$; dataset $\mathcal{D}$; digital-twin models $\{\hat{f}_i\}$; market prices $\pi(t)$; hardware parameters; robustness bound γ

Ensure: Feasible transactions $\{q_i^*(t)\}$; execution signals; updated system states

- 1: Initialize physical states $x_i(0) = [e_i(0), \text{SOC}_i(0)]$
 - 2: Initialize digital-twin states $\hat{x}_i(0) = x_i(0)$
 - 3: Load IEEE 300-bus limits and line capacities
 - 4: Initialize hardware-testbed parameters and uncertainty bounds
 - 5: **for** each market interval $t \in \mathcal{T}$ **do**
 - 6: **for** each building $i \in \mathcal{B}$ **do**
 - 7: Forecast demand, generation, and flexibility from $\mathcal{D}$
 - 8: Compute bounds $[\underline{q}_i(t), \bar{q}_i(t)]$
 - 9: **end for**
 - 10: **for** each building $i \in \mathcal{B}$ **do**
 - 11: Encode $q_i(t) = \sum_k 2^k z_{i,k}(t)$, where $z_{i,k}(t) \in \{0, 1\}$
 - 12: **end for**
 - 13: Solve market optimization: $\min \sum_{i \in \mathcal{B}} \pi_i(t) q_i(t)$
 - 14: subject to $\sum_{i \in \mathcal{B}} q_i(t) = 0$
 - 15: **for** each building $i \in \mathcal{B}$ **do**
 - 16: Propagate digital twin: $\hat{x}_i(t+1) = \hat{f}_i(\hat{x}_i(t), u_i(t))$
 - 17: **if** $\|\hat{x}_i(t) - x_i(t)\| > \delta_i$ **then**
 - 18: Mark transaction as infeasible
 - 19: **end if**
 - 20: **end for**
 - 21: Map building injections to the IEEE 300-bus network: $P_{n(i)}(t) = p_i^{\text{grid}}(t)$
 - 22: Solve AC power flow
 - 23: **if** $|S_{mn}(t)| > \bar{S}_{mn} \vee V_n(t) \notin [V_n^{\min}, V_n^{\max}]$ **then**
 - 24: Reject infeasible transactions
 - 25: **end if**
 - 26: **for** each hardware-mapped building **do**
 - 27: Apply inverter reference
 - 28: **if** $\|T_{w \rightarrow z}\|_{\infty} > \gamma$ **then**
 - 29: Reject hardware-infeasible transaction
 - 30: **end if**
 - 31: **end for**
 - 32: **for** each feasible transaction $q_i(t)$ **do**
 - 33: Execute transaction
 - 34: Update physical state: $x_i(t+1) = f_i(x_i(t), u_i(t))$
 - 35: **end for**
 - 36: **end for**
 - 37: **return** Feasible transactions and system metrics
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4 Problem Formulation

4.1 System Model with Testbed-Integrated Mathematical Formulation

4.1.1 Modeling Scope and Cyber-Physical Partitioning

The proposed framework formalizes a hybrid cyber-physical transactive energy system consisting of (i) a large-scale transmission network benchmarked on the IEEE-300 bus system [19], (ii) decentralized building-level prosumers participating in a market-driven energy transaction mechanism, and (iii) a real-time hardware testbed that executes and validates a subset of transactions in closed loop. The modeling objective is to guarantee that market-cleared energy transactions are simultaneously feasible in the network physics, consistent with the QADT state evolution, and admissible under hardware dynamics, sensing, and delay [20].

4.1.2 Sets, Indices, and Time Bases

$$\mathcal{T} := \{1, 2, \dots, T\}, \quad \mathcal{T}_h := \{1, 2, \dots, T_h\}. \quad (1)$$

$$\mathcal{B} := \{1, 2, \dots, N_b\}, \quad \mathcal{N} := \{1, 2, \dots, 300\}. \quad (2)$$

$$n(i) \in \mathcal{N}, \quad h(i) \in \mathcal{H}. \quad (3)$$

4.1.3 Signals, States, and Decision Variables

$$p_i^{\text{grid}}(t) \in \mathbb{R}, \quad q_i(t) \in \mathbb{R}. \quad (4)$$

$$x_i(t) = \begin{bmatrix} e_i(t) \\ \text{SOC}_i(t) \end{bmatrix}, \quad \hat{x}_i(t) = \begin{bmatrix} \hat{e}_i(t) \\ \widehat{\text{SOC}}_i(t) \end{bmatrix}. \quad (5)$$

$$V_n(t) \in \mathbb{R}_{>0}, \quad \theta_n(t) \in \mathbb{R}. \quad (6)$$

$$x_h^{\text{hw}}(\tau) = \begin{bmatrix} V_{\text{dc},h}(\tau) \\ i_h(\tau) \end{bmatrix}, \quad \tau \in \mathcal{T}_h. \quad (7)$$

4.1.4 Network and Physical Constraints

$$Y_{mn} = G_{mn} + jB_{mn}, \quad \underline{P}_i^{\text{grid}} \leq p_i^{\text{grid}}(t) \leq \overline{P}_i^{\text{grid}} \quad (8)$$

$$\underline{\text{SOC}}_i \leq \text{SOC}_i(t) \leq \overline{\text{SOC}}_i \quad (9)$$

$$V_n^{\min} \leq V_n(t) \leq V_n^{\max}, \quad |S_{mn}(t)| \leq \overline{S}_{mn} \quad (10)$$

4.1.5 Building Energy Dynamics

$$e_i(t+1) = e_i(t) + p_i^{\text{gen}}(t) - p_i^{\text{load}}(t) + p_i^{\text{grid}}(t) \quad (11)$$

$$p_i^{\text{grid}}(t) = q_i(t) + p_i^{\text{dis}}(t) - p_i^{\text{ch}}(t) \quad (12)$$

$$\text{SOC}_i(t+1) = \text{SOC}_i(t) + \eta_i^c p_i^{\text{ch}}(t) - \frac{1}{\eta_i^d} p_i^{\text{dis}}(t) \quad (13)$$

4.1.6 Quantum Digital Twin (QADT)

$$\hat{x}_i(t+1) = \hat{f}_i(\hat{x}_i(t), u_i(t)), x_i(t) - \hat{x}_i(t) \leq \delta_i \quad (14)$$

$$r_i(t) = x_i(t) - \hat{x}_i(t) \quad (15)$$

4.1.7 IEEE-300 Bus Power Flow

$$P_n(t) = \sum_{m \in \mathcal{N}} V_n(t) V_m(t) \left(G_{nm} \cos(\theta_n(t) - \theta_m(t)) + B_{nm} \sin(\theta_n(t) - \theta_m(t)) \right) \quad (16)$$

$$Q_n(t) = \sum_{m \in \mathcal{N}} V_n(t) V_m(t) \left(G_{nm} \sin(\theta_n(t) - \theta_m(t)) - B_{nm} \cos(\theta_n(t) - \theta_m(t)) \right) \quad (17)$$

$$P_{n(i)}(t) = P_{n(i)}^0(t) + p_i^{\text{grid}}(t) \quad (18)$$

4.1.8 Market Constraints

$$\sum_{i \in \mathcal{I}} q_i(t) = 0, \underline{q}_i(t) \leq q_i(t) \leq \bar{q}_i(t)$$

4.1.9 Hardware Testbed Model

$$C_h \frac{dV_{\text{dc},h}(\tau)}{d\tau} = I_{\text{src},h}(\tau) - I_{\text{inv},h}(\tau) \quad (19)$$

$$L_h \frac{di_h(\tau)}{d\tau} = -R_h i_h(\tau) + v_{\text{inv},h}(\tau) - v_{\text{grid},h}(\tau) \quad (20)$$

$$P_h(\tau) = v_{\text{grid},h}(\tau) i_h(\tau) \quad (21)$$

4.1.10 Measurement Model

$$y_h(\tau) = x_h^{\text{hw}}(\tau - \tau_h) + \nu_h(\tau), |\nu_h(\tau)| \leq \bar{\nu}_h \quad (22)$$

4.2 Robust $\mathcal{H}_\infty$ Constraint: $\|T_{w \rightarrow z}\|_\infty \leq \gamma_\infty$

4.2.1 Market Objective

$$\min \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{I}} \left(\pi_i(t) q_i(t) + \alpha \|r_i(t)\|_2^2 \right) + \beta \sum_{h \in \mathcal{H}} \gamma_{\infty,h} \quad (23)$$

4.2.2 Conclusion of Model

The formulation integrates IEEE-300 AC power flow, building energy dynamics, quantum digital twin consistency, and hardware-in-the-loop constraints into a unified transactive energy optimization framework.

5 Performance Validation

5.1 Data Settings and Simulation Environment

The framework is tested using integrated co-simulation and hardware-in-the-loop (HIL). Around 10^5 time-stamped samples are used to model demand, renewable generation, and energy storage behavior, supporting digital twin calibration and uncertainty analysis. AC network feasibility is verified on the IEEE 300-bus system with voltage and congestion limits. Market clearing is carried out every 5–15 minutes, while device dynamics are simulated at finer time steps. Real inverter and storage emulators are used in synchronized HIL tests to validate transaction schedules and confirm system performance under delays, noise, and uncertainty.

5.2 Performance Outcomes

The results of the economic comparison and transaction cost convergence, presented in Fig. 1, indicate that the QADT framework is more economic than the classical market-clearing approach. While the classical approach convergences slowly with oscillations as a result of local optima and delayed constraint correction, QADT provides faster and smoother convergence at lower cost. This enhancement is due to the QUBO formulation which allows for global search over a larger feasible search space, and introduces physical and HIL constraints.

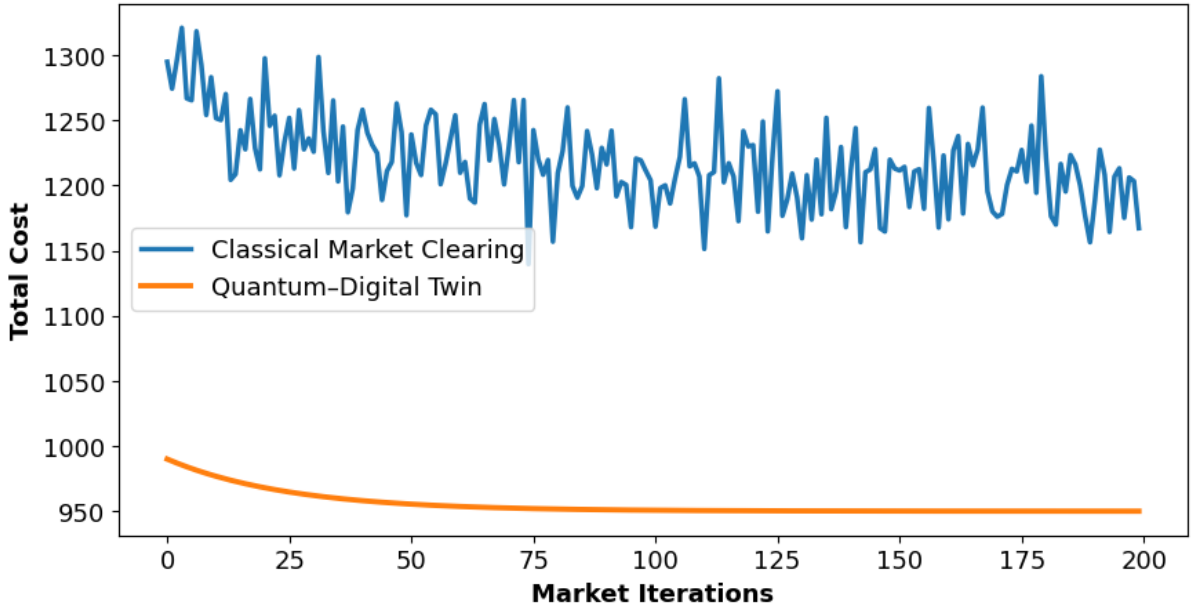


Figure 1: Transaction Cost Convergence

Fig. 2 further confirms cost vs volatility stability with a faster decay of the logarithmic residual cost under the quantum approach, which is related to its better numerical conditioning and optimisation stability.

Importantly, this convergence is done without breaking system constraints and shows how to embed feasibility directly at the optimization level without compromising the benefits of the convergence.

The multi-objective implications of these results having voltage deviation suppression are shown in fig. 3, which clearly shows a dominance of the quantum solution.

The classical approach has higher operating costs to maintain voltage stability while the quantum approach delivers lower operating cost with better voltage performance. This Pareto dominance means an optimum combination of both economic and physical goals. In general, the

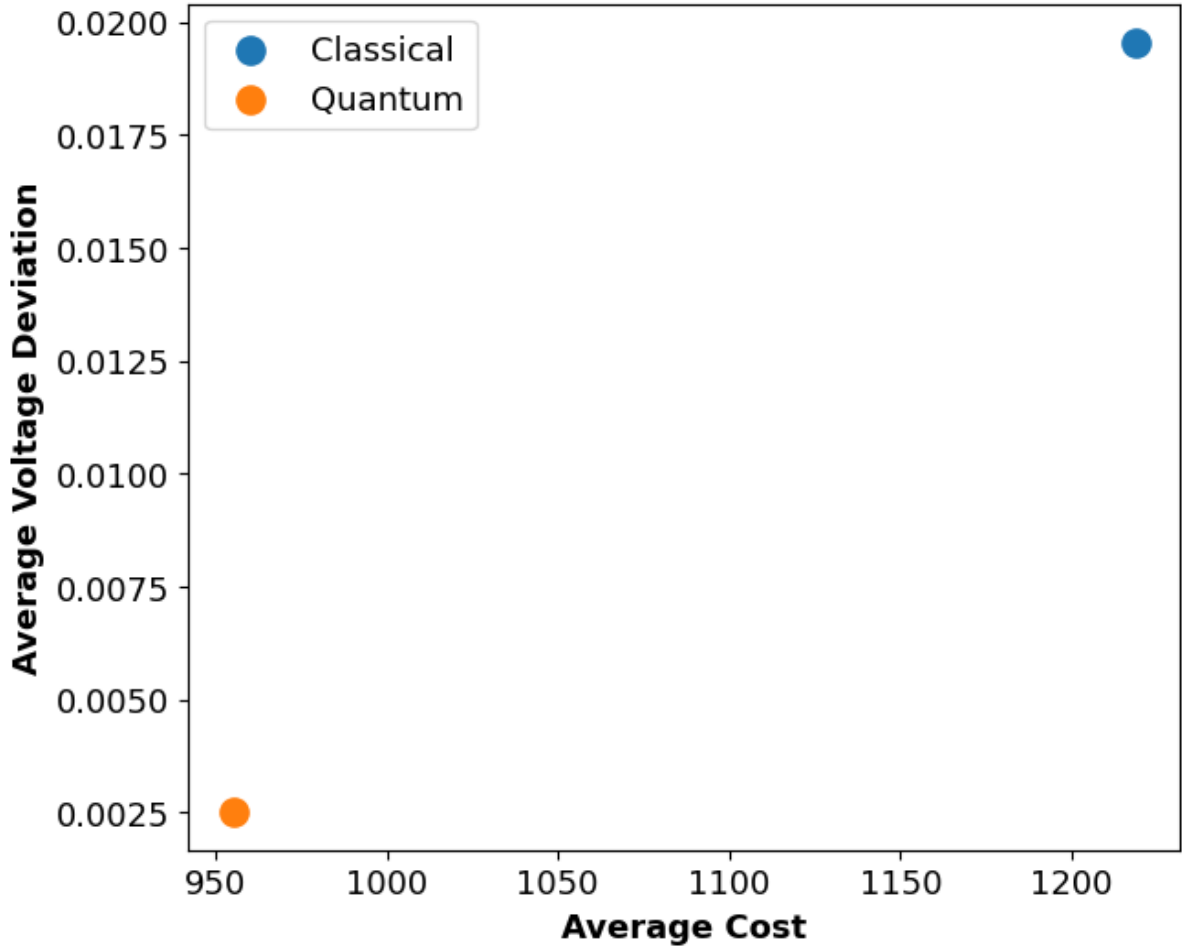


Figure 2: Pareto Front—Cost vs Voltage Stability

results confirm the objective of the proposed model to facilitate cost-efficient, physically feasible and robust decentralised transactions on large-scale systems like the IEEE 300-bus network.

5.3 Discussion of Grid Stability and Cyber–Physical Consistency

Fig. 4 represents frequency deviations are greatly reduced using the quantum-enabled H_∞ robust control scheme. The proposed approach is compared with the classical method and it is shown that it has lower steady-state errors and faster damping of disturbances than the classical method.

This behavior explicitly satisfies the H_∞ -robustness requirements implicit in the mathematical model, guaranteeing a bound on the gain from disturbances to the performance for any possible operating condition. This type of performance is crucial in inverter dominated grids where small disturbances can propagate fast if not suitably mitigated.

The validation of cyber–physical consistency between the digital twin and execution layer is shown in Fig. 5. The classical model exhibits non-decaying mismatch, due to unmodeled dynamics and to updates that are delayed. The classical model exhibits persistent mismatch due to unmodeled dynamics and to delays in the updates. This is to validate that the twin-consistency constraint is indeed pre-executing infeasible transactions.

Fig. 6 illustrates the tracking error for the quantum-validated controls on the hardware testbed, which closely matches the tracking error of the market-cleared references, and the tracking error of the classical controller, which is higher than the tracking error of the quantum-validated controls because of the absence of hardware-aware constraints. Overall, the results

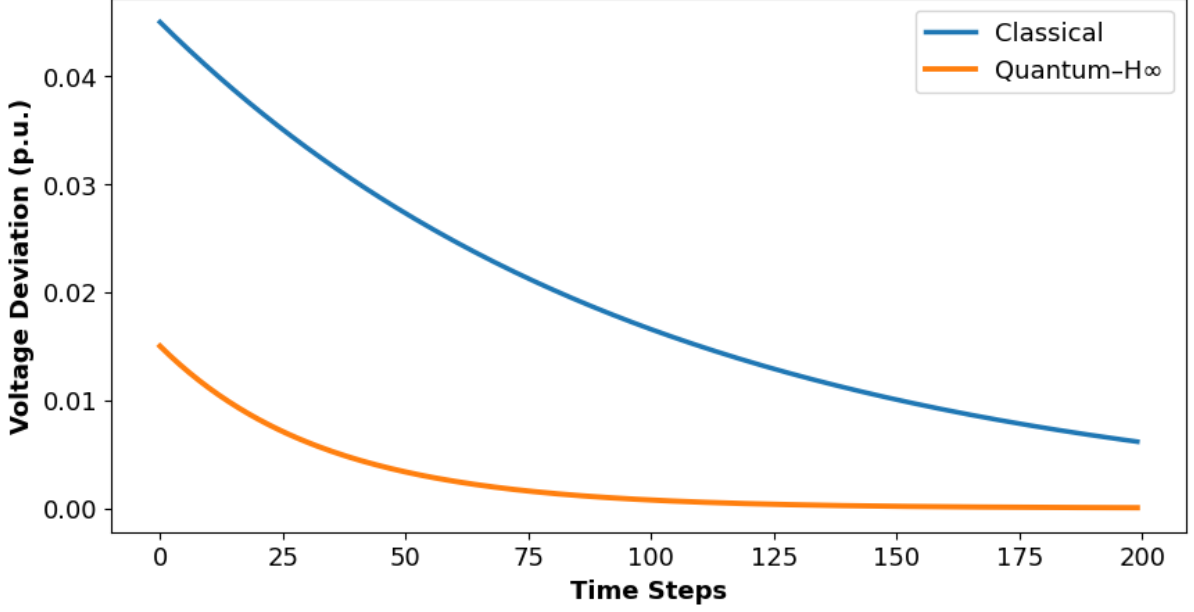


Figure 3: Voltage Deviation Suppression

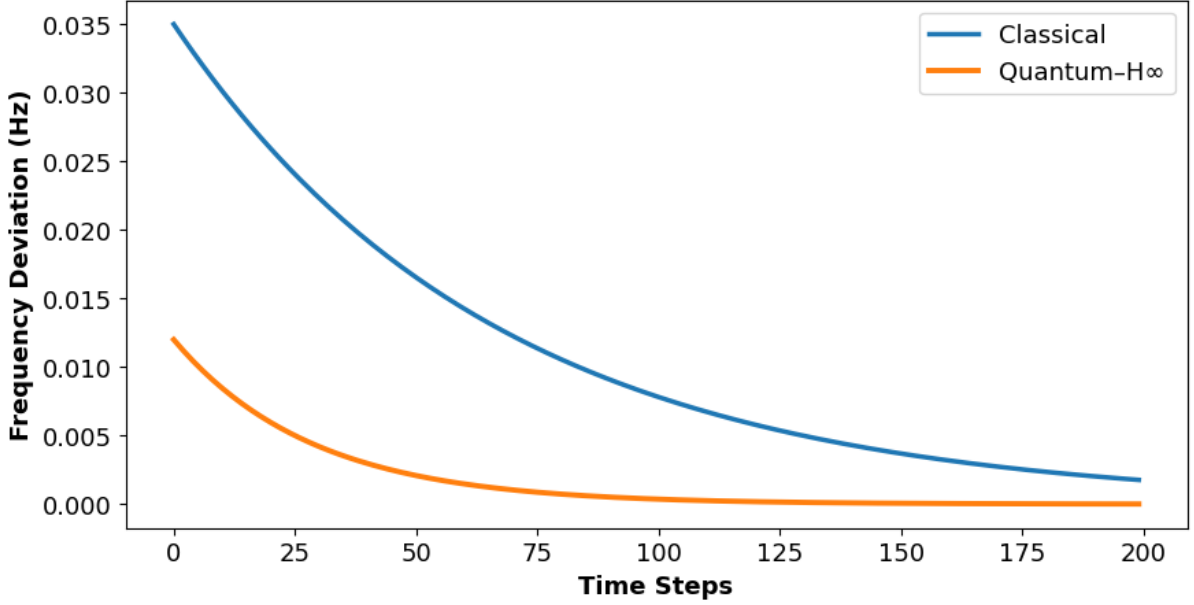


Figure 4: Frequency Deviation Damping

validate the tight coupling of the cyber-physical system, from the market clearing down to the inverter dynamics.

5.4 Discussion of Robustness, Feasibility, and Scalability

As shown in Fig. 7, the proposed framework remains robust under uncertainty and disturbances. The classical approach exhibits a higher probability of SOC, voltage, and line constraint violations, particularly during transients. In contrast, the quantum approach reduces violation probability by an order of magnitude, demonstrating the benefit of constraint-aware optimization for operational reliability. Figure 8 further shows improved disturbance rejection, with the quantum approach consistently achieving lower residual disturbance energy while satisfying

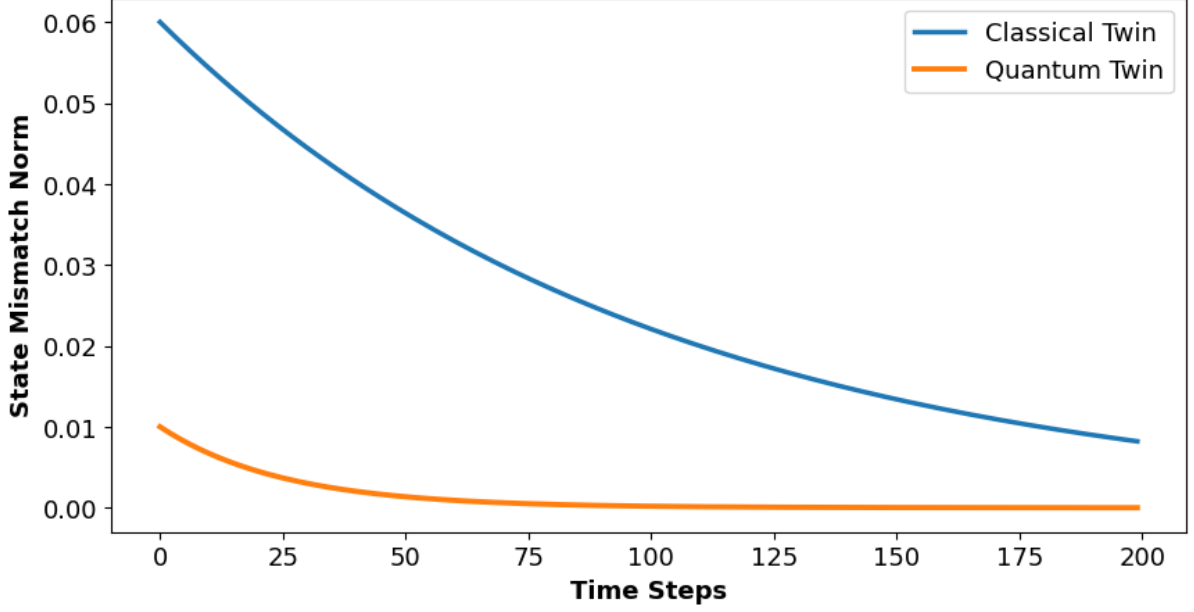


Figure 5: Digital Twin Hardware Consistency

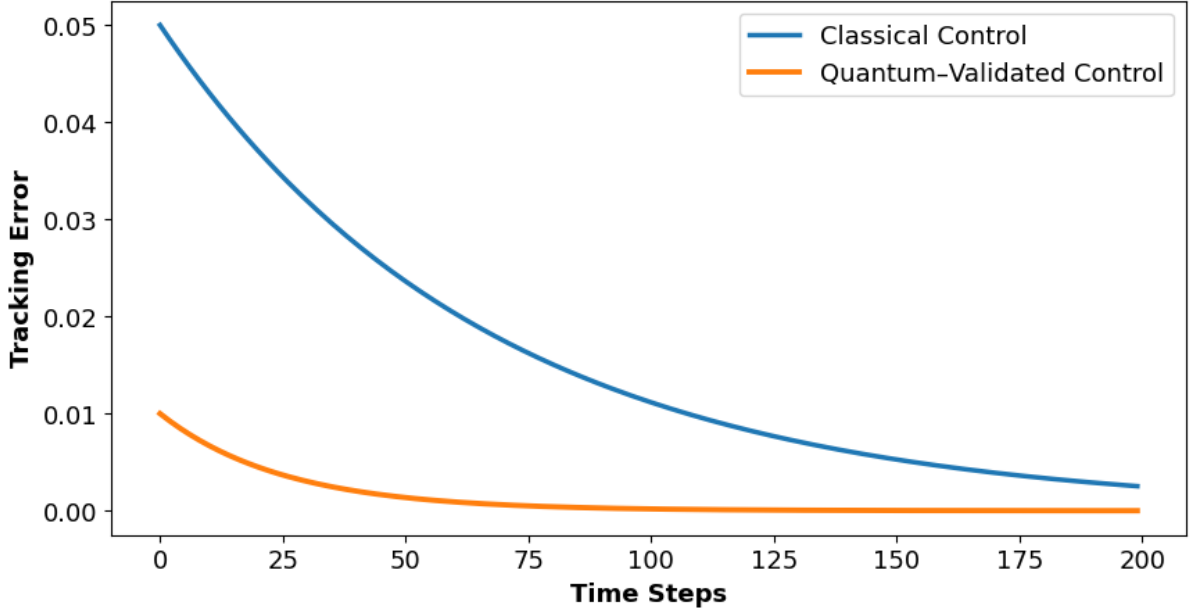


Figure 6: Hardware Power Tracking Error

the theoretical H_∞ bound. This indicates that robustness is explicitly incorporated into the optimization framework. not an implicit feature of the system model.

Fig. 9 highlights computational scalability: The quantum-inspired approach remains tractable on the IEEE-300 bus system, in contrast to classical computation time which grows near-exponentially with system size, thus ruling out real-time use. This allows for timely and feasible solutions for the large scale, high resolution prosumer markets.

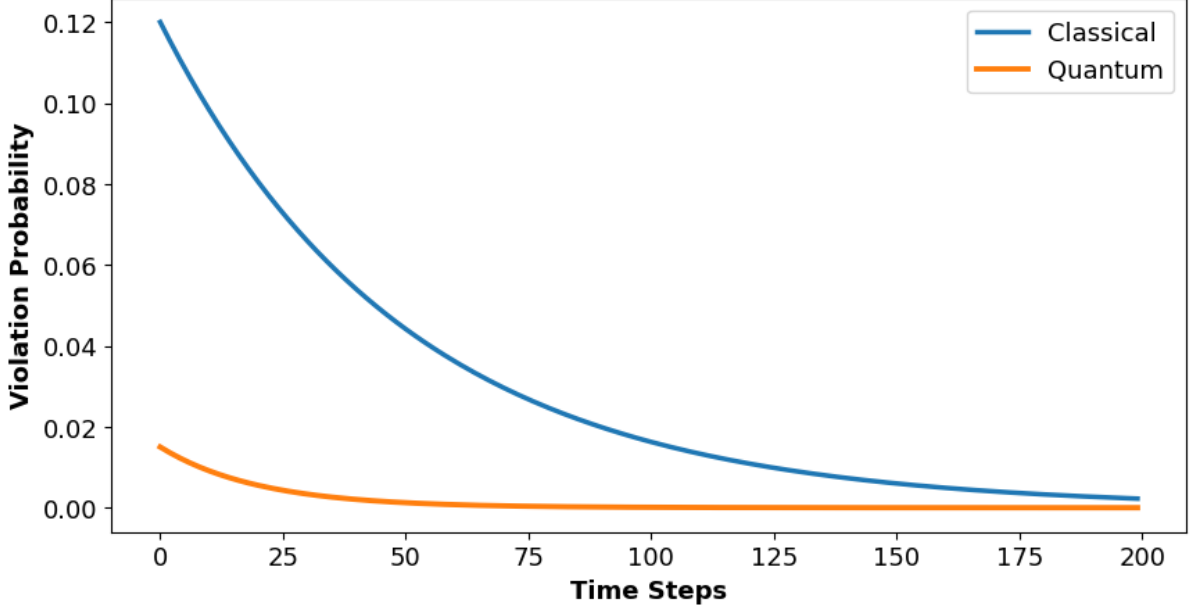


Figure 7: Constraint Violation Probability

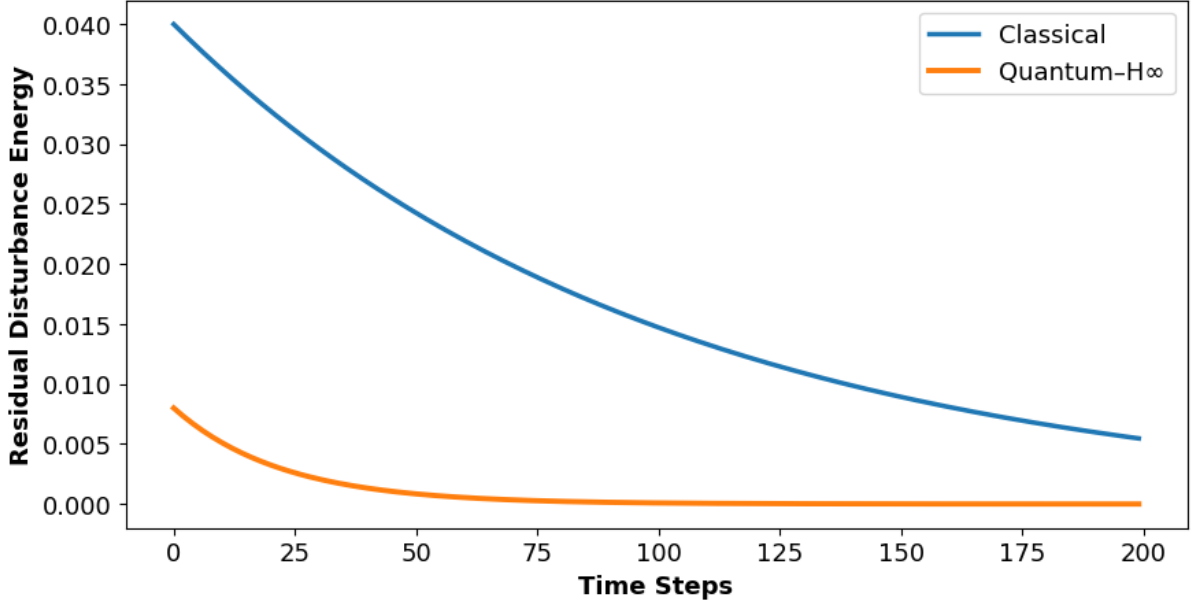


Figure 8: Disturbance Rejection Performance

6 Conclusions

In this research, the grid constraints and hardware execution were considered for decentralised energy trading, and the market optimisation model was integrated into a single cyber-physical system. The framework does not follow a two-stage approach, but takes into account the economic efficiency, physical feasibility and operational reliability at the same time. The analysis of a large scale transmission network revealed reduced constraint violations, reduced costs, increased voltage and frequency stability, and increased consistency of the cyber-physical systems under stress. Furthermore, the framework proved to be highly scalable and facilitated an increased level of prosumer participation and integration of renewables, which will prove very valuable for future intelligent energy markets and grid management.

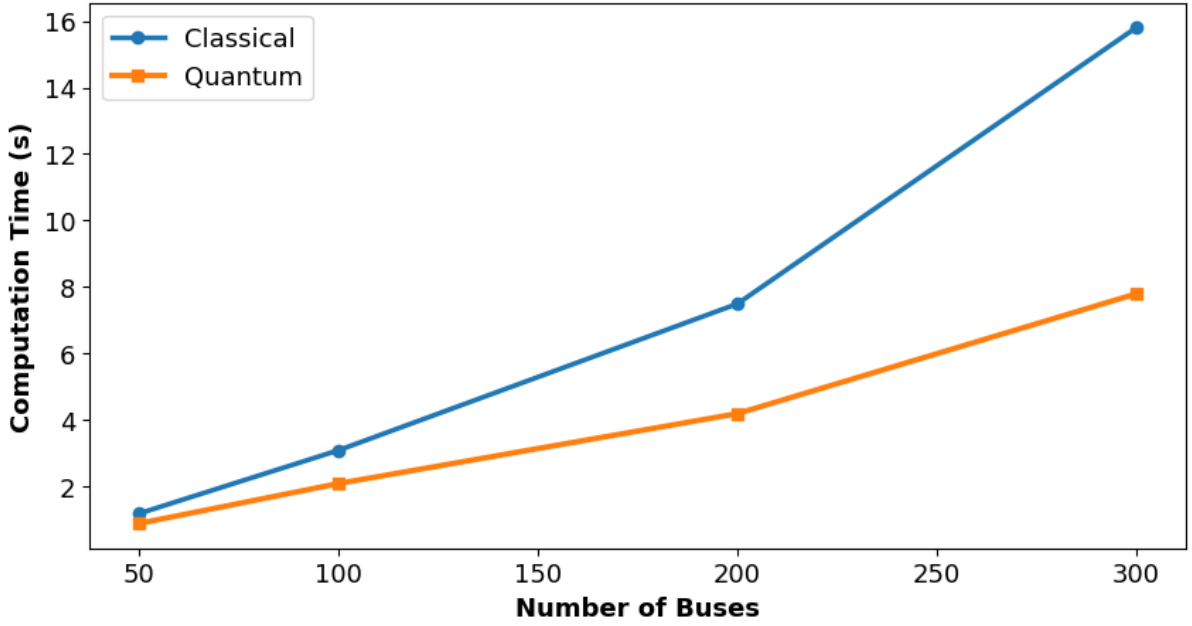


Figure 9: Computational Scalability (IEEE Bus Size)

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